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MARKET ENTRY COSTS, PRODUCER HETEROGENEITY, AND EXPORT DYNAMICS

BY SANGHAMITRA DAS, MARK J. ROBERTS, AND JAMES R. TYBOUT[1]

As the exchange rate, foreign demand, and production costs evolve, domestic producers are continually faced with two choices: whether to be an exporter and, if so, how much to export. We develop a dynamic structural model of export supply that characterizes these two decisions. The model embodies plant-level heterogeneity in export profits, uncertainty about the determinants of future profits, and market entry costs for new exporters. Using a Bayesian Monte Carlo Markov chain estimator, we fit this model to plant-level panel data on three Colombian manufacturing industries. We obtain profit function and sunk entry cost coefficients, and use them to simulate export responses to shifts in the exchange-rate process and several types of export subsidies. In each case, the aggregate export response depends on entry costs, expectations about the exchange rate process, prior exporting experience, and producer heterogeneity. Export revenue subsidies are far more effective at stimulating exports than policies that subsidize entry costs.

KEYWORDS: Dynamic export supply, plant heterogeneity, sunk costs, uncertainty.

1. INTRODUCTION

IN DEVELOPING COUNTRIES, industrial exporters are highly prized. They help to generate gains from trade through both comparative advantage effects and intra-industry resource re-allocations (Melitz (2003), Bernard, Eaton, Jensen, and Kortum (2003)). Also, because their product markets are diversified, they are well positioned to sustain their production and employment in the face of domestic recession. Finally, when their buyers provide them with blueprints or expertise, and when they monitor global market developments, exporting firms may facilitate the absorption of foreign technologies (Grossman and Helpman (1991), Westphal (2002)).

With these payoffs in mind, many countries have attempted to engineer industrial export booms. However, seemingly similar stimuli have given rise to very different export responses in different countries, industries, and time periods. Thus policy makers have often had trouble anticipating whether—and in which industries—a given devaluation, trade liberalization, or export subsidy scheme will generate a strong export response. This uncertainty has made it difficult to build political support for outward-oriented policy reforms (Fer-

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nandez and Rodrik (1991)). In some instances, unpredictable export responses also have increased the risk of postreform foreign exchange shortages.

To shed light on the issues of when and for which producers export promotion is likely to be effective, this paper develops a dynamic empirical model of firms' exporting behavior. The model embodies firm-level heterogeneity in export profits, uncertainty about the determinants of future profits, and sunk entry costs for firms breaking into foreign markets. It is motivated by the theories of export hysteresis first developed by Baldwin and Krugman (1989) and by Dixit (1989) to explain the unexpected persistence of the U.S. trade deficit during the mid-1980s.[2]

Like this earlier literature, the model highlights several key determinants of export supply responsiveness. First, expectations about future market conditions—for example, doubts about the permanence of policies that favor exports—affect firms' calculations concerning whether future export profits will cover entry costs. Second, entry costs make producers' export supply responses dependent on their previous exporting status. Those firms that already export can increase their volumes at marginal production costs, while those that do not must bear the sunk costs of breaking in before any exports are possible. These two margins of adjustment—volume and entry—have distinct determinants and lead to different supply elasticities, so seemingly similar industries with different degrees of foreign market presence may respond quite differently to exporting stimuli. Finally, depending on the distribution of exporting payoffs across firms within an industry, there may be many or few firms near their margin of indifference concerning whether to export.

We estimate our model using plant-level panel data on three Colombian manufacturing industries that differ in their exporting patterns and technologies: basic chemicals, leather products, and knitted fabrics. Then we use the results to simulate export responses to a shift in the mean of the exchange-rate process, a change in expectations about the exchange-rate process, and several types of export subsidies. For each experiment, we quantify the dependence of aggregate responses on sunk costs, exporting experience, and producer heterogeneity.

The simulations link each industry's export responsiveness to its microcharacteristics. They show that when many plants are clustered near their entry threshold, as in the knitted fabrics industry, the entry margin is a potentially important source of aggregate export response. Clustering can also make aggregate exports responsive to producers' expectations of future market conditions. In contrast, when plants are more heterogeneous and few are close to

[2]Several recent studies have suggested additional reasons for instability in exporting patterns. Yi (2003, p. 55) emphasized growing vertical specialization in response to falling trade costs, which increases "the amount of trade involved in getting a tractor to its final destination." Hooper, Johnson, and Marquez (2000) pointed to the effects of major structural shocks, particularly European reunification in the early 1990s.

their entry margins, as in the basic chemicals industry and the leather products industry, volume adjustments among incumbent exporters play a dominant role, while expectations are relatively unimportant. Finally, concerning export promotion schemes, the simulations show that policies targeting the volume margin generate much more export revenue per peso of subsidy than schemes that create incentives to enter foreign markets.

In addition to quantifying the microphenomena behind export responses, we make several methodological contributions. First, because we use a dynamic structural framework, we are able to estimate sunk entry costs in pesos, rather than simply test for their existence.[3] These costs are critical to policy evaluation, but they have rarely been estimated because they can be identified only by their very nonlinear effects on market participation patterns. Second, although we model producers as choosing foreign prices and export quantities, we cast the estimating equations in terms of the variables that we actually observe—export revenues and variable costs. We thus sidestep the problems of constructing proxies for prices and quantities from poorly measured variables that usually arise with plant-level survey data. Finally, we use a Bayesian Monte Carlo Markov chain (MCMC) estimator to estimate the export market participation rule and the export supply function in a single stage, thereby dealing with selection bias and efficiently exploiting the information in our data.

The remainder of the paper has four sections. Section 2 develops a dynamic empirical model of both the plant's discrete decision to participate in the export market and its continuous decision on the level of export revenue. Section 3 discusses econometric issues. Section 4 presents empirical results and Section 5 discusses their implications for export supply response. Finally, Section 6 offers concluding remarks.

2. AN EMPIRICAL MODEL OF EXPORTING DECISIONS WITH SUNK COSTS AND HETEROGENEITY

Our model of export supply is based on several key assumptions. First, domestic and foreign product markets are monopolistically competitive and segmented from one another. This rules out strategic competition but it ensures that firms face downward-sloping marginal revenue functions in each market. Second, marginal costs do not respond to output shocks. This assumption implies that shocks that shift the domestic demand schedule do not affect the optimal level of exports, so it allows us to focus on the export market only. Third, producers are heterogeneous in terms of their marginal production costs and the foreign demand schedules they face for their products, so export profit trajectories vary across firms. Fourth, future realizations on the exchange rate,

[3]Studies that infer the presence of sunk costs from persistence in exporting patterns include Roberts and Tybout (1997a), Campa (2004), Bernard and Jensen (2004), and Bernard and Wagner (2001).

marginal costs, and foreign demand shifters are unknown, but each evolves according to a known Markov process. Finally, firms must pay sunk start-up costs to initiate exports.

2.1. *Gross Export Profits and Revenues*

We begin by characterizing the export profit stream that awaits the ith firm, once it has broken into foreign markets. The magnitude of this stream depends on things that shift the marginal cost schedule, such as technology shocks and factor prices, and things that shift the foreign demand schedule, such as foreign income and the real exchange rate. We assume that marginal cost and foreign demand schedules are Cobb–Douglas functions of these factors, so that gross potential export profits are log linear in the same set of arguments:

$$\ln(\pi_{it}^*) = \psi_0 z_i + \psi_1 e_t + \nu_{it}. \tag{1}$$

Here π_{it}^* is firm i's gross potential export profit during year t ($i = 1, \dots, n$; $t = 1, \dots, T$), z_i is a k-element vector of time-invariant, firm-specific characteristics, e_t is the log of the real exchange rate, and ν_{it} is a stationary, serially correlated disturbance term that captures all idiosyncratic shocks to foreign demand and marginal production costs.[4]

Potential export profits evolve over time with exogenous shocks to e_t and ν_{it}. Without departing much from the available evidence, we assume that e follows a normal AR(1) process, with transition density

$$f_e(e'|e_t) = \phi\left(\frac{e' - \lambda_0 - \lambda_e e_t}{\sigma_w}\right)\sigma_w^{-1},$$

where $\phi(\cdot)$ is a standard normal density function.[5] Assuming that ν_{it} also follows a first-order process would be more problematic, given that profit shocks come from fluctuations in factor prices, productivity, and demand. We therefore express ν_{it} as the sum of m stationary, independent AR(1) processes, $\nu_{it} = \iota' x_{it}$, where ι is a column vector of m ones, and $x_{it} = (x_{1it}, x_{2it}, \dots, x_{mit})'$ is a column vector of m error components with joint transition density

$$f_x(x'|x_{it}) = \prod_{j=1}^{m} \phi\left(\frac{x'_{ji} - \lambda_x^j x_{jit}}{\sigma_{\omega j}}\right)\sigma_{\omega j}^{-1}.$$

[4]Conceptually, the model will accommodate additional time-varying profit determinants, such as capital stocks, foreign market size, and time trends. The cost of including such variables in the profit function is that it slows numerical solution of the dynamic optimization problem. In developing our specification, we experimented with time trends and found that they mattered little, so we opted to greatly improve our computation time by leaving a trend term out of equation (1).

[5]Rogoff (1996) and Froot and Rogoff (1995) surveyed the empirical literature on real exchange rate dynamics.

This formulation implies ν_{it} that has a stationary ARMA$(m, m-1)$ representation, which is quite general for large m. It also allows us to express profits exclusively in terms of first-order processes and to thereby keep calculations of firms' value functions simple. To simplify notation, let $\Psi = (\psi_{01}, \ldots, \psi_{0k}, \psi_1)$ collect the profit function parameters and let the diagonal matrices Σ_ω and Λ_x collect $\sigma^2_{\omega j}$'s and λ^j_x's, respectively.

As will be discussed shortly, our data set includes information on export revenues but not on export profits, so it is not possible to estimate Ψ, Λ_x, or Σ_ω directly from equation (1). To surmount this problem, we exploit the link between profits and revenues implied by profit maximization. Specifically, the domestic currency price of exports (P^f_{it}) is related to the marginal cost of their production (c_{it}) by $P^f_{it}(1-\eta_i^{-1}) = c_{it}$, where $\eta_i > 1$ is a firm-specific foreign demand elasticity. Multiplying both sides of this standard markup equation by the profit-maximizing quantity of foreign sales yields $R^{f^*}_{it}(1-\eta_i^{-1}) = C^{f^*}_{it}$, where $R^{f^*}_{it}$ and $C^{f^*}_{it}$ are potential export revenues and potential variable costs of exporting, respectively. Rearranging this result yields a simple expression for potential export profits in terms of potential export revenues:

$$\pi^*_{it} = R^{f^*}_{it} - C^{f^*}_{it} = \eta_i^{-1} R^{f^*}_{it}. \tag{2}$$

Finally, substituting (2) into (1) yields an export revenue function that can be used to identify Ψ, Σ_ω, and Λ_x:

$$\ln R^{f^*}_{it} = \ln \eta_i + \psi_0 z_i + \psi_1 e_t + \nu_{it}. \tag{3}$$

Equation (3) provides a basis for inference concerning the profit function parameters, but it also introduces a set of n firm-specific foreign demand elasticities, $\eta = \{\eta_i\}_{i=1}^n$, that must be estimated. To deal with this incidental parameters problem, we assume that the ratio of foreign demand elasticities to domestic demand elasticities is $(1+\upsilon)$ for all producers within an industry. Then by equation (2) and its analog for domestic sales (R^d_{it}) and domestic production costs (C^d_{it}), *total* production costs incurred by the ith producer are

$$C_{it} = C^f_{it} + C^d_{it} = R^f_{it}(1-\eta_i^{-1}) + R^d_{it}(1-\eta_i^{-1}\cdot(1+\upsilon)).$$

Rearranging this expression yields an equation in terms of observable variables that helps to identify foreign demand elasticities:[6]

$$1 - \frac{C_{it}}{R_{it}} = \eta_i^{-1}\left(1 + \upsilon\frac{R^d_{it}}{R_{it}}\right) + \xi_{it}. \tag{4}$$

[6]It is necessary to write our elasticity expression in terms of total production costs because survey data do not break down costs by product destination. Note that this formulation does not require that the marginal costs of producing for the foreign market match the marginal costs of producing for the domestic market; neither does it require that a given producer supply the same product to both destinations.

Here $R_{it} = R^d_{it} + R^f_{it}$ is total sales revenues, and we have added an error term, ξ_{it}, to accommodate noise in this relationship. We assume that ξ_{it} reflects discrepancies between reported variable costs and true variable costs, and that it follows a normal AR(1) process with transition density

$$f_\xi(\xi'|\xi_{it}) = \phi\left(\frac{\xi' - \lambda_\xi \xi_{it}}{\sigma_\varsigma}\right)\sigma_\varsigma^{-1}.$$

2.2. *The Export Market Participation Rule*

Because we have used a logarithmic functional form for equation (1), gross potential export profits are always positive. Nonetheless, firms may choose not to export for several reasons. First, firms that are not already exporting face the sunk start-up costs of establishing distribution channels, learning bureaucratic procedures, and adapting their products and packaging for foreign markets. Second, exporters incur some fixed costs each period to maintain a presence in foreign markets, including minimum freight and insurance charges, and the costs of monitoring foreign customs procedures and product standards.

Define the fixed costs of exporting to be $\gamma_F - \varepsilon_{1it}$, where γ_F is a parameter common to all firms and ε_{1it} captures all variation in fixed costs across firms and time. Also, define the start-up costs faced by the ith firm to be $\gamma_S z_i + \varepsilon_{1it} - \varepsilon_{2it}$, where γ_S is a $1 \times k$ vector of coefficients on the fixed plant characteristics z_i, and $\varepsilon_{1it} - \varepsilon_{2it}$ allows for cross-firm and intertemporal variation in start-up costs. Further, let $\varepsilon_{it} = (\varepsilon_{1it}, \varepsilon_{2it})$ be normally distributed, serially uncorrelated shocks, with transition density $f_\varepsilon(\varepsilon'|\varepsilon_{it}) = \prod_{j=1}^2 \phi(\varepsilon^{j'}/\sigma_{\varepsilon j})\sigma_{\varepsilon j}^{-1}$, and assume that ε_{it} is independent of x_{it} and e_t.[7] Also, to economize on notation, collect the parameters of f_ε in the matrix $\Sigma_\varepsilon = \text{diag}(\sigma^2_{\varepsilon 1}, \sigma^2_{\varepsilon 2})$, and collect the sunk and fixed costs parameters in the vector $\Gamma = (\gamma_{S1}, \dots, \gamma_{Sk}, \gamma_F)$.

Denote the gross profit function in equation (1) by $\pi^*(e_t, x_{it}, z_i)$ and assume that all sunk costs are borne in the first year of exporting. Then net current export profits for the ith firm in year t can be written as

$$u(\cdot) = \begin{cases} \pi^*(e_t, x_{it}, z_i) - \gamma_F + \varepsilon_{1it}, & \text{if } y_{it} = 1 \text{ and } y_{it-1} = 1, \\ \pi^*(e_t, x_{it}, z_i) - \gamma_F - \gamma_S z_i + \varepsilon_{2it}, & \text{if } y_{it} = 1 \text{ and } y_{it-1} = 0, \\ 0, & \text{if } y_{it} = 0, \end{cases} \tag{5}$$

where $y_{it} = 1$ if the ith firm exports during period t, and is zero otherwise. Note that net potential profits depend on the firm's export participation in the previous year, y_{it-1}, because that determines whether it must pay the sunk entry

[7]These conditional independence assumptions come from Rust (1988). They substantially simplify the numerical solution of the firm's dynamic optimization problem. Note that the errors ε_{it} can also be interpreted as the managers' transitory optimization errors when choosing export quantities or prices, as well as variation in fixed and sunk costs.

costs to export in year t.[8] Thus, as in Dixit (1989) and Baldwin and Krugman (1989), the return to becoming an exporter today includes the option value of being able to continue exporting next period without incurring start-up costs, which in turn depends on the perceived distribution of future potential exporting profits.

In period t, prior to making its exporting decision, the ith firm observes the current realizations on the arguments of its gross profit function (1): z_i, e_t, and x_{it}. These variables all follow first-order Markov processes, so they provide all of the information available at time t on the possible future paths for gross exporting profits. It follows that firm i maximizes its discounted expected profit stream over a planning horizon of H years by choosing the decision rule $y_{i\tau} = y(e_\tau, x_{i\tau}, z_i, \varepsilon_{i\tau}, y_{i\tau-1}|\theta)$ that solves

$$\max_{y(\cdot)} E_t \sum_{\tau=t}^{t+H} \delta^{\tau-t} u(e_\tau, x_{i\tau}, z_i, \varepsilon_{i\tau}, y_{i\tau-1}, y_{i\tau}|\theta). \tag{6}$$

Here E_t is the expectation operator conditioned on information available at time t, $\delta \in [0, 1)$ is a one-period discount factor, and $\theta = (\Psi, \eta, \upsilon, \Lambda_x, \Sigma_\omega, \Gamma, \Sigma_\varepsilon, \lambda_0, \lambda_e, \sigma_w, \lambda_\xi, \sigma_\varsigma)$ is the entire parameter vector.

To characterize the decision rule $y(\cdot)$, note that expression (6) is equal to the value function that solves the Bellman equation,[9]

$$V_{it} = \max_{y_{it}\in\{0,1\}} [u(e_t, x_{it}, z_i, \varepsilon_{it}, y_{it}, y_{it-1}|\theta) + \delta E_t V_{it+1}], \tag{7}$$

where

$$E_t V_{it+1} = \int_{e'} \int_{x'} \int_{\varepsilon'} V_{it+1} \cdot f_e(e'|e_t, \theta) \times f_x(x'|x_{it}, \theta) \cdot f_\varepsilon(\varepsilon'|\varepsilon_{it}, \theta)\, d\varepsilon'\, dx'\, de'.$$

Thus exporting choices maximize the bracketed term in (7), and the decision rule can be written as $y_{it} = I(y^*_{it} > 0)$, where $I(\cdot)$ is an indicator function,

$$y^*_{it} = u(e_t, x_{it}, z_i, \varepsilon_{it}, 1, y_{it-1}|\theta) + \delta\Delta E_t V_{it+1}(e_t, x_{it}, z_i|\theta), \tag{8}$$

[8] Equation (5) implies that firms completely lose their investment in start-up costs if they are absent from the export market for a single year. Thus all firms that did not export in year $t-1$ are treated the same in year t, regardless of their more distant history. Earlier studies suggest that these investments depreciate very quickly, and that firms that most recently exported 2 years ago must pay nearly as much to reenter foreign markets as firms that never exported (Roberts and Tybout (1997a)). In light of these findings, and given that more general representations make structural estimation intractable, we consider (5) to be a reasonable abstraction.

[9] The transition densities f_e, f_x, and f_ε and equation (6) satisfy the regularity conditions required for the existence and uniqueness of the value function: time separability of the profit function, a Markovian transition density for the state variables, and a discount rate less than 1. See Rust (1996, Section 2).

and

$$\Delta E_t V_{it+1}(e_t, x_{it}, z_i|\theta) = E_t[V_{it+1}|y_{it} = 1] - E[V_{it+1}|y_{it} = 0].$$

Note that the first component of y^*_{it} measures the current net operating profit from exporting and the second component measures the option value of being able to export next period without incurring entry costs.

To summarize the model, profit shocks (x_{it}), entry cost and fixed cost shocks (ε_{it}), and the exchange rate (e_t) follow exogenous processes. Together with exogenous plant characteristics (z_i), they determine the latent variables R^{f*}_{it} and y^*_{it}, which in turn determine observed export participation patterns $y_{it} = I(y^*_{it} > 0)$ and export revenues $R^f_{it} = I(y^*_{it} > 0) \cdot R^{f*}_{it}$. (Total costs ($C$) and domestic revenues (R^d) also respond to the strictly exogenous variables.) The next section describes our approach to estimating the structural parameters upon which these relationships depend.[10]

3. ESTIMATION

The data set that we use to estimate the model described above is typical of the plant-level panels collected by national statistical agencies. For each manufacturing industry, it includes plant- and year-specific information on total variable costs (C_{it}), domestic sales revenue (R^d_{it}), and realized export revenues (R^f_{it}). It also includes plant-specific information on some time-invariant characteristics such as location, size, and business type (z_i), but it does not include information on profits from exporting, exporting costs, producer-specific prices, or producer-specific quantities. Augmented by a log real effective exchange-rate series (e_t), the available sample information for the ith producer is thus $D_i = (y^T_{i0}, R^{fT}_{i0}, R^{dT}_{i0}, C^T_{i0}, e^T_0, z_i)$, where, for any variable W, we use W^t_s to denote $(W_s, W_{s+1}, \dots, W_t)$.

Intuitively, it is possible to associate different types of variation in the data with the identification of different parameters. Plant-specific demand elasticities are identified by plant-specific ratios of total revenues to total variable costs and by the fraction of revenues that come from exporting. The revenue function parameters—including the x_{it} process—are identified by variation in export revenues among incumbent exporters and through time. Sunk entry costs are identified by differences in exporting frequencies across plants that have comparable expected profit streams, but differ in terms of whether they

[10]Earlier models of the decision to export were based on reduced-form versions of equation (8), and thus have not identified the underlying structural parameters (Roberts and Tybout (1997a), Campa (2004), Bernard and Jensen (2004), and Bernard and Wagner (2001)). These authors tested for and found state dependence that is consistent with the presence of sunk entry costs. However, because they are not structural and they do not model the export volume decision, they do not provide a basis for linking industry-level export supplies to firm-level behavior.

exported in the previous period.[11] Finally, given profit streams and sunk costs, the frequency of exit among firms with positive gross profit streams identifies fixed costs.

More formally, we estimate the parameters of our model using a type II tobit likelihood function, generalized to deal with serially correlated errors (x_{it}'s), endogenous initial conditions (y_{i0}'s), and incidental parameters (η_i's). To develop this function, we first note that each element of $x_{i0}^T = (x_{i0}, \dots, x_{iT})$ can be written as a linear combination of the uncensored export profit shocks (ν_{it}'s) and a vector of mT independent and identically distributed standard normal variates (hereafter denoted μ_i).[12] This implies that there exist functions $x_{is}^t = x_s^t(\nu_i^+, \mu_i)$ and $x_{it} = x_t(\nu_i^+, \mu_i)$, where $\nu_i^+ = \{\ln R_{it}^f - \ln \eta_i - \psi_0 z_i - \psi_1 e_t; R_{it}^f > 0\}$ is the set of uncensored ν_{it}'s. Thus, letting the joint density functions for μ_i and ν_i^+ be $g(\mu_i)$ and $h(\nu_i^+)$, respectively, and ignoring for now the information contained in domestic sales revenues and production costs, we can write the ith plant's contribution to the likelihood function (suppressing θ) as[13]

$$
\begin{aligned}
(9)\qquad P[y_{i0}^T, R_{i0}^{fT} | e_0^T, z_i] &= P[y_{i0}^T, \nu_i^+ | e_0^T, z_i] \\
&= P[y_{i0}^T | \nu_i^+, e_0^T, z_i] \cdot h(\nu_i^+) \\
&= \left[\int_{\mu_i} P[y_{i0}^T | e_0^T, x_0^T(\nu_i^+, \mu_i), z_i] \cdot g(\mu_i)\, d\mu_i \right] \cdot h(\nu_i^+).
\end{aligned}
$$

The first equality in (9) reflects the fact that $(y_{i0}^T, R_{i0}^{fT} | e_0^T, z_i)$ and $(y_{i0}^T, \nu_i^+ | e_0^T, z_i)$ convey the same information. The second equality breaks the likelihood expression for $(y_{i0}^T, \nu_i^+ | e_0^T, z_i)$ into the product of the conditional distribution for $(y_{i0}^T | \nu_i^+, e_0^T, z_i)$ and the marginal density for ν_i^+. The last equality replaces ν_i^+ with x_{i0}^T in the set of conditioning variables for the probability of y_{i0}^T.

This change of variables in the last line of (9) links our likelihood expression to the exporting decision rule developed in Section 2. To see how, factor the joint probability of plant i's exporting decisions as

$$
\begin{aligned}
(10)\qquad & P[y_{i0}^T | e_0^T, x_0^T(\nu_i^+, \mu_i), z_i] \\
&\quad = P[y_{i1}^T | e_1^T, x_1^T(\nu_i^+, \mu_i), z_i, y_{i0}] \cdot P[y_{i0} | e_0, x_0(\nu_i^+, \mu_i), z_i].
\end{aligned}
$$

[11]Unlike x_{it}, sunk costs induce true state dependence. Chamberlain (1985) provided an early discussion of the reasons that these two sources of persistence are statistically distinguishable.

[12]This is possible because $\nu_{it} = \iota' x_{it}$ and the elements of x_{i0}^T are jointly normal. More precisely, if the ith plant exports in $q_i > 0$ years, the elements of x_{i0}^T can be expressed as $\mathbf{x}_{i0}^T = A\nu_i^t + B\mu_i$, where $\mathbf{x}_{i0}^T = (x_{i0}', \dots, x_{iT}')'$ is an $mT \times 1$ reshaping of x_{i0}^T, ν_{i0}^+ is a $q_i \times 1$ vector that consists of the uncensored profit shocks, and A and B are conformable matrices of parameters. The nonzero elements of A and B are functions of $(\Lambda_x, \Sigma_\omega)$, and q_i columns in B are zeros. For plants that never export, the function simplifies to $\mathbf{x}_{i0}^T = B\mu_i$. These results are developed and discussed in Section A.2.

[13]The density $g(\mu_i)$ is simply a product of mT univariate standard normal densities. The density $h(\nu_i^+)$ is multivariate normal with zero mean and covariance matrix determined by $(\Lambda_x, \Sigma_\omega)$. Section A.1 provides details.

Then, exploiting the serial independence of ε_{it}, further factor the first right-hand term in (10) to obtain

$$(11)\qquad P[y_{i1}^T|e_1^T, x_1^T(\nu_i^+, \mu_i), z_i, y_{i0}] = \prod_{t=1}^{T}\big(E_{\varepsilon_{it}} I[y_{it}^* > 0|e_t, x_t(\nu_i^+, \mu_i), z_i, \varepsilon_{it}, y_{it-1}]\big)^{y_{it}} \times \big(E_{\varepsilon_{it}} I[y_{it}^* \leq 0|e_t, x_t(\nu_i^+, \mu_i), z_i, \varepsilon_{it}, y_{it-1}]\big)^{1-y_{it}}.$$

Clearly, this expression allows one to calculate the joint probability of plant i's exporting decisions in years 1 through T using equation (8), $x_{it} = x_t(\nu_i^+, \mu_i)$, and f_ε.[14]

It remains to discuss evaluation of the second right-hand side term in (10)—the probability of exporting in year 0. This expression is not conditioned on lagged exports, so it cannot be constructed directly from (8) and y_{i0} cannot be treated as an exogenous conditioning variable.[15] In principle, it would be possible to deal with this "initial conditions problem" by treating $P[y_{i0}|e_0, x_0(\nu_i^+, \mu_i), z_i]$ as the steady state probability implied by equation (8), f_ε, and f_x.[16] However, it is time-consuming to simulate this probability and, as discussed below, we need to evaluate our likelihood function hundreds of thousands of times. We therefore use Heckman's (1981) method for dealing with the first sample year instead. This amounts to expressing the probability of exporting in the initial year as a reduced-form probit,

$$(12)\qquad P[y_{i0}|e_0, x_0(\nu_i^+, \mu_i), z_i] = \Phi(\alpha_0 + \alpha_1' z_i + \alpha_2' x_0(\nu_i^+, \mu_i))^{y_{i0}} \times \big[1 - \Phi(\alpha_0 + \alpha_1' z_i + \alpha_2' x_0(\nu_i^+, \mu_i))\big]^{1-y_{i0}},$$

where $\alpha' = (\alpha_0, \alpha_1', \alpha_2')$ is a vector of unconstrained parameters to be estimated, hereafter absorbed into θ. (Note that the exchange rate is common to all plants in period 0, so its effect is included in α_0.)

Identification of nonlinear panel data models with unobserved individual effects generally "requires distributional assumptions on the initial conditions process if there is serial correlation in the unobserved transitory error components and/or lags of the dependent variable are used as explanatory variables" (Honoré and Kyriazidou (2000, p. 840)). Our model exhibits these features and Heckman's (1981) method provides such a distributional assumption

[14]Section A.3 describes our procedure for evaluating y_{it}^*, given its arguments.

[15]Plant i's initial exporting status depends on x_{i0}, which in turn is correlated with x_{i1}^T. Thus y_{i0} is not independent of x_{i1}^T, and this dependence must be recognized when performing the integration described in the last line of equation (9). For recent discussions of this problem and further references, see Arellano and Honoré (2001) and Honoré and Tamer (2006).

[16]Hsiao (1986) describes this type of approach in the context of a simpler dynamic discrete choice model.

on y_{i0}. Nonetheless, for several reasons, this extra structure is not critical in the present context. First, as will be discussed shortly, we use a Bayesian estimator. Thus if point identification were to fail, it would simply affect the tightness of the posterior distributions. Second, identification is aided by the fact that the unobserved individual effects (x's) in the export revenue equation (3) are the same as the unobserved individual effects in the export market participation equation (8). Thus the uncensored realizations on $\nu_{it} = \iota' x_{it}$ help to identify the transition density f_x, as discussed above. Third, recent numerical experiments suggest that the long time dimension ($T = 10$) in our data set and the fact that z_i is time invariant both help to identify the model. More precisely, without imposing any distributional assumptions on y_{i0} and using a relatively simple dynamic discrete choice model with individual effects, Honoré and Tamer (2006) found that identification is more likely for data sets with longer time dimensions ($T > 3$) and with observations on different y realizations at the same explanatory variable realizations. These authors also find that when parameters are not point identified, the models they consider "restrict the parameters to lie in a region that is very small in many cases, and the failure of point identification may, therefore, be of little practical importance..." (p. 611).

Thus far, we have essentially generalized the type II tobit likelihood function to allow for a general form of serial correlation and endogenous initial conditions.[17] We now further depart from the standard type II tobit specification by

[17] To see the relationship between our likelihood function and a type II tobit function, note that if x_{it} were serially independent, y_{i0} would be independent of $(x_{i1}, \varepsilon_{i1}^T)$ and could be treated as exogenous. Thus there would be no initial conditions problem. Also, only one error component would be needed ($m = 1$) and, in exporting years, that error could be expressed in terms of observables $\nu_{it} \equiv x_{it} = \ln R_{it}^f - \psi_0 e_t - \psi_1 z_i$. It would not be necessary to introduce μ_i; neither would it be necessary to integrate over x_{it} in exporting years. Furthermore, serial independence of the profit shocks would allow one to write the unconditional density function for the uncensored export revenue shocks as

$$h(\nu_i^+) = \prod_{t=0}^{T} \left[\phi\left(\frac{\nu_{it}}{\sigma_\omega} \sigma_\omega^{-1} \right) \right]^{y_{it}} = \prod_{t=0}^{T} \left[\phi\left(\frac{\ln R_{it}^f - \eta_i - \psi_0 z_i - \psi_1 e_t}{\sigma_\omega} \right) \sigma_\omega^{-1} \right]^{y_{it}}.$$

Equation (9), conditioned on information from the initial sample year, would therefore become

$$P[y_{i1}^T, \nu_i^+ | e, z_i, y_{i0}, \nu_{i0}, \theta] = \prod_{t=1}^{T} \left\{ \left(\int_{\nu_{it}} P[y_{it}^* \leq 0 | e_t, \nu_{it}, z_i, y_{it-1}, \theta] \phi\left(\frac{\nu_{it}}{\sigma_\omega} \right) \sigma_\omega^{-1} \, d\nu_{it} \right)^{1-y_{it}} \right.$$
$$\left. \times \left(P[y_{it}^* > 0 | e_t, \nu_{it}, z_i, y_{it-1}, \theta] \cdot \phi\left(\frac{\nu_{it}}{\sigma_\omega} \right) \sigma_\omega^{-1} \right)^{y_{it}} \right\}.$$

So except for the nonlinearity in the relationship between y_{it}^* and $\nu_{it} \equiv x_{it}$, which prevents one from writing the integral in the last line in closed form, equation (9) would be equivalent to Amemiya's (1985, p. 386) likelihood function for a type II tobit. It is worth noting that if we were to abandon our ARMA$(m, m-1)$ representation of the profit function disturbance in favor of time-invariant plant effects, Kyriazidou's (1999) fixed-effects approach to tobit estimation would be a feasible alternative estimation strategy.

incorporating the information on demand elasticities that is contained in total variable cost realizations (C_{i0}^T) and domestic revenues (R_{i0}^{dT}). By equation (4), costs are a deterministic function of domestic and foreign revenues, up to measurement errors ξ_{it}. This error is independent of the other disturbances in the model, so the density for variable costs conditioned on revenues can be added multiplicatively to equation (9). Recognizing the dependence of the expressions developed above on θ, the likelihood function for the entire sample can then be expressed as

$$L(D|\theta) = \prod_{i=1}^{n} f_c(C_{i0}^T | R_{i0}^{fT}, R_{i0}^{dT}) \cdot P[y_{i0}^T, R_{i0}^{fT} | e_0^T, z_i], \tag{13}$$

where $D = \{D_i\}_{i=1}^n$ is the complete data set and $f_c(C_{i0}^T | R_{i0}^{fT}, R_{i0}^{dT})$ is the density for the sequence of $T+1$ realizations on C_{it} implied by f_ξ and equation (4).

The likelihood function is not globally concave in θ, so simple optimization algorithms may not find its maximum. It also poses an incidental parameters problem, given that each firm-specific demand elasticity is identified with only T observations. We deal with these problems by using a Bayesian Monte Carlo Markov chain (MCMC) estimator. This changes the estimation problem from one of finding a global optimum to one of characterizing a posterior distribution and makes the nonconvexity of the likelihood surface manageable. It has the added benefit of allowing us to exploit information from the existing literature on foreign demand elasticities.

To implement the estimator, we specify a prior density function $q(\theta)$ for the unknown parameters. Combining this with the likelihood function described above, we then obtain the posterior distribution for θ as the joint distribution for θ and the data, divided by the marginal distribution for the data: $P[\theta|D] = q(\theta) \cdot L(D|\theta) / \int_\theta q(\theta) \cdot L(D|\theta)\, d\theta$. Estimation then amounts to characterizing this distribution numerically. It is not possible to do so using closed-form expressions, but it is possible to sample from $P[\theta|D]$ using a Metropolis–Hastings sampling algorithm (e.g., Gilks, Richardson, and Speigelhalter (1996); Geweke (1997)). By drawing a large sample and constructing the associated moments, we impute the posterior means and variances of θ. We also experiment with the priors to determine their influence on the estimates.[18]

[18]A supplement to this paper, which is posted on the *Econometrica* web site (Das, Roberts, and Tybout (2007)), details the MCMC estimator and reports the results of the sensitivity experiments.

4. FITTING THE MODEL TO THREE COLOMBIAN INDUSTRIES

4.1. *The Data*

Because we are interested in studying why different industries respond differently to the same export stimuli, we estimate the structural parameter vector θ separately for three Colombian industries: leather products, knitted fabrics, and basic chemicals.[19] These country and industry choices reflect several considerations. First, partly because of real exchange-rate depreciation, Colombia experienced a manufacturing export boom during the sample period (1981–1991). Second, among manufacturers, these industries are relatively export oriented, and each exhibits export market entry and exit in most of the sample years. Thus they exhibit the type of variation needed to make inferences about sunk entry costs. Third, these industries differ in terms of their product markets and production technologies. Knitted fabrics and basic chemicals are exported mainly to Latin America, while leather products are exported mainly to the United States and Europe.[20] This provides us with some basis for generalization about the effects of sunk costs and heterogeneity in different settings. Finally, by developing the model on one industry (basic chemicals) and then applying it to each of the others, we are able to check the robustness of the specification.

Our data set describes the 32 leather products producers, 40 basic chemicals producers, and 64 knit fabric producers that operated continuously in the domestic market during the period 1981–1991.[21] It was originally collected by Colombia's Departamento Administrativo Nacional de Estadistica (DANE) and it was cleaned as described by Roberts and Tybout (1996, Chapter 10). Later we will provide more descriptive detail on the dynamic behavior of the plants in these samples. For now suffice it to note that between 1982 and 1991 each sector registered a strong export response. As Colombia's real effective exchange depreciated about 33 percent over this period, real exports of knitted fabrics, leather products, and basic chemicals grew at *annualized* rates of 26

[19]The data do not link plants common to a firm, so we treat the plant as the decision-making unit. This is potentially problematic because among multiplant firms, plant-level exports may partly respond to characteristics of other production units. However, the vast majority of Colombian firms operate a single plant.

[20]Statements concerning trade flows are based on the World Bank's Trade and Production Database, which is available at www.worldbank.org/research/trade. Our plant-level data do not reveal destination markets for exported goods.

[21]Our results describe decisions by existing domestic producers to diversify into foreign markets and/or to adjust their export volumes. A more general framework would treat each plant as making simultaneous decisions to enter or exit production and to enter or exit the export market. This would require us to model the sunk costs involved in setting up a plant. In Colombia, most exports over the sample period came from the plants that were continuously in operation; focusing solely on this group of plants is a reasonable starting point that substantially simplifies the empirical model.

percent, 16 percent, and 19 percent, respectively. Simultaneously, the percentage of plants engaged in exporting rose from 12 to 18 in knitted fabrics, from 50 to 58 in leather products, and from 42 to 50 in basic chemicals. By 1991, the share of export sales coming from plants that were nonexporters in 1982 was 66 percent for knitted fabrics, 21 percent for leather products, and only 2 percent for basic chemicals.

4.2. *Estimation Preliminaries*

Before estimating the model, we must choose the number of AR(1) processes m that will appear additively in the compound profit function disturbance ν. We cannot use the MCMC estimator to perform standard tests for the nature of serial correlation, given the time involved in generating a set of results. We therefore proceed under the maintained hypothesis that $m = 2$.[22] One interpretation for this specification is that profit shocks arise from both demand and cost shocks, and each follows an AR(1) process. The discount rate δ was set equal to 0.9. Some trials with other values of the discount rate showed it had little effect on the findings.

Next, we must be specific about the variables included in z_i. This vector is meant to capture time-invariant heterogeneity in operating profits and in sunk costs. We model this heterogeneity using a size dummy based on domestic sales in year 0. This dummy should proxy for both product quality and marginal production costs at the beginning of the sample period.[23]

Finally, we must specify a prior distribution, $q(\theta)$, for the parameters to be estimated. The distribution we choose, summarized in the last column of Table I, is a product of independent parameter-specific distributions; it reflects several considerations. First, to impose stationarity on all stochastic processes in the model but otherwise leave these parameters completely determined by the data, we specify that each root is uniform on the range $[-1, 1]$. Second, to impose nonnegativity on all variance parameters and leave them otherwise unconstrained, our prior is that their logs are distributed normally with mean 0 and standard deviation 20. This implies that the prior standard deviations for the parameters themselves are on the order of exp(400), so their distributions are essentially uniform on the positive domain. Third, for the parameters unconstrained by theory, we also want to impose very diffuse priors. Thus the profit function coefficients, the coefficients of the initial conditions equation, sunk costs, and fixed costs are all assigned a normal prior with mean zero and

[22] Exploratory tests based on equation (3) suggest that the disturbance of equation (3) follows an ARMA(2, 1) process, which implies that $m = 2$ is appropriate. Das, Roberts, and Tybout (2001) provided details.

[23] Experimentation with other dummies based on geographic location and business type yielded similar results, as did a larger set of dummies that distinguished producers by size quartiles. Given that computation time is approximately proportional to the number of plant types that we distinguish, we chose to economize on profit function parameters.

TABLE I

POSTERIOR PARAMETER DISTRIBUTIONS (MEANS AND STANDARD DEVIATIONS)

	Leather Products	Basic Chemicals	Knitted Fabrics	Priors
Profit Function Parameters				
ψ_{01} (intercept)	−13.645 (4.505)	1.143 (3.642)	−12.965 (3.058)	$\psi_{01} \sim \mathrm{N}(0, 500)$
ψ_{02} (domestic size dummy)	1.544 (0.789)	1.862 (0.813)	1.362 (0.449)	$\psi_{02} \sim \mathrm{N}(0, 500)$
ψ_1 (exchange rate coefficient)	4.323 (0.957)	0.975 (0.745)	4.047 (0.640)	$\psi_1 \sim \mathrm{N}(0, 500)$
λ_x^1 (root, first AR process)	0.787 (0.180)	−0.383 (0.186)	0.458 (0.258)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$
λ_x^2 (root, second AR process)	0.952 (0.018)	0.951 (0.022)	0.709 (0.103)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$
$\sigma_{\omega 1}^2$ (variance, first AR process)	0.282 (0.144)	0.320 (0.109)	0.469 (0.250)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$
$\sigma_{\omega 2}^2$ (variance, second AR process)	0.422 (0.146)	0.491 (0.137)	0.809 (0.264)	$\ln(\sigma_{\omega 2}^2) \sim \mathrm{N}(0, 20)$
υ (foreign elasticity premium)	−0.016 (0.022)	0.849 (0.126)	0.950 (0.047)	$\upsilon \sim \mathrm{U}(-1, 1)$
λ_ξ (root, measurement error)	0.336 (0.070)	0.962 (0.011)	0.935 (0.013)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$
σ_ξ (std. error, ξ innovations)	0.011 (0.001)	1.277 (0.389)	1.312 (0.264)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$
Foreign Demand Elasticities (quintiles only)				
η_{Q1} (demand elasticity, quintile 1)	8.020 (2.907)	12.098 (13.881)	10.289 (12.032)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$
η_{Q2} (demand elasticity, quintile 2)	12.282 (13.351)	12.974 (18.682)	12.314 (8.330)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$
η_{Q3} (demand elasticity, quintile 3)	17.866 (11.089)	14.139 (13.363)	13.780 (16.725)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$
η_{Q4} (demand elasticity, quintile 4)	37.189 (25.331)	24.604 (27.253)	36.279 (32.844)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$
Dynamic Discrete Choice Parameters				
γ_{S_1} (sunk cost, size class 1)	63.690 (1.934)	62.223 (3.345)	61.064 (2.628)	$\gamma_{S_1} \sim \mathrm{N}(0, 500)$
γ_{S_2} (sunk cost, size class 2)	52.615 (4.398)	50.561 (5.043)	59.484 (2.361)	$\gamma_{S_2} \sim \mathrm{N}(0, 500)$
γ_F (fixed cost)	−0.610 (1.042)	1.635 (0.983)	1.372 (1.340)	$\gamma_F \sim \mathrm{N}(0, 500)$
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	12.854 (6.171)	7.517 (4.109)	32.240 (8.382)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	30.627 (7.831)	32.432 (3.196)	17.630 (4.737)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$
Initial Conditions Parameters				
α_0 (intercept)	−3.559 (6.523)	−13.693 (7.069)	−40.811 (21.379)	$\alpha_0 \sim \mathrm{N}(0, 500)$
α_1 (domestic size dummy)	16.484 (9.965)	25.868 (11.959)	23.397 (14.762)	$\alpha_1 \sim \mathrm{N}(0, 500)$
$\alpha_2(x_1)$	29.388 (11.675)	−18.028 (11.658)	31.603 (18.165)	$\alpha_2 \sim \mathrm{N}(0, 500)$
$\alpha_3(x_2)$	3.451 (4.861)	8.908 (5.710)	16.561 (15.519)	$\alpha_3 \sim \mathrm{N}(0, 500)$

standard deviation 500. The latter is far greater than the expected range of values for all coefficients in this group. Finally, given that the data only contain 11 annual observations per plant, we use priors that impose relatively more structure on the foreign demand elasticities. Specifically, we use $\ln(\eta_i - 1) \sim \mathrm{N}(2, 1)$ which implies, in levels, that each η_i has a mean of 12.2 and a standard deviation of 16.0. This prior ensures that the posterior distributions for the demand elasticities are bounded above unity (a necessary condition for the model) and is consistent with the available evidence regarding product-level demand in foreign markets.[24] Also, to add some precision to the relationship between the data and foreign demand elasticities implied by equation (4), we impose the prior that the ratio of the foreign demand elasticity to the domestic demand elasticity $(1 + \upsilon)$ is uniform on $[0, 2]$.

4.3. *Exchange-Rate Process Parameters*

As mentioned in Section 3, the real exchange-rate process is identified exclusively by time series data on this variable. Accordingly, before estimating the other elements of θ, we obtain $(\lambda_0, \lambda_e, \sigma_w)$ by fitting a simple AR(1) process to the log of the real effective export exchange-rate series, 1968–1992, calculated by Ocampo and Villar (1995).[25] The coefficients (standard errors in parentheses) are $\hat{\lambda}_0 = 0.549$ (0.429), $\hat{\lambda} = 0.883$ (0.094), and $\hat{\sigma}_w^2 = 0.0043$. The Dickey–Fuller test statistic for stationarity is -1.93 and the critical value is -2.78 at a 90 percent confidence level. So, although our point estimates suggest that the exchange-rate process is stationary, the usual problem with test power prevents us from rejecting the null hypothesis of a unit root.[26] In the estimation of the remaining parameters in θ, we treat the exchange rate parameters as

[24] Yi (2003) noted that export demand elasticities around 12 or 13 are necessary to reconcile global export growth with reductions in trade barriers in the context of static trade models. Goldberg and Verboven (2001) estimated average price elasticities of demand for foreign cars ranging from 4.5 to 6.5. Goldberg and Knetter (1999) estimated residual demand elasticities for German beer and U.S. linerboard in various foreign markets. The average foreign demand elasticity in this study is 16.4 and the standard deviation across the estimated elasticities is 26.0. Excluding a large positive outlier, these figures become 10.4 and 12.4.

[25] An AR(2) process fits the data better, but the improvement is minor ($R^2 = 0.85$ versus $R^2 = 0.79$), and the cost of adding an additional state variable to the model in terms of computational speed is substantial. Given that the focus of this paper is not on modeling the exchange-rate process, we have chosen to keep this aspect of the model as simple as possible.

[26] Because of limited power, many studies of real exchange-rate dynamics have failed to reject a random walk (Rogoff (1996)). However, those studies that exploit long time series or pool countries are often able to do so (Froot and Rogoff (1995)). In one such paper, Frankel and Rose (1996) fit an AR(1) process to a panel of real exchange-rate series from 150 countries, obtaining our estimate of λ_e exactly. Country dummies, time dummies, and an error-correction term do very little to affect their finding. It is worth noting that even if the Colombian exchange rate were to follow a random walk, our analysis would be qualitatively unaffected because we are using a finite horizon model and only need to simulate the exchange-rate movements over a 30-year horizon to calculate the value function.

fixed at these values and, because of the computation time required, have not attempted to incorporate the effect of sampling error in these estimates on the remaining parameter estimates.

4.4. *Profit Function Parameters*

Moments of the posterior density for the model's remaining parameters are reported in Table I. Note that, with the exception of the demand elasticities, the standard deviations of the priors (rightmost column) are generally orders of magnitude greater than the standard deviations of the posterior distributions. Thus, conditioned on our elasticity priors, these posteriors basically reflect the information in the data.

The profit function coefficients exhibit the expected general pattern in all industries. Firms that begin the sample period with large domestic sales (hereafter large producers) typically stand to profit more from exporting than those that do not (hereafter small producers). This presumably reflects their relatively low initial production costs and/or relatively desirable products. Also, the elasticity of profits with respect to the exchange rate is substantial in leather products and knitted fabrics, indicating that for these sectors devaluation increases foreign revenues substantially more than it increases the costs of their inputs. Although positive, responsiveness to the exchange rate is much more modest in the basic chemicals sector.

Residual profit shocks reflect the combined effects of plant-specific shocks to foreign demand and marginal costs. Not surprisingly, the posterior distributions for the roots of these compound shocks (λ_x^1 and λ_x^2) imply strong serial correlation. Furthermore, the two roots are distinct in each industry, so a simple AR(1) specification (i.e., setting $m = 1$) would have been inappropriate. Most roots are positive, but the basic chemicals sector has one negative root, implying a fundamentally different error process in this sector.

Rather than summarize all of the plant-specific elasticity posteriors, the middle panel of Table I reports results for the four plants in each industry that fall at the quintile cutoffs.[27] Pooling plants within each industry, we calculate an average mean elasticity of 12.7 for knitted fabrics, 13.0 for basic chemicals, and 14.2 for leather products. These figures imply that, on average, producers keep about 0.07 of each peso of their export revenues as gross operating profits (equation (2)).

The posterior distribution for the foreign elasticity premium, v, differs substantially across sectors. Among leather products producers, foreign and domestic demand elasticities appear to be very similar, but among knitted fabric

[27]Note that, generally, the larger the mean elasticity, the more diffuse its posterior distribution. This is because producers with very small markups must have very large demand elasticities and these elasticities are very sensitive to small changes in markups.

producers, the mean ratio of foreign to domestic demand elasticities is approximately 1.95, and among basic chemicals producers, it is 1.85. These latter two industries follow the expected pattern in that foreign markets, being larger than domestic markets, are likely to offer stiffer competition.

4.5. *Sunk Costs and Fixed Costs*

Because we use a structural model to characterize export market participation, we are able to go beyond previous studies and quantify the sunk entry costs that potential exporters face. The findings are remarkably similar across sectors. Among small producers, average entry costs range from 64 million 1986 pesos ($430,000; U.S. dollars throughout) for leather producers to 61 million 1986 pesos ($412,000) for knitting mills. (Of course, entrants tend to get favorable entry cost draws, so average entry costs *incurred* are considerably lower.) For large producers, the average cost of foreign market entry is lower, ranging from an average of 51 million 1986 pesos ($344,000) for basic chemical producers to 59 million 1986 pesos ($402,000) for knitting mills. The posterior distributions are fairly concentrated for all sunk cost parameters, despite relatively diffuse priors. Standard deviations in millions of 1986 pesos range from 1.9 to 5.0. The lower entry costs for large producers could reflect differences in the types of goods they are exporting and/or the markets they service. Size advantages may also derive from existing contacts and distribution channels among large plants or from larger front office operations.

The means of the posterior fixed cost (γ_F) distributions are very close to zero for all three sectors, and variances of these distributions are sufficiently large to imply that these costs, on average, are negligible. Recall, however, that fixed costs for the ith plant are $\gamma_F - \varepsilon_{1it}$ and the posterior distribution for $\sigma_{\varepsilon 1}$ is bounded well above zero. So fixed costs are important at least some of the time for some of the plants.

4.6. *The Role of the Priors*

As discussed in the supplement to this paper (Das, Roberts, and Tybout (2007)), we reestimate the model using substantially more diffuse priors. This has little effect on the posterior distributions for the sunk cost parameters, fixed cost parameter, slope parameters of the profit function (domestic size dummies, exchange-rate coefficients), and quartiles of the cross-plant distribution of foreign demand elasticities. The only parameters that prove sensitive to priors characterize the gap between foreign and domestic demand elasticities. In particular, when the width of the uniform interval is increased by a factor of 5, $(1 + \upsilon)$ is estimated to be substantially larger. Thus, domestic markets may be less competitive than the figures in Table I suggest. However, the competitiveness of the domestic market is irrelevant for the export analysis that follows, so the sensitivity of υ to our priors has no bearing on our inferences.

4.7. *In-Sample Model Performance*

To assess the in-sample fit of the model, we set all parameters to their posterior means $\overline{\theta}$ and we simulate a set of revenue trajectories R_{i0}^{fT} for a hypothetical set of plants. This set begins with the same base-year pattern of export market participation and domestic sales volume (small versus large) that we observe in the first year of the data set. Thereafter it evolves with random draws on the model's exogenous stochastic variables x_{it} and ε_{it}. More precisely, for each instance of a particular (y_{i0}, z_i) combination in the 1981 data set, we draw an initial x_{i0} vector from the conditional density $f_{x|y}(x_{i0}|y_{i0}, z_i, e_0, \overline{\theta})$. (Section A.4 provides details.) Then we simulate each draw forward for 10 periods using the AR(1) process $x_{it} = \overline{\Lambda} x_{it-1} + \omega_{it}$ and pair each x_{it} realization with an ε_{it} draw from $N(0, \overline{\Sigma}_\varepsilon)$. Finally, period by period, we substitute the simulated $(x_{it}, \varepsilon_{it})$ realizations and actual exchange-rate realization into equations (3) and (8), evaluated at $\overline{\theta}$, thereby imputing foreign sales trajectories for each hypothetical plant. Note that these simulations do not incorporate any post-1981 information on plants characteristics or, aside from the real exchange rate, on foreign market conditions.

We repeat the entire simulation process 300 times per plant and, for each set of simulations, we construct trajectories for entry rates, exit rates, export market participation rates, export revenue quantiles, and total export revenues. Table II juxtaposes cross-simulation averages of these results (labeled "predicted trajectories") with analogous statistics based on the sample data (labeled "actual" trajectories). To summarize the degree of variation across simulations, Table II also reports 10th and 90th percentiles.

The top panel of Table II summarizes producer turnover in the export market. For example, the first cell shows that the actual entry rate for knitting mills, averaged over 10 sample years, is 0.041; the average predicted entry rate for the same 10 years is 0.038, and the 10th and 90th percentiles are 0.025 and 0.050. The bottom panel describes exporters—both their share in the population of plants and their frequencies by export revenue quartile. (Ignoring rounding error, quartile frequencies sum to the aggregate export rate.) Overall, the simulations do a good job of replicating the data, both in terms of turnover patterns and in terms of exporter size quartiles. Most predicted values are close to their actual values and, with one exception, all actual values lie within the 10th and 90th percentile bounds.[28]

[28]Additional simulations (reported in the supplement) summarize the ability of the model to predict aggregate export trajectories. They show that general tendencies to expand or contract are captured by the model, and that actual trajectories always fall within the 10th and 90th percentile bounds. Similar comments apply concerning the number of exporters, although the model shows some tendency to underpredict in the later sample years.

TABLE II

ENTRY RATES, EXIT RATES, AND EXPORT MARKET PARTICIPATION RATES (10TH AND 90TH PERCENTILE BOUNDS IN PARENTHESES)

	Knitting Mills		Leather Products		Basic Chemicals	
	Predicted (lower, upper)	Actual	Predicted (lower, upper)	Actual	Predicted (lower, upper)	Actual
			Exporter Turnover Rates			
Entry	0.038 (0.025, 0.050)	0.041	0.047 (0.031, 0.063)	0.041	0.034 (0.020, 0.050)	0.028
Exit	0.025 (0.016, 0.036)	0.020	0.028 (0.016, 0.044)	0.025	0.040 (0.028, 0.054)	0.035
			Export Market Participation Rates			
Exporting	0.170 (0.118, 0.235)	0.163	0.592 (0.131, 0.278)	0.585	0.309 (0.254, 0.365)	0.325
Broken down by export revenue quartiles						
First quartile	0.047 (0.023, 0.071)	0.036	0.203 (0.131, 0.278)	0.139	0.097 (0.059, 0.140)	0.073
Second quartile	0.047 (0.023, 0.071)	0.040	0.131 (0.093, 0.175)	0.145	0.081 (0.055, 0.109)	0.086
Third quartile	0.031 (0.020, 0.053)	0.038	0.131 (0.093, 0.175)	0.142	0.061 (0.040, 0.078)	0.080
Fourth quartile	0.042 (0.028, 0.063)	0.046	0.114 (0.069, 0.162)	0.156	0.069 (0.040, 0.098)	0.091

5. IMPLICATIONS FOR EXPORT SUPPLY

5.1. *Profits, Option Values, and Transition Probabilities*

To explore the implications of sunk costs and plant profit heterogeneity for aggregate export responsiveness, we calculate the mean value of exporting for each plant in year t, gross of entry costs:

$$\begin{aligned}\widetilde{V}_{it}|_{\nu_i^+} = \int_{\mu_i} \big\{ & \pi(e_t, x_t(\nu_i^+, \mu_i), z_i) - \gamma_F \\ & + \delta\big(E_t[V(e_{t+1}, x_{it+1}, z_i)|x_t(\nu_i^+, \mu_i), y_{it} = 1] \\ & - E_t[V(e_{t+1}, x_{it+1}, z_i)|x_t(\nu_i^+, \mu_i), y_{it} = 0]\big)\big\} g(\mu_i)\, d\mu_i.\end{aligned}$$

Note that, except for the entry costs that new exporters would incur, this expression measures the value of the two basic payoffs to exporting: current profits, $\pi(\cdot) - \gamma_F$, and the option value of being able to continue exporting next period without paying entry costs, $\Delta E_t V_{it+1}(e_{t+1}, x_{it+1}, z_i)$. Note also that $\widetilde{V}_{it}$ is an expectation over the unobservable x_{it}, ε_{it}, and exchange-rate realizations, so it shows less variation than was actually present.[29]

The gross expected value of exporting is compared with expected sunk entry costs $\gamma_S z_i$, plant by plant, in Figure 1. Plants are grouped by their presample domestic sales category (small versus large) and then sorted in order of ascending $\widetilde{V}_{it}$. Small plants appear on the left in each panel. Both the first (1982, $t = 1$) and the last (1991, $t = 10$) sample year are presented to show the sensitivity of exporting values to the observed changes in the exchange rate. The two horizontal lines in each panel are the posterior mean sunk costs for each plant type.

Figure 1 suggests that responsiveness on the entry–exit margin is likely to vary considerably across industries. Within each industry, expected export profit streams are similar across small plants and are insufficient to cover the costs of entry. The magnitude of the shortfall is much larger in basic chemicals than in the other two sectors, implying that a given exchange-rate devaluation is likely to trigger relatively less small plant entry in this industry. Among large producers, there is much more within-industry heterogeneity in leather products and basic chemicals. For large producers in these sectors, the entry margin will probably be active, but relatively few nonexporters are likely to respond to devaluation. Large knitting mills are much more homogeneous. Nonexporters among these plants are likely to respond similarly to devaluation, so a sufficiently large change in the exchange rate may well induce a wave of entry.

Finally, comparisons of beginning-of-sample values ($\widetilde{V}_{i,1}$) and end-of-sample values ($\widetilde{V}_{i,10}$) reveal that the effects of Colombia's 33 percent exchange-rate depreciation were not uniform across producers. Expected payoffs to large producers are much more sensitive to the exchange rate than payoffs to small producers, simply because exchange-rate effects are roughly proportional to expected revenue streams.

Figure 1 should not be used to predict which plants will *actually* participate in the export market because it averages out noise in sunk costs and profits due to x_{it} and ε_{it}. Furthermore, this figure does not distinguish which producers were already in the export market. Those plants that currently export will remain in the market as long as their expected profit streams are positive—their profits need not exceed the cost of entry.

To illustrate the importance of this latter phenomenon, we calculate the probability that each plant will remain an exporter, assuming it exported in the previous year, and the probability that each plant will enter the export market,

[29]Comparing across the 300 sets of trajectories for the model shocks, we find a great deal of heterogeneity, indicating there is considerable scope for improving forecasts of industrial exports by bringing in additional information on the sources of these shocks, including foreign market conditions.

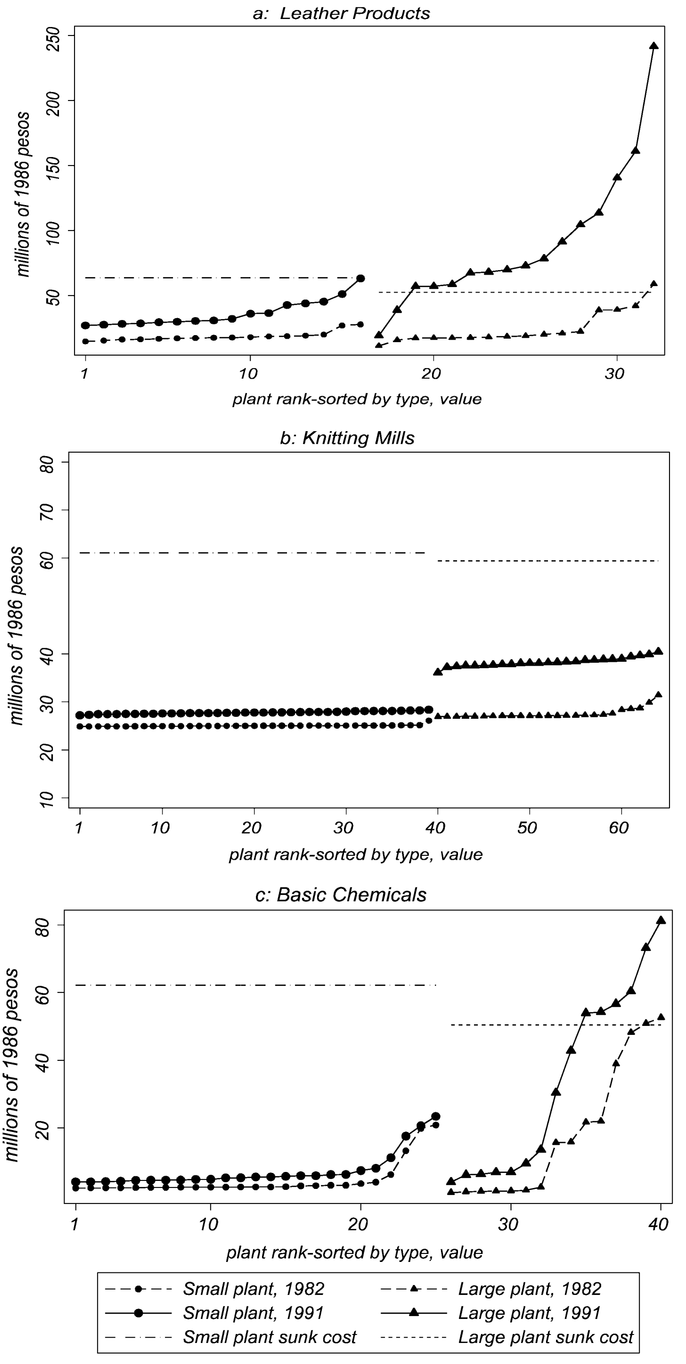

FIGURE 1.—Plant export value and sunk entry costs.

assuming it did not export in the previous year. Figure 2 plots these values for plants in 1991, once again taking expectations over $x_{i,10}$ and $\varepsilon_{i,10}$. The probability of remaining an exporter, once in, is above 0.8 for knitted fabric producers, above 0.9 for leather producers, and varies from 0.6 to 0.9 for basic chemical producers. That is, $P(\widetilde{V}_{i,10} + \varepsilon_{1i,10} > 0)$ is quite high for most plants. In contrast, the probability of *entering* the market $P(\widetilde{V}_{i,10} - \gamma_S z_i + \varepsilon_{2i,10} > 0)$ is generally below 0.2 in knitting and basic chemicals, although entry is more likely for a subset of leather products producers. The gap between the probability of getting in and the probability of staying in is as large as 0.7 for many producers; this figure is similar to estimates based on a reduced-form model of the decision to export (Roberts and Tybout (1997a)).

Because we have estimated a dynamic structural model, we are able to measure the option value of being able to export next period without paying entry costs. This value is illustrated for nonexporters in Figure 3 as the difference between gross export value, $\widetilde{V}_{i,10}$, and net current profits, $\int_{\mu_i} \pi(e_t, x_i(\nu_i^+, \mu_i), z_i) g(\mu_i)\, d\mu_i$. If there were no entry costs, the option value would be zero and exporting behavior could be described with a static model. However, option values are, in fact, the largest component of export value for most producers and they are overwhelmingly important among knitting mills. One implication is that changes in option values due, for example, to changing expectations about future market conditions, can induce large changes in the return to becoming an exporter, even if current profits are unaffected.

5.2. *Simulated Effect of a Devaluation*

The export supply response to a devaluation reflects adjustments on two margins: entry–exit and output adjustments among incumbents. To quantify each type of response we simulate plants' reactions to a permanent change in the exchange-rate process that depreciates the steady state value of the peso by 20 percent.[30] The regime shifts take place in period 1 and we track plants reactions over the following nine periods. Plant-specific exporting trajectories are generated as described in connection with Table II (Section 4.7), except all realizations on both x and e are simulated. We calculate expected reactions by simulating 300 exchange-rate trajectories under each scenario and averaging each plant's responses.

The effect on the number of exporting plants, relative to a base case of no

[30]This is accomplished by increasing the intercept of the estimated autoregressive process for the log of the exchange rate. Given the parameter estimates reported in Section 4.2, the steady state mean of the logarithmic exchange rate is $0.549/(1 - 0.883) = 4.69$. Using the relationships between the mean and variance of a normal and a lognormal random variable, an increase in the intercept from 0.549 to 0.572 amounts to a 20 percent change in the long-run expected exchange rate.

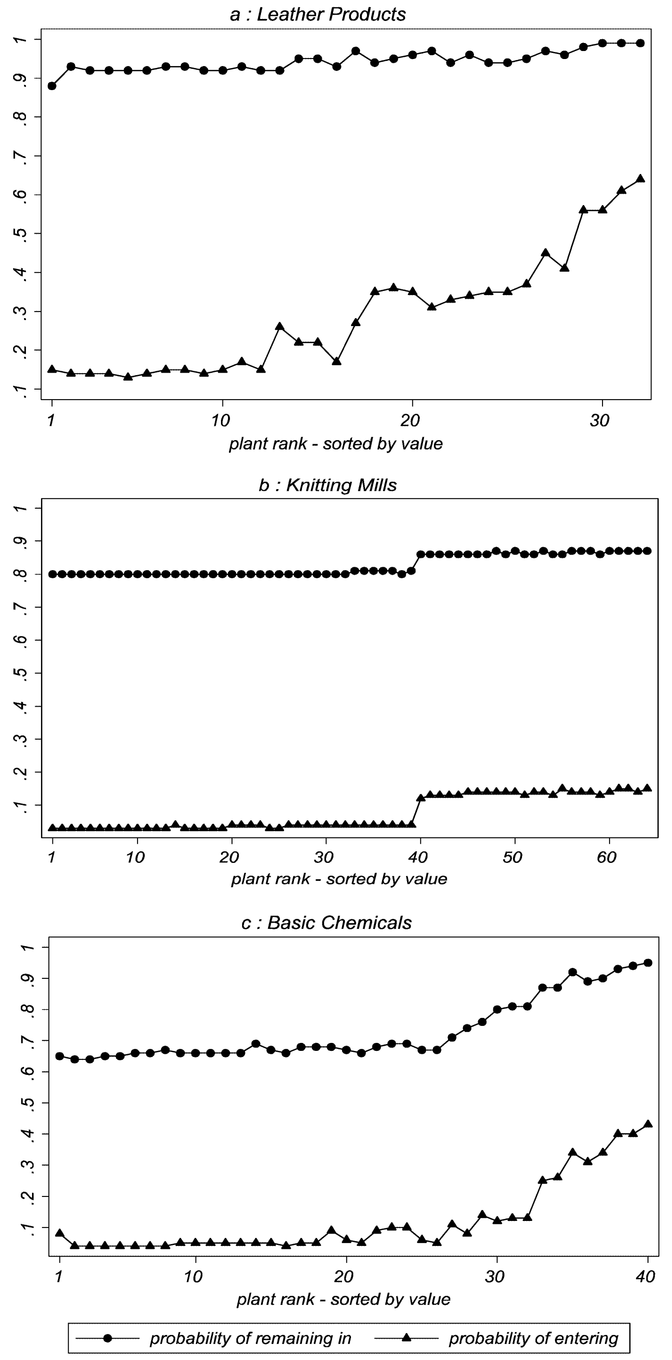

FIGURE 2.—Probability of exporting conditional on plant history.

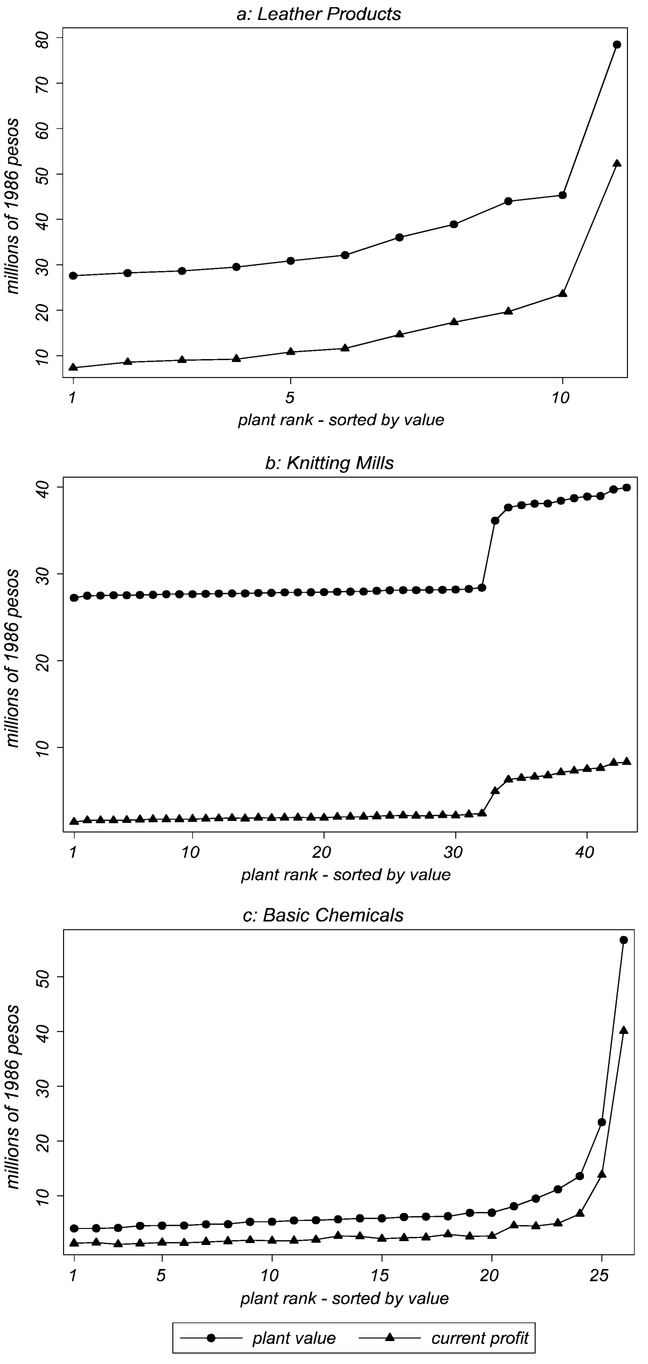

FIGURE 3.—Value of exporting and current profit for nonexporting plants.

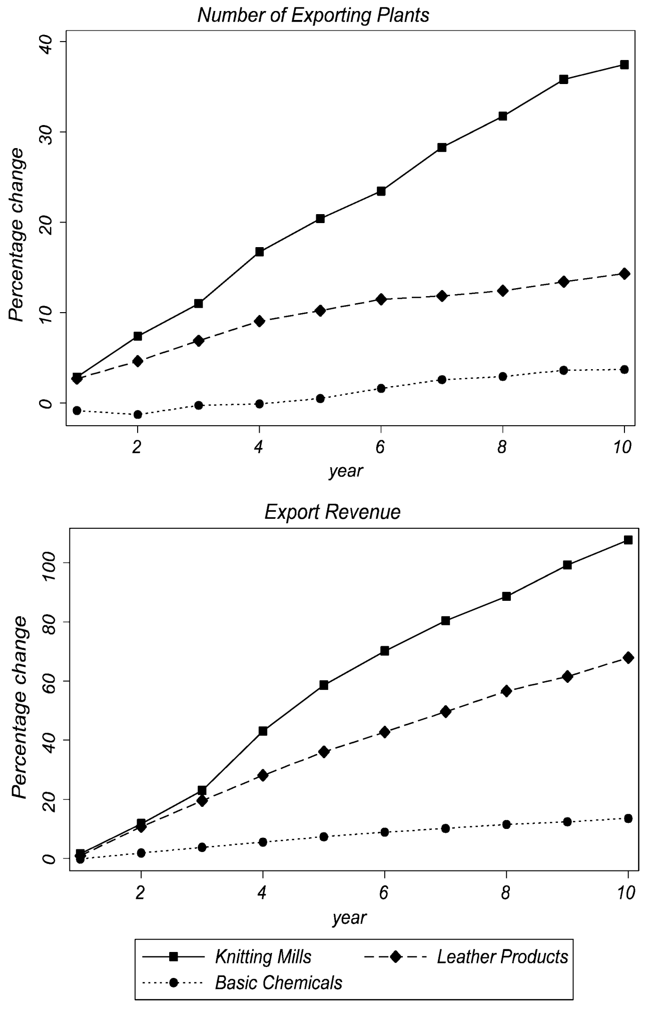

FIGURE 4.—Export response to a correctly perceived 20 percent devaluation.

regime change, is summarized in Figure 4. In the top panel, the predicted cumulative percentage change in the number of exporters is graphed for each industry. Knitting mills show a 37 percent increase in the number of exporters over a 10-year period, while the number of leather products exporters only rises 14 percent, and the number of basic chemicals exporters only rises 4 percent. This relatively strong entry response among knitting mills largely reflects the fact that few mills were exporting in 1981. (Only 5 of 64 knitting mills were already exporting, compared to 17 of 32 basic chemical plants and 14 of 40 leather products plants.) It also reflects the relative homogeneity of knitting mills in terms of their expected export profit streams and their relative proximity to their entry threshold (Figure 1).

The bottom panel of Figure 4 tracks percentage changes in export revenues for the same counterfactual regime change. These responses are generally larger, reflecting the fact that incumbent exporters responded to the new regime by increasing their foreign sales volumes. After 10 years, the combined effect of entry and volume adjustments leads to a 107 percent increase in exports among knitting mills, a 68 percent increase among leather products producers, and 14 percent increase among basic chemicals producers. The large variation in responses across industries is due both to differences in entry patterns and to differences in the elasticity of export profits with respect to the exchange rate.

Perceptions of the policy regime can also matter. Once again, consider a policy reform that promotes exports by increasing the intercept of the exchange-rate process. If managers persist in believing that the exchange-rate realizations they observe were generated by the pre-reform exchange-rate process, they underestimate the increase in the value of becoming an exporter. For a 20 percent depreciation in the steady state value of the peso, this type of misperception makes little difference for leather products producers and basic chemicals producers, because few of them are near their entry threshold, but it matters for knitting mills, as illustrated by Figure 5. If producers in this industry had persisted in believing they were in the pre-reform regime, the number of exporters would have grown by 18 percent rather than 37 percent over the 10-year simulation period. Similarly, their total export volume would have been 90 percent higher than the base case rather than 107 percent. (Differences in responses for the other two industries are very small, so we do not provide figures for them.) Together, Figures 4 and 5 demonstrate that intra-industry differences in exporting history and heterogeneity help to explain why some industries respond more than others to a given stimulus.

Finally, exchange-rate volatility can matter, but not dramatically. A 100 percent increase in the variance of the exchange-rate shocks (which is fully anticipated by the plants) does not affect the expected aggregate exports of basic chemicals. However, in the knitting industry, the same regime change generates a 3 percent increase in the predicted number of exporting plants and a 17 percent in export volume after 5 years. The magnitudes are about half as large in the leather products industry. These findings are driven by the convexity of the profit function rather than by a widening of the hysteresis band: a larger variance of the exchange rate shocks leads to higher average profits and higher average exports for the plants.

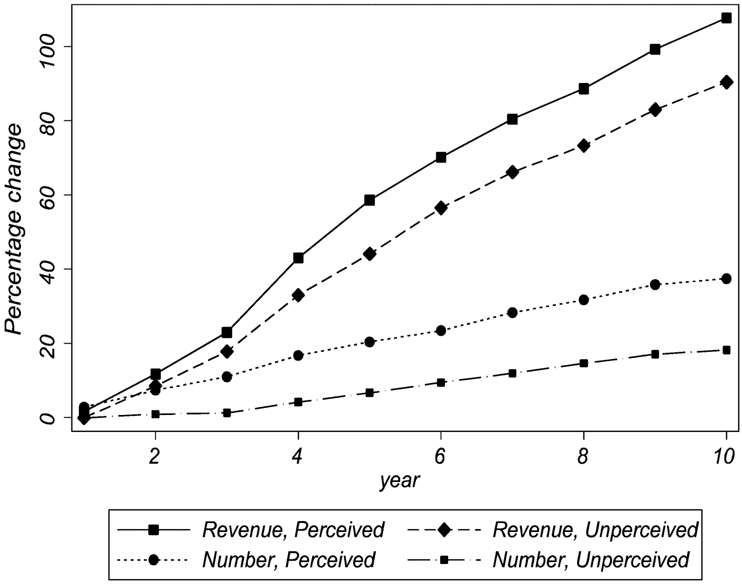

FIGURE 5.—Response to a perceived versus unperceived regime shift: 20 percent steady state devaluation, knitting mills.

5.3. *Alternative Policies to Subsidize Exports*

The case for export promotion policies is controversial.[31] Nonetheless, it is quite common to find significant promotional regimes in place. In this section, we shall ignore the question of whether export promotion is desirable and address the positive issue of how effective various types of promotion are in terms of their impact on export volumes.

Aside from currency devaluation, governments in developing countries and elsewhere have used a variety of tools to encourage manufactured exports. (Panagariya (2000), provided a critical review.) In terms of value, the most significant incentives are usually direct subsidies linked to plants' export revenues.[32] Preferential credit and insurance are commonly provided by official export promotion agencies and/or administered through the financial sec-

[31]Those who advocate export promotion (e.g., Westphal (2002)) argue that exports generate various positive spillovers, while those who are opposed to export promotion (e.g., Panagariya (2000)) discount the importance of these spillover effects.

[32]In Colombia, the most important subsidy has been a tax rebate that is proportional to foreign sales. This rebate has been delivered in the form of negotiable certificates (Certificado Abono Tributarios) that recipients can use to retire their taxes or sell on a secondary market. Other export subsidies have included a duty drawback scheme (Plan Vallejo), insurance against exchange rate risk on dollar-denominated export loans (discontinued in 1977), and subsidized export credit (from PROEXPO). As Ocampo and Villar (1995) documented, the combined value of these subsides fluctuated between 16 and 27 percent of export sales for manufacturing overall during the

tor. Export processing zones provide duty-free access to imported inputs that are subject to tariffs among nonexporters. Policies that affect transport costs through the public development of port facilities do the same. All of these subsidies increase the profits of plants once they are in the export market and thus tend to induce volume adjustments among incumbent exporters, as well as net entry.

A second policy option is to directly subsidize the sunk costs that plants incur to enter export markets.[33] Matching grant programs that subsidize information acquisition or investments in technology acquisition for export development fall under this heading, presuming that these are one-shot start-up costs.[34] Support for participation in trade fairs might also be classified as this type of policy, given that it reduces the costs of establishing a foreign clientele. Sunk cost subsidies encourage entry, but if they do not affect marginal production costs, they should not affect export volume decisions, *given* foreign market participation. Furthermore, they also encourage exit if they are available repeatedly to the same producer because they reduce the incentive to avoid reentry costs by remaining in foreign markets during unprofitable periods.

A third type of export promotion provides subsidies that are not directly tied to plants' export level, but rather are flat payments designed to cover the annual fixed costs of operating in the export market. The same types of policies that help to reduce entry costs can fall under this heading, provided that regular expenditures are required to maintain foreign clients and/or adapt the product to evolving tastes, technologies, and characteristics of competing products. Unless they shift the marginal production cost schedule, fixed cost subsidies resemble sunk cost subsidies in that they operate on the entry–exit margin but not the volume margin. However, given that they do not affect the threshold costs associated with exit and reentry, their effect should be primarily on the number of exporters rather than the long-run rate of turnover among exporting plants.

Using our estimated model, we simulate each of these policy options. First we explore the effects of per-unit subsidies equal to 2, 5, and 10 percent of their export revenue. Second, we simulate fixed cost subsidies that amount to 2

sample period. We use Ocampo and Villar's real effective export exchange rate to estimate our model, so although we do not isolate their effects, these subsidies are built into our analysis.

[33]Alternatively, creation of export trade groups that collect information on sources of demand and match foreign buyers and domestic producers can also act to reduce one substantial cost of entry for new exporters. Information deficiencies were identified as significant impediments to exporting by Colombian manufacturers in a recent survey. See Roberts and Tybout (1997b) for discussion.

[34]Pursell (1999) noted that such programs have gained popularity rapidly at the World Bank during the past decade. "The justification for these projects is generally that there are exporting firms that would increase their exports and non-exporters that would start to export, but do not do so because they lack crucial information and services, e.g., information on export markets, production techniques, packaging and delivery requirements, product standards, etc." (Pursell (1999, pp. 20–21)).

million pesos and 10 million pesos. Finally, we simulate a reduction of sunk entry costs by 25, 50, and 100 percent. (As Figure 3 demonstrates, these subsidies constitute a substantial fraction of export profits for some plants.) To compare these policies, we construct a benefit–cost ratio for each one by calculating the total gain in export revenue that would accrue in each year and dividing it by the direct cost of the subsidy in that year.

The effects of these policies do not vary greatly over time, so we report benefit–cost ratios for each hypothetical policy 5 years after it was introduced. This time interval is long enough that most of the adjustment in the number of plants has already occurred. All subsidies are viewed as permanent changes in the export environment by the plants.

The first panel of Table III shows that in all cases, extra export revenue per peso spent by the government is highest for revenue subsidies. This policy generates ratios that range from 7.5 to 19.7.[35] In contrast, fixed cost subsidies generate no more than 4 pesos of revenue per unit cost and entry cost subsidies generate no more than 2 pesos of revenue per unit cost. The revenue subsidy is the most potent because it acts on the volume margin, which is relevant for *all* producers, while fixed cost and entry cost subsidies affect only the decision concerning whether to export.

A key difference between the fixed cost subsidy and the entry cost subsidy is that the latter reduces the option value of remaining an exporter and en-

TABLE III

EXPORT REVENUE/COST RATIOS FOR ALTERNATIVE SUBSIDY PLANS (MEANS OVER 300 SIMULATIONS)

	Knitting Mills	Leather Products	Basic Chemicals
	Revenue Subsidies		
2 percent	19.23	11.81	11.17
5 percent	15.67	9.94	9.56
10 percent	10.09	7.74	7.52
	Entry Cost Subsidies		
25 percent	2.03	−0.54	−0.068
50 percent	1.02	−0.67	−0.49
100 percent	0.14	−0.26	−0.23
	Fixed Cost Subsidy		
2 million pesos	3.96	2.22	2.66
10 million pesos	0.99	0.68	0.69

[35]The benefit–cost ratios decline as the subsidy rate increases because of our assumption of constant (albeit plant-specific) demand elasticities for each producer. This ensures that the elasticity of quantity exported with respect to the subsidy rate is constant and, thus, so is the elasticity of the subsidy's cost with respect to the subsidy rate. Diminishing marginal revenue implies that the elasticity of revenue with respect to the subsidy rate gets progressively smaller.

courages exit along with entry. That is, entry subsidies make it less costly to reenter, so producers have less incentive to continue exporting during periods when their net exporting profits are negative. Thus when sunk costs are entirely eliminated, turnover increases by a factor of 3 or more in each industry. This effect on exit is sufficiently strong that it creates a *negative* return to export promotion in both the leather products and the basic chemicals industries, where the firms that are encouraged to exit generated more foreign sales than the entrants who replaced them.

6. SUMMARY

In this paper we develop a dynamic structural model that characterizes firms' decisions about whether to export as well as quantifies the volume of foreign sales among those who do. It embodies uncertainty, plant-level heterogeneity in export profits, and sunk entry costs for plants breaking into foreign markets. Using a one-step MCMC estimator that deals with unobserved heterogeneity, self-selection, and initial conditions problems, we fit this model to plant-level data on sales revenue and production costs for three Colombian manufacturing industries. We then use the results to quantify sunk entry costs and export profit heterogeneity, and to conduct dynamic policy analysis.

Our results imply that entry costs are substantial. Consequently, producers do not begin to export unless the present value of their expected future export profit stream is large. They also tend to continue exporting when their current net profits are negative, thus avoiding the costs of reestablishing themselves in foreign markets when conditions improve. Furthermore, for many of the smaller plants, the option value of being able to export in future years without paying entry costs substantially exceeds the export profits that they expect to earn in the current year. In this sense, history and expectations are important for many producers. Intra-industry profit heterogeneity is also important. In the basic chemicals industry and the leather products industry, few producers are near their margin of indifference between exporting and not exporting. In contrast, knitting mills are relatively homogeneous and are more likely to respond *en mass* to significant changes in the return to exporting.

These features of Colombian industries shape the results of our policy simulations. First, because patterns of producer heterogeneity differ across industries, so do patterns of export response. For example, among leather product suppliers, the payoff from becoming an exporter varies widely, and few firms are near their foreign market entry threshold. Even with large changes in the expected payoff from exporting, entry and exit contribute little to changes in the total foreign sales of this industry. On the other hand, many producers of knitted fabrics are nearly indifferent concerning whether or not they export. So in this sector a relatively modest shift in the return to exporting is sufficient to change their exporting status, and entry and exit significantly affect total export responses.

Second, the fact that sunk entry costs are large makes expectations about future exporting conditions important for many plants. Therefore, a moderate shift in the mean of the log exchange-rate process can induce sustained net entry by new exporters and rising export volumes *if* producers recognize that the shift has taken place. On the other hand, the same change in the exchange-rate process induces far less entry when producers retain their old beliefs.

Finally, policies that promote exports through per-unit subsidies generate far larger responses per peso spent than policies that promote exports through lump-sum transfers for new exporters. The reasons are that (1) exporters that need a subsidy to get into export markets are almost always marginal suppliers, (2) these same exporters face relatively high entry costs, and (3) large incumbent exporters, who account for most of the industry's foreign sales, are unaffected by entry subsidies, but positively affected by volume subsidies.

Planning Unit, Indian Statistical Institute, 7SJS Sansanwal Marg, New Delhi 110016, India; dasm@isid.ac.in,

Dept. of Economics, Pennsylvania State University, 513 Kern Building, University Park, PA 16802, U.S.A., and National Bureau of Economic Research; mroberts@psu.edu,

and

Dept. of Economics, Pennsylvania State University, 517 Kern Building, University Park, PA 16802, U.S.A., and National Bureau of Economic Research; jtybout@psu.edu.

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APPENDIX

This appendix provides more details concerning construction of the likelihood function for plant i (equation (9)), calculation of the option value of exporting, and simulation procedures.

A.1. *Constructing* $h(\nu_i^+)$

To derive the density function for the $q_i = \sum_{t=0}^{T} y_{it}$ uncensored realizations on log profit shocks, $\nu_i^+ = \{\nu_{it} \equiv \iota' x_{it}; R_{it}^f > 0\}$, we assume that the x_{it} process is in long-run equilibrium. Then f_x implies $x_{it} \sim \mathrm{N}(0, \Sigma_\omega (I - \Lambda_x^2)^{-1})$ and $h(\nu_i^+) = \mathrm{N}(0, \Sigma_{vv})$, where the diagonal elements of Σ_{vv} are determined by $E[\nu_{it}^2] = \iota'(x_{it} x_{it}')\iota = \iota' \Sigma_\omega (I - \Lambda_x^2)^{-1} \iota$ and the off-diagonal elements are determined by $E[\nu_{it}\nu_{t-k}] = \iota'[\Lambda_x^{|k|} \Sigma_\omega (I - \Lambda_x^2)^{-1}]\iota\ \forall k \neq 0$.

A.2. *Constructing* $x_0^T(\nu_i^+, \mu_i)$

To construct $x_0^T(\nu_i^+, \mu_i)$, reshape x_{i0}^T as an $mT \times 1$ vector, $\mathbf{x}_{i0}^T = (x_{i0}', \ldots, x_{iT}')'$, and express the set of uncensored log profit shocks, ν_i^+, as a $q_i \times 1$ vector.

Then by well known properties of multivariate normal distributions, $\mathbf{x}_{i0}^T|\nu_i^+ \sim \mathrm{N}(\Sigma_{xv}\Sigma_{vv}^{-1}\nu_i^+, \Sigma_{xx} - \Sigma_{xv}\Sigma_{vv}^{-1}\Sigma_{xv}')$, where $\Sigma_{xx} = E[\mathbf{x}_{i0}^T\mathbf{x}_{i0}^{T'}]$ and $\Sigma_{xv} = E[\mathbf{x}_{i0}^T\nu_i^{+'}]$. Furthermore, the elements of these matrices are determined by $E(x_{it}x_{it+s}') = \Lambda_x^{|s|}\Sigma_\omega(I - \Lambda_x^2)^{-1}$ and $E(x_{it}\nu_{it+s}) = \Lambda_x^{|s|}\Sigma_\omega(I - \Lambda_x^2)^{-1}\iota$, respectively (Chow (1983, Section 6.3)).

Several features of these expressions merit comment. First, although the notation does not show it explicitly, the dimensions and composition of Σ_{xv} and Σ_{vv} vary across plants with their export market participation patterns. Second, because x_{it} is serially correlated, information from all exporting years is used to calculate each element of $E[\mathbf{x}_{i0}^T|\nu_i^+]$. Third, because the x_{it} process is stationary, uncensored profit shocks (v_{it}'s) receive the heaviest weight in determining contemporaneous expected values ($E[x_{it}|\nu_i^+]$) and their importance in determining expected values for other years ($E[x_{it+s}|\nu_i^+]$) declines monotonically with $|s|$.

Given the distributions described above, we can write the vector of profit shock components as

$$\text{(A.1)} \qquad \mathbf{x}_{i0}^T = \begin{cases} A\nu_i^+ + B\mu_i, & \text{if } q > 0, \\ B\mu_i, & \text{if } q = 0, \end{cases}$$

where $A = \Sigma_{xv}\Sigma_{vv}^{-1}$, $BB' = \Sigma_{xx} - \Sigma_{xv}\Sigma_{vv}^{-1}\Sigma_{xv}'$, and μ_i is an $mT \times 1$ vector of independent and identically distributed standard normal random variables with density $g(\mu_i) = \prod_{j=1}^{mT}\phi(\mu_{ij})$. Note that $\Sigma_{xx} - \Sigma_{xv}\Sigma_{vv}^{-1}\Sigma_{xv}'$ has rank $mT - q_i$, reflecting the cumulative constraints $\nu_{it} = \iota' x_{it}$ that hold in each exporting year. Thus B has q_i zero columns and only $mT - q_i$ elements of μ_i actually play a role in determining $\mathbf{x}_{i0}^T$.

The rows of equation (A.1) imply the functions $x_{it} = x_t(\nu_i^+, \mu_i)$ and $x_{is}^T = x_s^T(\nu_i^+, \mu_i)$ that appear in Section 3 of the text. These functions allow us to simulate $P[y_{i0}^T|\nu_i^+, e_0^T, z_i] = \int_{\mu_i} P[y_{i0}^T|e_0^T, x_0^T(\nu_i^+, \mu_i), z_i]g(\mu_i)\,d\mu_i$ in equation (9) by drawing a set of S μ_i vectors from $g(\mu_i)$, using $x_0^T(\nu_i^+, \mu_i)$ to evaluate $P[y_{i0}^T|e_0^T, x_0^T(\nu_i^+, \mu_i), z_i]$ at each μ_i and averaging the results over the S outcomes.

A.3. *Calculating the Latent Value of Exporting, y_{it}^**

By equation (8), $y_{it}^* = u(e_t, x_{it}, z_i, \varepsilon_{it}, 1, y_{it-1}|\theta) + \delta\Delta E_t V_{it+1}(e_t, x_{it}, z_i|\theta)$. The first right-hand side term in this expression—net current operating profits—is straightforward to evaluate using equations (2), (3), and (5). The second right-hand side term—the option value of exporting— is more difficult to calculate. We begin by using backward induction with a 30-year horizon to obtain the expected value of staying out of the export market (V^0), the expected value of entering the export market (V^E), and the expected value of staying in the export market (V^S) as functions of the current state variables:

$$V_{it}^0 = \delta E_t V_{it+1}(e_{t+1}, x_{it+1}, z_i|y_{it} = 0, \theta),$$

$$V_{it}^{E} = \pi(e_t, x_{it}, z_i, \theta) - \gamma_F - \gamma_S z_i + \delta E_t V_{it+1}(e_{t+1}, x_{it+1}, z_i | y_{it} = 1, \theta),$$
$$V_{it}^{S} = \pi(e_t, x_{it}, z_i, \theta) - \gamma_F + \delta E_t V_{it+1}(e_{t+1}, x_{it+1}, z_i | y_{it} = 1, \theta).$$

The induction algorithm first evaluates V^0, V^E, and V^S in the terminal period, $t + 30$ years in the future, when $E_t V_{it+1} = 0$. Then backing up one period at a time, it calculates each preceding year, eventually arriving at the period t. At each stage, Rust's (1997) random grid algorithm is used to integrate numerically over one-step-ahead realizations on the state variables x and e.

Once these functions have been evaluated, we construct the value of the future export profit stream conditioned on current exporting status as

$$\begin{aligned}
&E_t[V_{it+1} | y_{it} = 1] \\
&\quad = E_t \max(V_{it+1}^{0}, V_{it+1}^{S} + \varepsilon_{1it+1}) \\
&\quad = \int_{x_{it+1}} \int_{e_{t+1}} \Bigg[\Phi\left(\frac{V_{it+1}^{S} - V_{it+1}^{0}}{\sigma_{\varepsilon 1}} \right) \\
&\qquad\qquad \times \left\{ V_{it+1}^{S} + \sigma_{\varepsilon 1} \phi\left(\frac{V_{it+1}^{S} - V_{it+1}^{0}}{\sigma_{\varepsilon 1}} \right) \Big/ \Phi\left(\frac{V_{it+1}^{S} - V_{it+1}^{0}}{\sigma_{\varepsilon 1}} \right) \right\} \\
&\qquad\qquad + \Phi\left(\frac{V_{it+1}^{0} - V_{it+1}^{S}}{\sigma_{\varepsilon 1}} \right) \cdot V_{it+1}^{0} \Bigg] \\
&\qquad\qquad \times f_x(x_{t+1} | x_t) f_e(e_{t+1} | e_t) \, de_{t+1} \, dx_{t+1}
\end{aligned}$$

and

$$\begin{aligned}
&E_t[V_{it+1} | y_{it} = 0] \\
&\quad = E_t \max(V_{it+1}^{0}, V_{it+1}^{E} + \varepsilon_{2it+1}) \\
&\quad = \int_{x_{it+1}} \int_{e_{t+1}} \Bigg[\Phi\left(\frac{V_{it+1}^{E} - V_{it+1}^{0}}{\sigma_{\varepsilon 2}} \right) \\
&\qquad\qquad \times \left\{ V_{it+1}^{E} + \sigma_{\varepsilon 2} \phi\left(\frac{V_{it+1}^{E} - V_{it+1}^{0}}{\sigma_{\varepsilon 2}} \right) \Big/ \Phi\left(\frac{V_{it+1}^{E} - V_{it+1}^{0}}{\sigma_{\varepsilon 2}} \right) \right\} \\
&\qquad\qquad + \Phi\left(\frac{V_{it+1}^{0} - V_{it+1}^{E}}{\sigma_{\varepsilon 2}} \right) \cdot V_{it+1}^{0} \Bigg] \\
&\qquad\qquad \times f_x(x_{t+1} | x_t) f_e(e_{t+1} | e_t) \, de_{t+1} \, dx_{t+1}.
\end{aligned}$$

The difference between these two expressions is the object of interest: $\Delta E_t V_{it+1}$.

A.4. *Simulating the Conditional Density of Initial Profit Shocks,* $f_{x|y,z}(x_{i0}|y_{i0}, z_i, e_0, \overline{\theta})$

In addition to providing a basis for estimation, the likelihood function components described above allow us to construct the conditional density for the initial x_{i0} vector, given initial exporting status and size: $f_{x|y,z}(x_{i0}|y_{i0}, z_i, e_0, \overline{\theta})$. As discussed in the text, we use this function to draw starting values for the simulations reported in Tables II and III, and in Figures 1–5. First, using the results of Section A.2, write the unconditional density of an initial x realization as

$$f_{x_0}(x_{i0}|\theta) = \mathrm{N}(0, \Sigma_\omega (I - \Lambda_x)^{-1}).$$

Next, using estimates of equation (12), multiply this expression by an approximation to $P[y_{i0}|x_{i0}, z_i, e_0, \theta]$ to obtain the approximate joint density for initial realizations on (x_{i0}, y_{i0}), conditioned on exogenous variables. Finally, divide this density by a version of the probit equation (12) that excludes x_{i0} to obtain

$$f_{x|y}(x_{i0}|y_{i0}, z_i, e_0, \theta) = \frac{P(y_{i0}|x_{i0}, z_i, e_0, \theta) \cdot f_{x_0}(x_{i0}|e_0, z_i, \theta)}{P(y_{i0}|z_i, e_0, \varsigma)}.$$

It is not possible to sample directly from this distribution, so we use MCMC sampling techniques to generate the needed x_{i0} draws.

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