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ABSTRACT

As the exchange rate, foreign demand, production costs and export promotion policies evolve, manufacturing firms are continually faced with two issues: 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 and estimate the model using plant-level panel data on several Colombian industries. The model embodies uncertainty, plant-level heterogeneity in export profits, and sunk entry costs for plants breaking into foreign markets.

Our estimates, and the simulation exercises that they support, yield several implications. First, expected market entry costs for new exporters range from $US 300,000 to $US 500,000. Thus producers don't initiate exports unless the expected present value of the resulting profit stream is sufficiently large to cover these expenses. Similarly, incumbent exporters tend to maintain a presence in foreign markets when their current profits are negative, thus avoiding the costs of re-establishing themselves in foreign markets when conditions improve. Second, however, firms are very heterogeneous. Exports revenues and profits accrue mainly to a handful of dominant suppliers, and very few firms are close to being indifferent between exporting and not-exporting. Thus, while history and expectations matter for a few marginal producers, most of the aggregate export response to a change in the exchange rate regime comes from volume adjustments among large incumbents.

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1. Overview

In developing countries, manufacturing sectors that respond to export stimuli are highly prized. By making greater imports feasible, these sectors help to generate the traditional gains from trade. They also stabilize domestic employment by venting surplus production in foreign markets, and they may even generate efficiency gains through trade-related technology diffusion (e.g., Westphal, 2001). But export supply responses are poorly understood. Seemingly similar stimuli have given rise to very different export responses in different countries and time periods, making it difficult to know whether the next devaluation or export subsidy scheme will generate a surge or a trickle of new exports.

Several micro explanations might account for the puzzle of export responsiveness. First, a strong export response may require the entry of non-exporters into foreign markets. But to break into foreign markets, firms must establish marketing channels, learn bureaucratic procedures, and develop new packaging or product varieties. In the presence of these entry costs, expectations about future market conditions can critically affect current behavior, and doubts about the permanence of export promotion packages may discourage foreign market entry.[1]

Second, entry costs make firms' export supply responses dependent upon their previous exporting status. Firms that already export can adjust 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.

[1] Start-up costs are the focus of the analytical literature on export hysteresis (Baldwin and Krugman, 1989; Dixit, 1989; Krugman, 1989).

Finally, even within narrowly-defined industries, firms are heterogeneous in terms of their production costs and their product characteristics. Depending upon the distribution of these characteristics across firms, there may be many firms poised on the brink of foreign market entry, or just a few. Thus, when these cross-plant distributions of marginal cost and foreign demand are unobservable, widely different export responses are possible under seemingly similar conditions.

In this paper we develop a dynamic optimizing model of export supply that captures each of these micro phenomena, and we econometrically fit the model to plant-level panel data on several Colombian industries. We use our estimates to simulate export responses to a shift in the mean of the exchange rate process. In doing so we quantify the roles of sunk costs, exporting experience and firm heterogeneity in shaping export responsiveness.

In addition to quantifying the micro phenomena behind export responses, our model of exporting behavior makes several methodological contributions. First, because we use a dynamic structural framework, we are able to estimate sunk costs in dollars rather than simply test for their existence.[2] These costs are critical to policy evaluation but they have rarely been estimated because they can only be identified by their very non-linear 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 usual problem that arises with plant-level survey data of constructing proxies for prices and quantities from poorly measured variables.

[2] Earlier studies of export market participation have focused on the null hypothesis that sunk costs don't matter, but have not been structural and thus have not *quantified* sunk costs (Roberts and Tybout, 1997a; Campa, 1998; Bernard and Jensen, 2001; Bernard and Wagner, 2001).

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 it's 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, products are differentiated across firms, and the foreign and domestic market for each is monopolistically competitive. This eliminates strategic competition, but it ensures that each firm faces a downward-sloping marginal revenue function in each market. Second, 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. Third, future realizations on the exchange rates, marginal costs, and foreign demand shifters are unknown, but each evolves according to a known Markov process. Fourth, firms must pay stochastic sunk start-up costs to initiate exports. Finally, 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.[3]

[3] The assumption appears to be reasonable for the industry, country, and time period we will study, since some excess capacity was present. Estimates of average variable cost functions revealed little dependence on within-plant temporal output fluctuations.

2.1 *Gross export profits and revenues*

We begin by characterizing the export profit stream that awaits the i^{th} firm, once it has broken into foreign markets. The magnitude of this stream depends upon things that shift the marginal cost schedule, like technology shocks and factor prices, and things that shift the foreign demand schedule, like foreign aggregate demand and the real exchange rate. We assume that marginal costs and foreign demand are Cobb-Douglas functions of these factors, so that gross potential export profits are log-linear in the same set of arguments:

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

Here π_{it}^{*} is firm i's gross potential export profit during year t ($i = 1, \ldots n$; $t = 1, \ldots, T$), z_i is a k by one vector of time-invariant, firm-specific characteristics that lead to differences in marginal costs and product desirability, and e_t is the log of the real exchange rate.[4] Finally, ν_{it} is a stationary, serially-correlated disturbance term that captures all idiosyncratic shocks to foreign demand and marginal production costs. Hereafter we will denote the vector of profit function coefficients by $\Psi = \left(\psi_{01}, \ldots, \psi_{0k}, \psi_1\right)$.

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 an AR(1) process, $e_t = e_0 + \lambda_e e_{t-1} + w_t$, where $w_t \sim i.i.d.N(0, \sigma_w^2)$. Assuming that the ν_{it} process is first order 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: $\nu_{it} = \sum_{j=1}^{m} x_{it}^{j}$, where $x_{it}^{j} = \lambda_x^j x_{it-1}^{j} + \omega_{it}^{j}$ and $\omega_{it}^{j} \sim i.i.d.N(0, \sigma_{\omega j}^2)$. This

[4] Some characteristics, such as domestic market size or capital stock, do change over time but including these as time-varying state variables requires an increase in the complexity of the model that makes it intractable. Earlier versions of the profit function included a time trend. This never proved statistically significant so we have dropped it to speed computation time.

specification implies that ν_{it} has a stationary *ARMA*(*m*, *m-1*) representation, which is quite general for large *m*, yet it allows us to express our model exclusively in terms of first-order processes. To economize on notation, we collect the AR(1) processes in the vector $x_{it} = (x_{it}^1, x_{it}^2, \ldots, x_{it}^m)'$, and we collect $\sigma_{\omega j}^2$ and λ_{xj} in the diagonal matrices Σ_{ω} and Λ_x respectively.

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 assume that firms incur no adjustment costs when changing from one positive level of exports to another. Then, among exporting firms, short-run profit maximization implies the standard mark-up relationship between export price (P_{it}) and marginal cost (α_{it}): $P_{it}(1 - \eta_i^{-1}) = \alpha_{it}$, where $\eta_i > 1$ is a firm-specific foreign demand elasticity and α_{it} is plant- and time-specific marginal cost. Multiplying both sides of this mark-up equation by the profit-maximizing quantity of foreign sales yields $R_{it}^{f*}(1 - \eta_i^{-1}) = C_{it}^{f*}$, where R_{it}^{f*} and C_{it}^{f*} are potential export revenues and the potential variable costs of exporting, respectively. Re-arranging this result yields a simple expression linking potential export profits and potential export revenues:

$$\pi_{it}^* = R_{it}^{f*} - C_{it}^{f*} = \eta_i^{-1} R_{it}^{f*}. \tag{2}$$

Finally, using (2) to eliminate π_{it}^* in (1) renders the dependent variable observable in exporting years:

$$\ln R_{it}^{f*} = \ln \eta_i + \psi_0 Z_i + \psi_1 e_t + \nu_{it} \tag{1'}$$

Equation (1') provides a means to identify Ψ , but it also adds a vector of firm-specific foreign demand elasticities, $\eta = \{\eta_i\}$, $i=1,2,...n,$ into the set of unknown parameters.

2.2 *The export market participation rule*[5]

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 aren't 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. We now characterize firms' exporting decisions in the face of these costs.

Denote the fixed costs of exporting $\gamma_F - \varepsilon_{1it}$, where γ_F is a component common to all firms and ε_{1it} captures all variation in fixed costs across firms and time. Also, if the i^{th} firm did not export in period *t-1*, assume it must pay the additional start-up costs, $\gamma_S z_i + \varepsilon_{1it} - \varepsilon_{2it}$, where γ_S is a vector of coefficients on the fixed plant characteristics, z_i, and $\varepsilon_{it} = (\varepsilon_{1it}, \varepsilon_{2it})$ is a vector of firm specific shocks that is normally distributed with zero mean and covariance matrix $\Sigma_\varepsilon = diag\left(\sigma^2_{\varepsilon 1}, \sigma^2_{\varepsilon 2}\right)$. Following Rust (1988), we assume that each component of ε_{it} is serially uncorrelated and independent of x_{it} and e_t.[6] Hereafter we will denote the vector of sunk and

[5]Dixit (1989), Baldwin and Krugman (1989) and Krugman (1989) develop theoretical models that characterize export market participation decisions in the presence of sunk entry costs. Our representation of the decision to export is a variant of their basic framework.

[6] These are Rust's (1988) conditional independence assumptions. 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.

fixed costs parameters $\Gamma = \left(\gamma_{S1},\ldots,\gamma_{Sk},\gamma_F\right)$.

Finally, define the binary variable y_{it} to take a value of one during periods when the firm exports and zero otherwise. Then, denoting the gross profit function in equation (1) by $\pi^*(x_{it}, z_i, e_t)$, and assuming that all sunk costs are borne in the first year of exporting, net current export profits accruing to the i^{th} firm in year t may be written as:

$$u(\cdot)=\begin{cases}\pi^*(x_{it},z_i,e_t)-\gamma_F+\varepsilon_{1it} & if\ \ y_{it}=1\ and\ \ y_{it}=1\\ \pi^*(x_{it},z_i,e_t)-\gamma_F-\gamma_S z_i+\varepsilon_{2it} & if\ \ y_{it}=1\ and\ \ y_{it}=0\\ 0 & if\ \ y_{it}=0\end{cases} \quad (3)$$

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 costs to export in year t.[7] Thus 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 upon the perceived distribution of future gross exporting profits (e.g., Dixit, 1989).

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

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[7] Equation (2) implies that firms completely lose their investment in start-up costs if they are absent from the export market for a single year. Earlier studies suggest that these investments depreciate very quickly, and that firms which most recently exported two years ago must pay nearly as much to re-enter 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 (2) to be a reasonable abstraction.

$$\max_{y(\cdot)} \quad E_t \sum_{\tau=t}^{t+H} \delta^{\tau} u(y_{i\tau-1}, y_{it}, x_{it}, z_i, e_t, \varepsilon_{it} | \theta) \tag{4}$$

Here E_t is the expectation operator conditioned on information available at time t, δ is a discount factor $0 < \delta < 1$, and $\theta = \left(\Psi, \Lambda_x, \Sigma_\omega, \Gamma, \Sigma_\varepsilon, \lambda_e, \sigma_w\right)$ is the entire parameter vector.

To characterize the decision rule $y(\cdot)$, note that expression (4) is equal to the value function that solves the Bellman equation:

$$V_{it} = \max_{y_t \in \{0,1\}} \left[u(x_{it}, e_t, z_i, y_{it}, y_{it-1}, \varepsilon_{it} | \theta) + \delta E_t V_{it+1}\right] \tag{5}$$

where $E_t V_{it+1}$ is the expected value of V_{it+1} taken over the future paths of the state variables e, x, and ε, given the information available at t :

$$E_t V_{it+1} = \int_{e_{t+1}} \int_{x_{it+1}} \int_{\varepsilon_{it+1}} V_{it+1}\left(e_{t+1}, x_{it+1}, z_i, y_{it}, \varepsilon_{it+1} | \theta\right) \cdot dF_{e,x}\left(e_{t+1}, x_{it+1} | e_t, x_{it}, \Lambda_x, \lambda_e, \Sigma_\omega, \sigma_w\right) \cdot dF_\varepsilon\left(\varepsilon_{it+1} | \varepsilon_{it}, \Sigma_\varepsilon\right) \tag{6}$$

Here dF_{ex} and dF_ϵ are the conditional distribution functions for the period t+1 values of the vectors (e, x) and ε, respectively.[8] Thus the sequence of optimal decision rules satisfies:

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

Given the parameter vector θ and our distributional assumptions for the exogenous state variables $(e_t, x_{it}, \epsilon_{it})$, equations (7) and (1) determine optimal foreign market participation patterns and export profits for the i^{th} firm. Also (2) converts profits to revenues. Hence,

[8] This model satisfies 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 one. See Rust (1995), section 2.

aggregating over firms, these three equations provide a framework for assessing the roles of heterogeneity, sunk costs, expectations, and history in shaping export responsiveness at the industry level. In the next section we discuss the econometric issues that arise in estimating equations (1), (2) and (7) with micro panel data.

3. Econometric Issues

3.1 *The likelihood function*

To estimate the elements of θ, we exploit annual panel data describing all Colombian industrial chemical plants that operated continuously over an 11 year period.[9] For each plant and year this data set reports a few fixed plant characteristics (z_i), total variable costs (C_{it}), domestic sales revenues (R_{it}^{d}) and censored export revenues:

$$R_{it}^{f} = \begin{cases} R_{it}^{f*} & if \;\; y_{it} = 1 \\ 0 & if \;\; y_{it} = 0 \end{cases}$$

We do not observe plants' gross export profits, output prices, input prices, physical quantities sold, or any direct information on the sunk and fixed costs of exporting. Finally, we augment our plant-level panel with time-series observations on the real peso-dollar exchange rate (e_t), adjusted for the relevant export subsidies (Ocampo and Villar, 1995).

The exchange rate process is unlikely to depend upon our plant-level data, so we estimate the parameters (λ_e, σ_w) by simply fitting an AR(1) process to time series on the real effective exchange rate. Then, fixing the vector (λ_e, σ_w) at its estimated values, we base our estimates of

[9] Firm-level data would have been preferable but these were unavailable. The vast majority of Colombian firms operate a single plant, so do not expect that this data limitation has led to major problems.

the remaining elements of θ on the log likelihood function for the observed plant level data, $L(D|\theta)$. Here $D = \{D_1, \ldots, D_n\}$ and D_i = (y_i, R_i^{f*}, R_i^d, C_i e, z_i) is the data set for the i^{th} plant. Except for R_i^{f*}, variables without time subscripts are plant-specific vectors that collect all T years of observations. The vector R_i^{f*} collects all uncensored observations on export revenues for the i^{th} plant, so it has $\sum_{t=1}^{T} y_{it} \leq T$ elements.

To further explain our approach, let us suppose for the moment data on plants' variable costs and domestic sales are unavailable. Then the log likelihood function is $\ln L(D|\theta) = \sum_{i=1}^{n} \ln L(D_i|\theta)$, where:

$$L(D_i|\theta) = \int_{x_i} P(y_i|e, x_i, z_i, \theta) g(x_i| R_i^{f*}, e, z_i, \theta) h(R_i^{f*}|e, z_i, \theta) dx_i \qquad (8)$$

The product of the three components of the integrand is the joint distribution for y_i, R_i^{f*} and x_i, conditioned on z_i and e. (Here x_i is an mT by one-dimensional vector obtained by vertically concatentating the m columns of $\begin{bmatrix} x_{i1}' \\ \vdots \\ x_{iT}' \end{bmatrix}$.) The first component of this product, $P(\cdot|\cdot)$, is the conditional probability for the observed sequence of exporting decisions, y_i. It is based on the decision rule (7), given the exogenous state variables, after taking expectations over ε_i. The second component, $g(\cdot|\cdot)$, gives the distribution for the unobservable exogenous state variables, x_i, conditional on R_i^{f*}, e, and z_i. It is based on the potential export revenue function, (1'). The last component, $h(\cdot|\cdot)$, is the density for the uncensored export revenues, given the observable exogenous state variables. It too is based on equation (1'). Details on each of the components of (8) may be found in appendix 1.

In principle, the entire parameter vector θ could be estimated using a likelihood function based on equation (8). But if we were to treat the vector of demand elasticities as free parameters to estimate, we would encounter an incidental parameters problem. We therefore exploit the unused information on costs and domestic revenues in our data set to impose more structure on our model.[10] By equation (2), when the i^{th} plant exports, it incurs variable costs $C_{it}^{f} = R_{it}^{f}(1-\eta_i^{-1})$ to do so. Also, assuming that foreign demand elasticities exceed domestic elasticities by some common factor $(1+\upsilon)$, a similar condition for variable costs due to domestic sales: $C_{it}^{d} = R_{it}^{d}\left[1-\eta_i^{-t}(1+\upsilon)\right]$. Adding these expressions together and introducing an error term, ξ_{it}, we arrive at an equation that relates foreign elasticities and the factor (1+ υ) to total variable costs ($C_{it} = C_{it}^{d} + C_{it}^{f}$), total reported revenues ($R_{it} = R_{it}^{d} + R_{it}^{f}$), and domestic sales revenues:

$$1-\frac{C_{it}}{R_{it}} = \eta_i^{-1}\left(1+\upsilon\frac{R_{it}^{d}}{R_{it}}\right)+\xi_{it}$$

We interpret ξ_{it} to reflect discrepancies between plants' reported variable costs and their true variable costs. We assume this error follows a normal, first-order auto-regressive process with root λ_ξ and innovation $\varsigma \sim i.i.d.N(0,\sigma_\varsigma^2)$, and that ξ_{it} is independent of other disturbances in the model. Thus we incorporate the density $c(\cdot)$ for the i^{th} plant's observed variable cost trajectory multiplicatively into the likelihood function (8), obtaining $L^b(D|\theta) = \prod_{i=1}^{n} L^b(D_i|\theta)$, where:

$$L(D_i|\theta) = c(C_i|R_i,S_i,\theta,\upsilon,\rho_\xi,\sigma_\xi)\int_{x_i} P(y_i|e,x_i,z_i,\theta)\cdot g(x_i|R_i^{f*},e,z_i,\theta)\cdot h(R_i^{f*}|e,z_i,\theta)\cdot dx_i \tag{9b}$$

3.2 *The MCMC estimator*

Neither version of our likelihood function is globally concave. Accordingly, simple

[10] An alternative estimation strategy is to treat the foreign demand elasticities as random effects. We implemented this version of the model as well. It generated smaller demand elasticities, on average, but had little effect on the other parameters. These results are available upon request.

gradient-based optimization algorithms fail to find the maximum. We deal with this problem by using a Bayesian Monte Carlo Markov chain (MCMC) estimator. More precisely, we specify priors on the parameter vector θ, then we sample repeatedly from its posterior distribution using a Metropolis-Hastings algorithm (e.g., Gilks et al, 1996).

Some parameters in our model are constrained. Specifically, all roots must lie on the open interval (-1,1), all variances must be non-negative, and all elasticities must be greater than unity. We deal with these constraints by expressing such parameters as transformations of unconstrained parameters, then we draw from the unconstrained parameter space using Gaussian random walk proposal distributions.[11] We also block the components of our parameter vector into seven sub-vectors to improve the computational efficiency of the sampling process. These blocks are: Ψ , Λ_x , Σ_ω , Γ , Σ_ε η, and $(\upsilon, \lambda_\xi, \sigma_\varsigma)$.

Our priors for all unconstrained coefficients are independent normal, with mean 0 and standard deviation 500. For the foreign elasticity premium υ, our prior has mean 0 and standard deviation 10. For roots, we use uniform priors but we impose stationary. Thus our priors for $(\lambda_{x1}, \lambda_{x2})$ and λ_ξ are independent uniform on the interval (-1, 1). For all variances, we use lognormal priors. For $\ln(\sigma_\xi)$, $\ln(\sigma_{\varepsilon 1})$ and $\ln(\sigma_{\varepsilon 2})$, our priors are independent normal with mean 0 and standard deviation 20. For $(\sigma_{1\omega}, \sigma_{2\omega})$ we specify that $\ln(\sigma_{\omega 1}^2 + \sigma_{\omega 2}^2)$ is normally distributed with mean 0 and standard deviation 20, and our prior concerning the share of total variation attributable to the smaller root is uniform on the (0,1) interval. Finally, our priors on the logs of the foreign demand elasticities, less one, $\left(\ln(\eta_1 - 1), \ldots, \ln(\eta_n - 1)\right)$, are normal with mean 1 and standard deviation 2. Thus, the elasticities themselves have prior mean 8.38 and prior

[11] More precisely, parameters that must be greater than some constant *a* are expressed as $\theta_j = a + \exp(\tilde{\theta}_j)$, and parameters constrained to the open interval (-1,1) are expressed as $\theta_j = (1 - \exp(\tilde{\theta}_j) / (1 + \exp(\tilde{\theta}_j))$

standard deviation 18.67.

As will be seen shortly, the standard deviations of our priors are orders of magnitude larger than the standard deviations of the posterior distributions. Thus the data essentially drive the estimation. We do modestly constrain the posterior distribution for the foreign demand elasticities, $(\eta_1, \ldots, \eta_n)$, given that each is identified with only 11 years of data. Even this did little to constrain the range of estimated values.

We adjust the variances and covariances of our proposal distributions until acceptance rates for all seven parameter blocks fell in the range [0.15, 0.50]. Because each evaluation of the likelihood function involved multi-dimensional numerical integration (see below), and because one complete iteration involves seven evaluations, we were only able to generate approximately 5 iterations per minute. We treat the first 10,000 iterations as our burn-in, and base our analysis on the 90,000 following iterations. Visual inspection of the chains suggests that most parameters mix very well and remain within a stable range, although the parameters $(\sigma_{\varepsilon 1}, \sigma_{\varepsilon 2})$ appear to mix rather slowly. We cannot rule out the possibility that the chain is trapped in the neighborhood of one mode, but several experiments with different starting values all led back to the same support. Given the slow rate at which we can generate draws, we have not attempted to do a more comprehensive battery of tests for convergence.

4. Fitting the Model to Two Colombian Industries

4.1 *Overview of the export patterns*

Although our framework should describe any industry in which exporting is potentially profitable for some firms, it is easiest to identify parameters in those industries which have many exporters, and which exhibit substantial variation in the set of exporters over time. For these reasons, we choose to estimate our model using data on Colombian leather product producers and industrial chemicals producers for the period 1982 through 1991. The former is a relatively capital-intensive industry that exports mainly to South America and Mexico. The latter is a more labor-intensive industry that exports mainly to the United States.[12] **(Check capital intensities)** By treating these very different industries, we hope to get some sense for the extent of variation in sunk costs and heterogeneity patterns across sectors. Also, given that we developed our model using the industrial chemicals data, our application to the leather products model serves as a check on the specification.

Export market participation patterns for both industries are summarized in table 1 below. Our data describe the 60 major industrial chemical producers and 32 leather products producers that operated continuously during the sample period.[13] It was originally collected by Colombia's Departamento Administrativo Nacional de Estadistica (DANE), and was cleaned as described in Roberts and Tybout (1996).

Note that the Colombian peso depreciated substantially in real terms during the sample

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[12]Statements concerning trade flows are based on the World Bank's Trade and Production Database, which is available at www.worldbank.org/research/trade.

[13]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 and focusing solely on this group of plants is a reasonable starting point that substantially simplifies the empirical model.

period, and that exports from both industries simultaneously grew. The expansion was partly due to an increase in the number of exporters, and partly due to increases in the magnitude of foreign sales at the typical exporting plant.[14] Colombian chemicals (leather products) plants produced 35.00 billion pesos (9.63 billion pesos) worth of exports in 1991, of which 29.94 billion (**XX** billion) came from plants that were exporting in 1984. So entry by new exporters contributed 5.06 (**XX)** out of the 27.10 (**XX**) expansion. Also, of the 60 (32) chemicals (leather products) plants that existed during the entire sample period, 18 (11) exported in all ten years, 24 (10) never exported, and 18 (13) switched exporting status at least once. So, although there were a number of switches, the data exhibit substantial persistence. This could be due to serial correlation in the plant-specific state variables, x_{it} , or it could be due to sunk entry costs, or some combination of both. Our estimates will shed light on the relative importance of these different forces.

4.2 *Estimation Preliminaries*

Before estimating our model we must choose the number of AR(1) processes, *m*, that will appear additively in the disturbance to equation (1'). We cannot use our 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 $m = 2$.[15] One interpretation for this specification is that profit shocks arise from both demand and cost shocks, and each follows an AR(1) process.

Next, we must be specific about the variables included in z_i . This vector is meant to

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[14] The number of chemical plants remains fixed at 62 during the sample because we have excluded producers who enter or exit to simplify the econometrics, so there is some potential for selectivity bias.

[15] Exploratory tests based equation 1' suggest that the disturbance of equation (1') follows an ARMA(2,1) process, which implies that m =2 is appropriate. Das et al (2001) provides details.

capture time-invariant heterogeneity in operating profits and in sunk costs. We model these using a set of four size dummies based on domestic sales in the pre-sample year. (The first is omitted in the profit function because an intercept is included.) These dummies should proxy for both product quality and marginal production costs at the beginning of the sample period. Experimentation with other dummies based on geographic location and business type yielded similar results.

To estimate the exchange rate parameters (λ_e, σ_w), we fit a simple AR(1) process to the log of the real effective export exchange rate series, 1972-1992, calculated by Ocampo and Villar (1995).[16] The coefficients (standard errors in parentheses) are $\hat{e}_0$ = 0.549 (.429), $\hat{\lambda}_e$ = 0.883 (.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 the exchange rate process is stationary, the usual problem with test power prevents us from rejecting the null hypothesis of a unit root.

4.3 Profit Function Parameters

We now turn to our MCMC results, which are reported in Table 2. Consider the profit function parameters first. As the reader may note, the posterior parameter distributions for the intercept and size dummies are relatively diffuse. Given our priors we cannot say with much confidence that any of these coefficients is far from zero in either industry. On the other hand, the elasticity of profits with respect to the exchange rate is rather tightly concentrated around its mean value of 1.5 for industrial chemicals and 1.9 for leather products. Since this same elasticity

[16] An AR(2) process fits the data significantly better, but the improvement is minor (R^2 = .85 versus R^2 = .79), and the cost of adding an additional state variable to the model is substantial. Given that the focus of the paper is not on modeling the exchange rate process, we have chosen to keep this aspect of the model as simple as possible.

describes responses of export *revenues*, it implies that devaluations do more than simply revalue a fixed physical quantity of exports—volumes respond too.

The parameters of the x_{it} process are identified with plant-specific variation, and thus are estimated with a good deal of precision. The mean λ_{x1} and λ_{x2} values are more than two standard deviations away from one and zero in absolute value. For industrial chemicals, the two roots are very different from one another, but for leather products they are nearly identical. Thus, for the former industry one root (m=1) would have been inadequate, but for the latter it would have sufficed. The posterior distributions of the variances, $\sigma_{\omega 1}$ and $\sigma_{\omega 2}$, are also concentrated away from zero.[17]

Our estimates of υ, the foreign demand elasticity premium, are surprisingly precise. They imply that, on average, the ratio of foreign to domestic demand elasticities is around 0.87 for industrial chemicals, and 0.99 for leather products. We expected foreign demand elasticities to be a bit *larger* than domestic demand elasticities, given that global markets usually contain more substitutes for one's product than local markets. The relatively low foreign demand elasticities for chemicals may reflect the fact that producers in this industry export go to small South American markets, with relative few domestic producers. It might also reflect the fact that transport costs reduce the fraction of each dollar of foreign revenue that firms retain as profit. Finally, the measurement error in marginal costs appears to be fairly small–one standard deviation amounts to about 5 percent of costs for chemicals and 1 percent of costs for leather products. These errors are serially correlated for both industries, as one would expect.

Rather than report posterior means for the 60 foreign elasticity estimates individually, we

[17]GMM and maximum likelihood estimates applied to equation 1 alone yield very similar values for roots and variances–see appendix 2 and Das, et al, 2001, respectively.

have sorted them in ascending order and graphed them, along with their standard errors. Note that generally, the larger the mean elasticity, the more diffuse its posterior distribution. The cross-plant average elasticity is 12.5 for industrial chemicals and 14.7 for leather products. These figures imply that on average, about one twelfth of each peso earned abroad accrues to the exporting plant as operating profits.

4.4 *Sunk Costs and Fixed Costs*

The parameters that characterize plants' dynamic patterns of export market participation are reported in the bottom panel of Table 2. Here we reap one of the payoffs to structural estimation, in that we can put a peso or dollar value on the sunk costs of entering foreign markets. Our results imply that for industrial chemicals producers, the expected sunk costs of breaking into export markets varies from 51 to 70 million 1986 pesos ($US 344,000 to $US 477,000), depending upon which plant size category we are describing. Similarly, for leather products, expected entry costs range from 40 million to 69 million 1986 pesos ($US 270,000 to $US 466,000). Further, although we have used very diffuse priors for these parameters, their posterior distributions are fairly concentrated. Standard deviations in millions of pesos range from 1.5 to 8.0.

For both industries, sunk entry costs appear to fall with plant sizes, suggesting that big plants with large domestic market shares are in a better position to step into international markets. (γ_{s1} is the average export market entry cost among plants in the smallest size quartile, γ_{s2} is the average entry cost for plants in the second quartile, and so on.) This pattern could reflect existing contacts and distribution channels among large firms, the types of products large firms produced, or to the mix of people they employ. Finally, among the larger producers, sunk costs appear to be smaller among industrial chemicals producers than among leather products producers.

The means of our posterior fixed cost (γ_F) distributions are very close to zero for both sectors, and variances of these distributions are sufficiently large to imply that these costs are negligible. Recall, however, that fixed costs for the i^{th} plant are $\gamma_F - \varepsilon_{it}^1$, and our posterior σ_{ε_1} distribution is bounded well above zero. So fixed costs are important at least some of the time for some of the plants. Finally, note that $\sigma_{\varepsilon 2}$ is larger than $\sigma_{\varepsilon 1}$ among chemicals producers. This is what one would expect, given that ε_{2it} captures the combined effects of shocks to sunk entry costs and fixed costs. No such patten emerges for leather products producers.

4.5 *In-sample model performance*

To assess our model, we simulate export market participation patterns using our estimated parameters and compare them to the actual data set. First we use the mean estimated $(\Lambda_x, \Sigma_\omega)$ values to construct the steady state distribution for *x* realizations. Drawing repeatedly from this distribution, we obtain initial *x* values for a set of 6000 hypothetical chemical producers and 3200 hypothetical leather product producers. (That is, we draw 100 times as many starting values as the actual data sets contain.) These we simulate forward using the transition density implied by $(\Lambda_x, \Sigma_\omega)$: $x_{it} = \Lambda x_{it-1} + \omega_{it}$. Next we combine these trajectories with our (Ψ, η) estimates and the actual exchange rate realizations to generate profit trajectories for our hypothetical plants. Finally, using our $(\Gamma, \Sigma_\varepsilon)$ estimates, we solve each hypothetical producer's dynamic optimization problem at randomly drawn $(\varepsilon_{1it}, \varepsilon_{2it})$ sequences to generate their export market participation patterns. After running this simulation 22 periods for each producer to reduce the importance of starting values, we look at participation patterns over an 11 period time horizon. These we compare to the actual patterns observed in our panel data.

The results of this exercise are summarized in figure 2. For industrial chemicals, the generated data match the actual data quite well, although there is a tendency to under-predict the number of firms that never export and over-predict the number of firms that export only a few years. For leather products, there is a tendency to understate the frequency with with firms exports.

5. Implications for Export Supply

5.1 *Profits, option values and transition probabilities*

To explore the implications of sunk costs and plant profit heterogeneity, we calculate the plant-specific gross expected value of exporting in year *t* before netting out sunk costs:

$$\widetilde{V}_{it} = \int_{x_{it}} \left[\pi\left(x_{it}, e_t, z_i | \theta\right) - \gamma_f + \delta\left(E_t V_{t+1}|_{y_{it}=1} - E_t V_{t+1}|_{y_{it}=0} \right) \right] g(x_{it} | R_{it}^f, e_t, z_i, \theta) dx_{it}$$

This expression has a current profit component, $\pi - \gamma_f$, and an option value component, $\delta\left(E_t V_{t+1}|_{y_{it}=1} - E_t V_{t+1}|_{y_{it}=0} \right)$. The latter measures the value of being able to export next period without paying entry costs. Note that $\widetilde{V}_{it}$ is an expectation over the unobservable x_{it} values, so it shows less cross-plant heterogeneity than one would actually observe.

The gross expected value of exporting for the first year in our sample (*t*=1982) is compared with expected sunk entry costs, $\gamma_S z_i$, plant by plant, in figures 3a and 3b. Plants are sorted by sunk cost category, then by ascending $\widetilde{V}_{i,1982}$. The circled lines in the figure are the sunk costs that are estimated for each of the four plant types, where the type is defined by the plant's size in the domestic market. (We have excluded one very large leather products exporter from figure 3b in order to provide a more detailed picture of the remaining producers.)

Expected export profit streams are typically insufficient to cover entry costs among small producers. (An exception to this pattern occurs among small chemical producers, which tend to export basic chemical products to South American markets.[18]) Thus, ignoring noise in sunk costs and in $x_{i,1982}$ realizations, few non-exporters in either industry would find it profitable to enter the export market. For the remaining two groups of plants a number of producers expect export profit streams sufficient to warrant entry. Perhaps most interestingly, figure 3a and 3b suggest that relatively few firms were poised on the verge of becoming exporters in 1982, so modest changes in the exchange rate and modest subsidies to exporters probably would not have induced a wave of entry. That is, heterogeneity appears to limit export responsiveness, at least on the entry margin.

Of course, Figures 3a and 3b should not be used to predict which plants will *actually* participate in the export market because it averages out noise in sunk costs (ϵ_{it}) and profits ($x_{i,1982}$). More importantly, it provides no information on plants' prior export experience. To illustrate the difference that prior experience makes, we construct the 1982 plant-specific transition probabilities, once again taking expectations over $x_{i,1982}$. Figures 4a and 4b show 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, assuming it did not export in the previous year. Plants are sorted in order of ascending $\widetilde{V}_{i,1982}$. The probability of remaining an exporter, once in, is above 0.7 for virtually all plants. That is, P($\widetilde{V}_{i,1982} + \varepsilon_{1i,1982} > 0$) is quite high for most plants. In contrast, the probability of *entering* the market P($\widetilde{V}_{i,1982} - \gamma_S z_i + \varepsilon_{1i,1982} > 0$) is much lower for virtually all plants, and the gap between the two probabilities is as large as 0.7 for many producers. These probabilities are similar to earlier estimates based on a reduced-form model of the decision

[18]Industry 3511 (basic chemical products) is dominated by relatively small firms, and aggregate trade flow data show that more than two-thirds of its exports went to South America in 1982. In contrast, industry 3512 (fertilizers and pesticides) is dominated by large firms, and more than half of its exports went to the United States in 1982.

to export (Roberts and Tybout, 1997).

We now isolate the role of option values in determining export market participation patterns. This component of $\widetilde{V}_{i,1982}$ depends on the plants' expectations of future market conditions and is bounded by their sunk costs. To illustrate how important the option value is as a source of the plant's total export value, Figures 5a and 5b plot current profit (net of fixed costs, γ_F) and total export value for each of the non-exporting plants in 1982. The difference between the two curves is the option value. If there were no sunk costs of entry, the option value would be zero and the two curves would coincide. The figure demonstrates that the option value is a large component of the total value of the plant, particularly among smaller firms. In fact, in a number of cases the current profits that would be earned by being an exporter are close to zero, so that the option value is the largest component of $\widetilde{V}_{i,1982}$. Even among firms with substantial current profits from exporting, the option value still accounts for more than one-third of total export value. Thus as expectations of future market conditions improve, the option value term increases and can induce entry even if current profits are unaffected. That is, sunk costs make expectations a potentially important determinant of exporting patterns.

Total industry exports depend on both the number of plants exporting and the foreign sales volume of each plant. Figures 6a and 6b illustrate the distribution of export revenue for all plants in 1982, sorted by potential export revenue. The line marked with circles indicates how much each plant *would have* contributed if it were exporting, and the line marked with triangles indicates how much each firm *actually* contributed to export revenues. Thus the two lines correspond for exporting plants. Differences in the size of the exporters are obvious, with the largest two chemical plants accounting for almost half of the industry revenue, and the largest leather plant accounting for sixty percent of industry export. In contrast, none of the non-exporting plants would account for more than several percent points of export revenue by itself if it were to initiate foreign sales. Thus the contribution of new exporters to total export revenues is likely to be substantially less than proportional to the entry rate.

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 firms' reactions to a permanent change in the exchange rate process that depreciates the steady state value of the peso by 10 percent.[19] We then repeat the experiment for a 20 percent devaluation. The regime shifts take place in period 1 and we track firms reactions over the following nine periods. Firms always begin period 1 in their observed state, thereafter all realizations on x and e are simulated. We calculate expected reactions by simulating 300 exchange rate trajectories under each scenario and averaging each firm's responses.

The effect on the number of exporting plants, relative to a base case scenario, is reflected in the bottom two trajectories of figures 7a and 7b. The darker of the two lines corresponds to our 10 percent experiment; the other to our 20 percent experiment. Clearly, in both cases the expected increase in the number of exporters is modest, even after one decade. For leather products it amounts to 2.6 percent in the 10 percent devaluation experiment, and 4.2 percent in the 20 percent devaluation experiment. The effects are even smaller for industrial chemicals–1.5 percent and 3.0 percent, respectively–reflecting the fact that entry costs are bit higher for big firms in this industry,

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[19] 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 .549/(1-.883) = 4.69. Using the relationships between the mean and variance of a normal and a log normal random variable, an increase in the intercept from 0.549 to 0.560 amounts to a 10 percent change in the long run expected exchange rate..

and profits are bit less sensitive to the exchange rate. These results are a direct consequence of the heterogeneity patterns documented in figure 3. That is, very few firms are poised on the verge of exporting, so modest upward shifts in the value of being an exporter don't affect the participation decisions of most managers.

Total export *sales* respond much more dramatically in each industry because all incumbent exporters adjust their export volumes in response to exchange rate movements. After 10 years, export revenues for the leather products industry are 13 percent higher than in the base case for the first policy experiment, and they are 26 percent higher for the second policy experiment. The analogous figures for industrial chemicals are 15 percent and 30 percent, respectively. However, the contribution of net entry to devaluation-induced export growth is trivial, not only because entry is modest, but also because the marginal entrants are small scale exporters, as demonstrated by figure 6. For this reason, we have not included separate series that isolate the contribution of net entry in our graphs.

Because figures 7a and 7b are averages over 300 sets of randomly drawn trajectories for each firm in our sample, they give the misleading impression that export responses to devaluation are quite smooth and predictable. This is far from true. Comparing the 300 sets of aggregate trajectories for each industries, we find a great deal of heterogeneity. This implies that accurate forecasts of industrial exports are probably not possible without bringing in additional information on the shocks that affect foreign demand.

6. Summary

In this paper we develop a dynamic structural model that characterizes firms' decisions concerning whether to export and the volume of foreign sales among those who do. The model embodies uncertainty, plant-level heterogeneity in export profits, and sunk entry costs for plants breaking into foreign markets. We estimate the model with plant-level panel data on sales and production costs among Colombian chemical and leather products producers. Then we use the results to quantify sunk entry costs and export profit heterogeneity, and we conduct dynamic policy analysis.

Our results imply that entry costs are substantial. Consequently, producers don't initiate exports unless the present value of their expected future export profit stream is large. They also tend to continue exporting when their current profits are negative, thus avoiding the costs of re-establishing themselves in foreign markets when conditions improve. For example, we calculate that plants exporting in year *t* generally remain exporters in year *t+1* with probability 0.7 or greater. But if these same plants were, for some reason, not to have exported in year *t*, only a handful would have exported in year *t+1* with probability greater than .5. Further, for many of the smaller plants, the option value of being able to export next year without paying entry costs substantially exceeds the *current* profits that they expect to earn by exporting. In this sense, history and expectations are important for many producers.

On the other hand, if one is concerned with total export sales rather than the behavior of small producers, it is heterogeneity that really matters. In both industries, a few dominant producers supply the bulk of foreign sales, and these producers find it profitable to maintain their foreign market presence under any reasonable policy scenario. Thus entry and exit, when they take place, are limited to fringe producers. Furthermore, in the industries and time periods we studied, few of these fringe producers are near the margin of indifference between exporting and not exporting. Thus modest shifts in the exchange rate regime have small effects on the expected patterns of foreign market participation, and even smaller (percentage-wise) effects on export volumes attributable to net entry. For the same reasons, policies that simply affect managers' beliefs about future exchange rate trajectories are unlikely to induce much export response.

It is easy to imagine that patterns of heterogeneity and sunk costs might be different in different industries, and we are hopeful further applications of approach might reveal a basis for generalization. More broadly, while the parameter estimates we report and the quantitative effects they imply are specific to the issue of export dynamics, we believe that the methodology we have describe herein is fairly general, and that it should be adaptable to other contexts involving market diversification.

References

Baldwin, Richard E. and Paul Krugman. 1989. "Persistent Trade Effects of Large Exchange Rate Changes." *Quarterly Journal of Economics* 104(4), 635-54.

Bernard, Andrew, Jonathan Eaton, J. Bradford Jensen and Samuel Kortum. 1999. "Plants and Productivity in International Trade: A Ricardian Reconciliation." working paper, Boston University.

Bernard, Andrew and J. Bradford Jensen. 1999. "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics* 47 (February), 1-25.

Bernard, Andrew and J. Bradford Jensen. 2001. "Why Some Firms Export," Working Paper, Dartmouth College, Tuck School of Business .

Bernard, Andrew and Joachim Wagner. 2001. "Export Entry and Exit by German Firms," *Welktwirtschaftliches Archiv* 137, 105-123.

Brooks, Eileen. 2001. "Why Don't Firms Export More?" Working Paper, Department of Economics, U.C. Santa Cruz.

Campa, Jose. 1998. "Exchange Rates and Trade: How Important is Hysteresis in Trade?" Working Paper, Stern School of Business, New York University.

Chow, Gregory. 1983. *Econometrics*. New York: McGraw-Hill.

Clerides, Sofronis, Saul Lach, and James Tybout.1998. "Is Learning by Exporting Important? Micro Dynamic Evidence from Colombia, Mexico and Morocco," *Quarterly Journal of Economics*, August, pp. 903-947.

Das, Sanghamitra 1992. "A Micro-Econometric Model of Capital Utilization and Retirement: The Case of the U.S. Cement Industry," *Review of Economic Studies*, 59, 277-297.

Das, Sanghamitra, Mark Roberts and James Tybout. 2001. "Market Entry Costs, Producer Heterogeneity and Export Dynamics." NBER Working Paper No. 8629.

Dixit, Avinash K. 1989. "Entry and Exit Decisions Under Uncertainty." *Journal of Political Economy* 97(3), 620-38.

Gilks, Walter A., Sylvia Richardson and David J. Speigelhalter. 1996. *Markov Chain Monte Carlo in Practice*. New York: Chapman and Hall/CRC.

Goldberg, Penelopi and Micheal Knetter.1999. "Measuring the Intensity of Competition in Export Markets," *Journal of International Economics* 47(1), pp. 27-60.

Krugman, Paul R. 1989. *Exchange Rate Instability*. Cambridge, MA: The MIT Press.

Ocampo, Jose Antonio and Leonardo Villar. 1995. Colombian Manufactured Exports, 1967-91," in G.K. Helleiner, ed., *Manufacturing for Export in the developing World*: *Problems and Possibilities*. New York, NY: Routledge.

Roberts, Mark J. and James R. Tybout. 1997a. "The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Cost," *American Economic Review,* September, pp. 545-564.

Roberts, Mark and James Tybout. 1997b. *What Makes Exports Boom?* The World Bank. Directions in Development Monograph.

Roberts, Mark, Theresa A. Sullivan and James R. Tybout. 1995. "Micro Foundations of Export Booms," Working Paper, Department of Economics, Pennsylvania State University.

Rubinstein, Reuven Y. (1986), *Monte Carlo Optimization, Simulation and Sensitivity of Queueing Networks*, New York: John Wiley & Sons.

Rust, John. 1988. "Maximum Likelihood Estimation of Discrete Control Processes," *SIAM Journal of Control and Optimization*, 26(5), 1006-1023.

Rust, John. 1995. "Numerical Dynamic Programming in Economics," in *Handbook of Computational Economics*, edited by H. Amman, D. Kendrik and J. Rust.

Rust, John. 1997. "Using Randomization to Break the Curse of Dimensionality," *Econometrica* 65(3), May, pp. 487-516.

Westphal, Larry. 2001. "Technology Strategies for Economic Development in a Fast-Changing Global Economy," forthcoming in *Economics of Innovation and New Technology*.

Appendix 1: Evaluating the Likelihood Function

This appendix provides more details on the components of the likelihood function (9). Consider first the density function for the uncensored export revenues, $h(R_i^{f*}|e,z_i,\theta)$. By earlier assumption, the disturbance term of the potential export revenue function (1') can be written as $\nu_{it} = \ell' x_{it}$, where $\ell = \begin{pmatrix}1, & 1, & \cdots & 1\end{pmatrix}'$. Assuming that each plant begins with a random draw from the steady state distribution of x_{it}, the unconditional distribution for the potential export profit shocks ν_{it} is $N\left(0, \ell'\Sigma_{\omega}[I-\Lambda^2]^{-1}\ell\right)$. Also, for all $k \neq 0$, $E[\nu_{it}\nu_{it-k}] = \ell'\Lambda_x^{|k|}\Sigma_{\omega}\left[(I-\Lambda_x^2)^{-1}\right]'\ell$ and $E[\nu_{it}\nu_{jt-k}] = 0 \ \forall\, i \neq j$ (e..g., Chow, 1983). These relationships define the conditional density $h(R_i^{f*}|\, e,z_i,\theta)$.[20]

The density $g(x_i\,|R_i^{f*},e,z_i,\theta)$ is also based on (1'). Collecting all of the uncensored realizations on ν_{it} for the i^{th} plant in the vector ν_i^* (which is $\sum_{t=1}^{T} y_{it}$ by one), and exploiting well-known properties of the multivariate normal distribution, we obtain:[21]

$$g(x_i\,|R_i^{f*},e,z_i,\theta) \equiv g(x_i\,|\,\nu_i\,) = N\left(\Sigma_{x\nu}\Sigma_{\nu\nu}^{-1}\nu_i^*,\ \Sigma_{xx} - \Sigma_{x\nu}\Sigma_{\nu\nu}^{-1}\Sigma_{x\nu}'\right). \qquad \text{(A1.1)}$$

. Representative blocks of the matrices that appear in (A1.1) are defined by:

$$\begin{aligned}\textstyle\sum_{xx} &= \left\{E(x_{it}x_{it+s}')\right\} = \left\{\Lambda_x^{|s|}\Sigma_{\omega}(I-\Lambda_x^2)^{-1}\right\},\\ \textstyle\sum_{x\nu} &= \left\{E(x_{it}\nu_{it+s})\right\} = \left\{\Lambda_x^{|s|}\Sigma_{\omega}(I-\Lambda_x^2)^{-1}\ell\right\} \qquad \text{and}\\ \textstyle\sum_{\nu\nu} &= \left\{E(\nu_{it}\nu_{it+s})\right\} = \left\{\ell'\Lambda_x^{|s|}\Sigma_{\omega}(I-\Lambda_x^2)^{-1}\ell\right\}.\end{aligned}$$

Several features of the density (A1.1) merit comment. First, although our notation does not

[20]Note that $h(\,)$ depends only on $(\Psi, \Lambda_x\ \Sigma_{\omega},\ \eta) \subset \theta$.

[21] The number of years that the i^{th} firm exports determines the number of rows of ν_i. Note also that, g( ) depends only on $(\Psi, \Lambda_x\ \Sigma_{\omega},\ \eta) \subset \theta$.

show it explicitly, the dimensions and composition of $\Sigma_{x\nu}$ and $\Sigma_{\nu\nu}$ vary across firms with their export market participation patterns. Second, the density A1.1 uses information on a plant's observed exporting revenue to extrapolate to non-exporting years, given the autoregressive processes summarized by (Λ_x, Σ_ω). Finally, if the i^{th} firm never exports, we do not observe a ν_{it} value in any year so the distribution of x_i is unconditional: $E(x_i) = 0$ and $E(x_i x_i') = \Sigma_{xx}$. This is the only case in which Σ_{xx} is full rank; otherwise the constraint $\ell' x_{it}$ $= \ln R_{it}^* - \ln \eta_i - \left[\psi_0 z_i + \psi_\cdot e_t\right]$ makes one component of x_{it} a deterministic function of the others in the exporting years.

Finally, consider the discrete probability distribution $P(y_i | e, x_i, z_i, \theta)$. Given that ε_{it} is serially uncorrelated, and that both x_{it} and e_t are first-order Markov processes, exporting decisions in year *t* depend only upon exporting status in year *t-1* and current year information. So, taking expectations over ε_i, the probability of the participation trajectory y_i may be written as a product of year-to-year transition probabilities, conditioned on the other variables:

$$P(y_i \mid e, x_i, z_i, \theta) = \prod_{t=1}^{T} [P(y_{it}=0 | e_t, x_{it}, z_i, y_{it-1}=0, \theta)^{(1-y_{it})(1-y_{it-1})} P(y_{it}=0 | e_t, x_{it}, z_i, y_{it-1}=1, \theta)^{(1-y_{it})(y_{it-1})}$$

$$P(y_{it}=1 | e_t, x_{it}, z_i, y_{it-1}=1, \theta)^{y_{it}y_{it-1}} \; P(y_{it}=1 | e_t, x_{it}, z_i, y_{it-1}=0, \theta)^{y_{it}(1-y_{it-1})}] \qquad \text{(A1.2)}$$

To calculate these transition probabilities, we first evaluate $E_t V_{t+1}|_{y_{it}=1}$ and $E_t V_{t+1}|_{y_{it}=0}$ using backward induction. (At each stage in the induction, we integrate over the state variables x_{it+h} and e_{t+h} using Rust's (1997) random grid algorithm.) Then we substitute these values into right-hand side of the decision rule (7) along with the net profit function (2), and we take the expectation of the implied y_{it} choice over ε_{it} using closed-form expressions. We repeat these calculations firm by firm for each sample year, every time the likelihood function is evaluated. Further details are provided in Das et al (2001).

Table 1

Colombian Leather Products and Industrial Chemicals Producers: Exporting Patterns

Year	*Real Exchange Rate*	*Leather Products*[a]				*Industrial Chemicals*[b]			
		Value of Exports[c]	*Number of Exporters*	*Number of Entrants*	*Number of Quitters*	*Value of Exports*[c]	*Number of Exporters*	*Number of Entrants*	*Number of Quitters*
1982	79.5	1.27	15	1	2	6.18	25	1	1
1983	80.5	1.14	14	2	3	8.60	30	6	1
1984	89.8	3.24	16	2	0	7.90	28	1	3
1985	102.2	4.13	21	5	0	11.79	25	3	6
1986	113.6	5.74	20	0	1	14.10	24	1	2
1987	113.7	6.59	20	0	0	15.40	23	1	2
1988	112.3	7.59	20	1	1	21.97	28	6	1
1989	115.2	7.17	21	1	0	20.62	27	2	3
1990	127.2	10.16	21	0	0	27.10	28	1	0
1991	121.1	9.63	21	1	1	35.00	30	2	0
Average	105.51	5.67	20.5	1.3	.8	16.866	26.8	2.4	1.9

[a] Data describe the 32 Colombian producers of leather products continually observed over the period 1982-91.

[b] Data describe the 60 Colombian producers of industrial chemicals continually observed over the period 1982-91.

[c] Billions of 1986 pesos (deflation done using manufacturing-wide wholesale price deflator). To convert to millions of 1999 US dollars, multiply by 6.75.

Table 2: Posterior Parameter Distributions

	Industrial Chemicals	Leather Products	Priors
	Profit Function Parameters		
ψ_0 (Intercept)	1.763 (1.351)	-1.846 (0.641)	$\psi_0 \sim N(0, 500)$
ψ_{01} (Size class 2 dummy)	-2.578 (1.318)	-0.227 (0.841)	$\psi_{01} \sim N(0, 500)$
ψ_{02} (Size class 3 dummy)	-0.389 (1.111)	0.206 (0.671)	$\psi_{02} \sim N(0, 500)$
ψ_{03} (Size class 4 dummy)	-0.381 (1.155)	1.274 (0.675)	$\psi_{03} \sim N(0, 500)$
ψ_1 (Exchange rate coefficient)	1.475 (0.121)	1.880 (0.158)	$\psi_1 \sim N(0, 500)$
λ_{x1} (Root, first AR process)	-0.503 (0.168)	0.947 (0.016)	$\lambda_{x1} \sim U(-1,1)$
λ_{x2} (Root, second AR process)	0.957 (0.014)	0.948 (0.015)	$\lambda_{x2} \sim U(-1,1)$
$\sigma^2_{1\omega}$ (Variance, first AR process)	0.179 (0.074)	0.270 (0.131)	$\ln(\sigma^2_{1\omega}) \sim N(0,20)$
$\sigma^2_{2\omega}$ (Variance, second AR process)	0.450 (0.089)	0.458 (0.135)	$\ln(\sigma^2_{2\omega}) \sim N(0,20)$
υ (Foreign elasticity premium)	-0.126 (0.024)	-0.007 (0.019)	
λ_ξ (Root, measurement error)	0.706 (0.043)	0.349 (0.064)	
σ_ξ (Std. error, ξ innovations)	0.048 (0.007)	0.011 (0.001)	$\ln(\sigma_\xi) \sim N(0,20)$
	Dynamic Discrete Choice Parameters		
γ_{S_1} (Sunk cost, size class 1)	70.422 (1.942)	69.047 (1.521)	N(0, 500)
γ_{S_2} (Sunk cost, size class 2)	51.726 (3.459)	56.902 (2.836)	N(0, 500)
γ_{S_3} (Sunk cost, size class 3)	53.453 (6.145)	38.869 (8.046)	N(0, 500)
γ_{S_1} (Sunk cost, size class 4)	51.219 (5.555)	40.001 (2.939)	N(0, 500)
γ_F (Fixed cost)	1.277 (1.451)	1.988 (1.467)	N(0, 500)
$\sigma_{\varepsilon 1}$ (Std. error, ε_1)	10.363 (8.363)	22.621 (6.940)	$\ln(\sigma_{\varepsilon 1}) \sim N(0,20)$
$\sigma_{\varepsilon 2}$ (Std. error, ε_2)	29.117 (5.892)	17.524 (4.325)	$\ln(\sigma_{2\varepsilon}) \sim N(0,20)$

Figure 1a

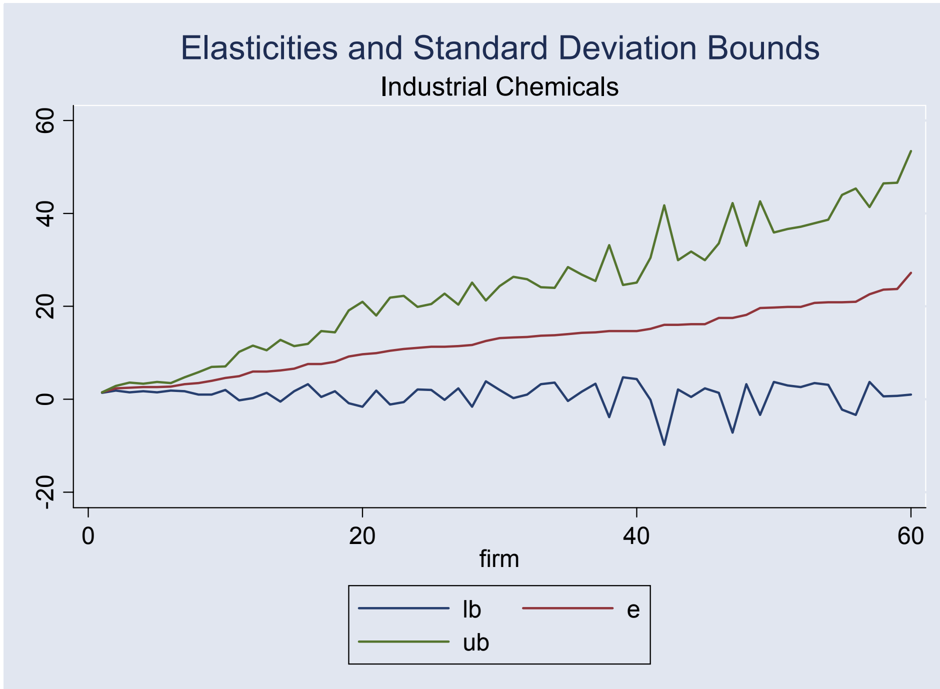

Figure 1b

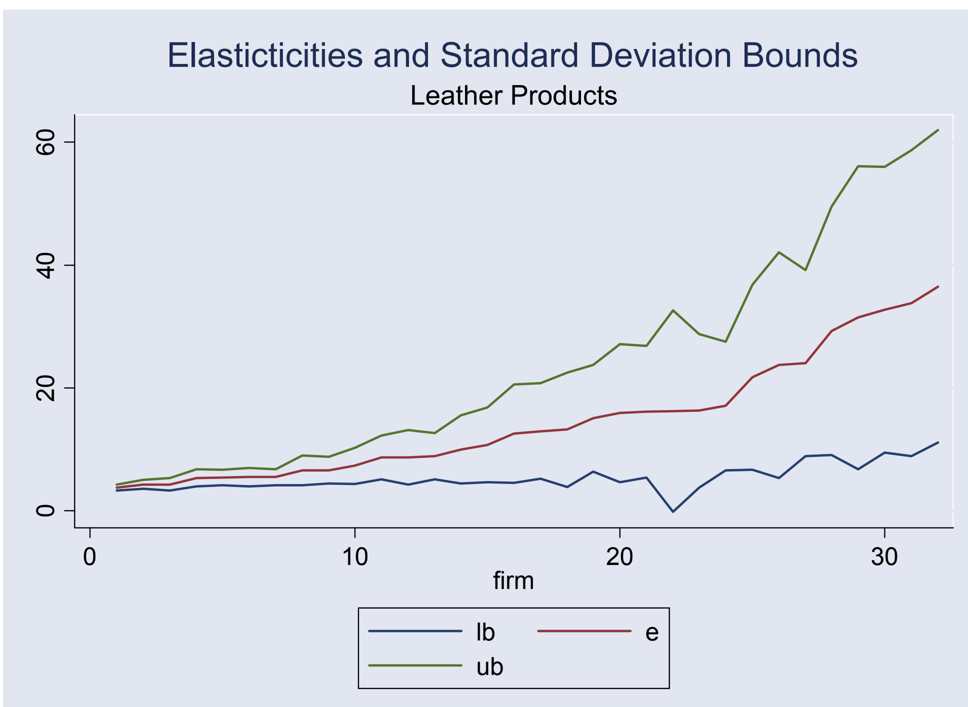

Figure 2a

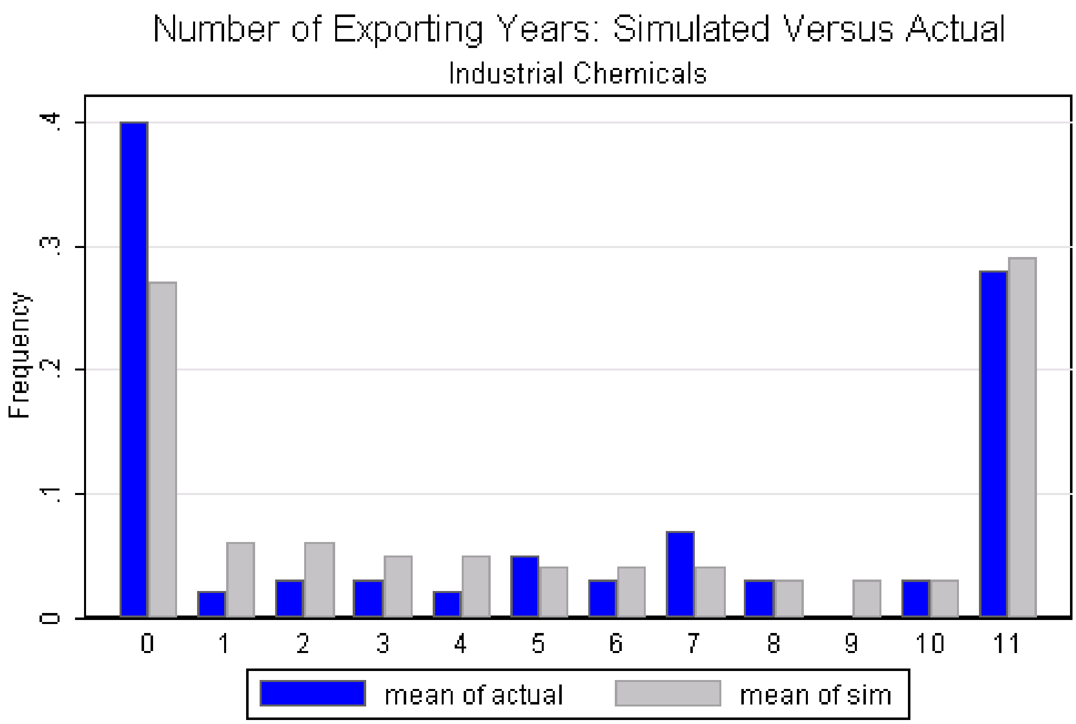
Number of Exporting Years: Simulated Versus Actual
Industrial Chemicals
Frequency
0
.1
.2
.3
.4
0 1 2 3 4 5 6 7 8 9 10 11
mean of actual
mean of sim

Figure 2b

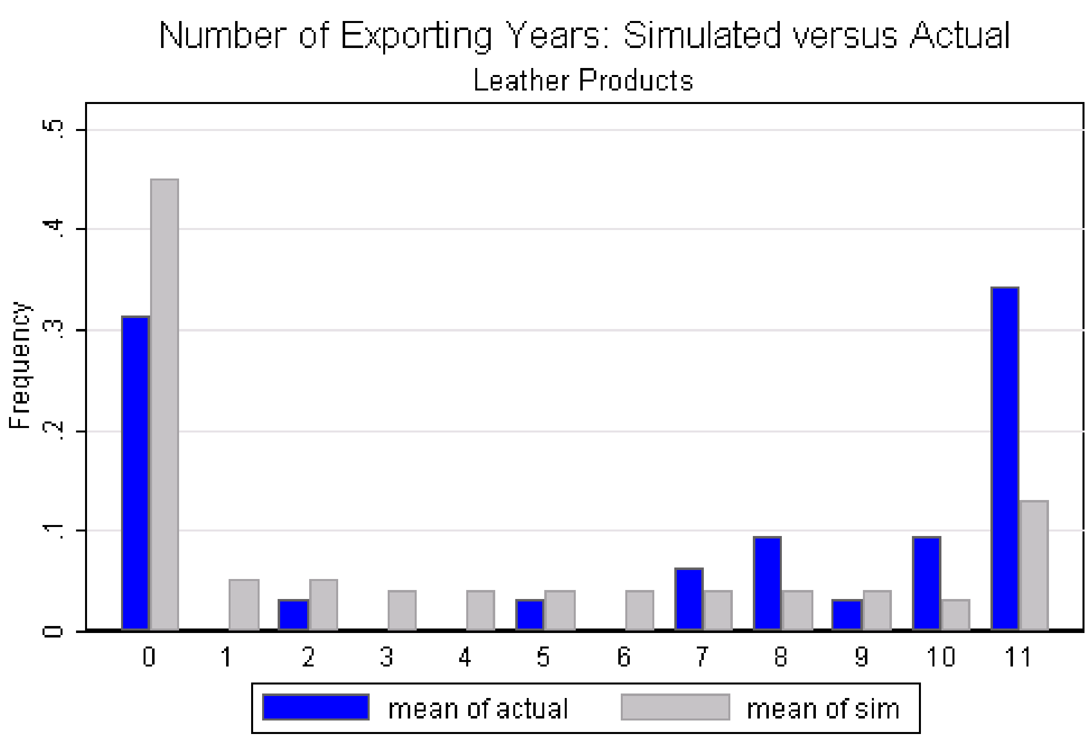
Number of Exporting Years: Simulated versus Actual
Leather Products
Frequency
0
.1
.2
.3
.4
.5
0 1 2 3 4 5 6 7 8 9 10 11
mean of actual
mean of sim

Figure 3a: Industrial Chemicals

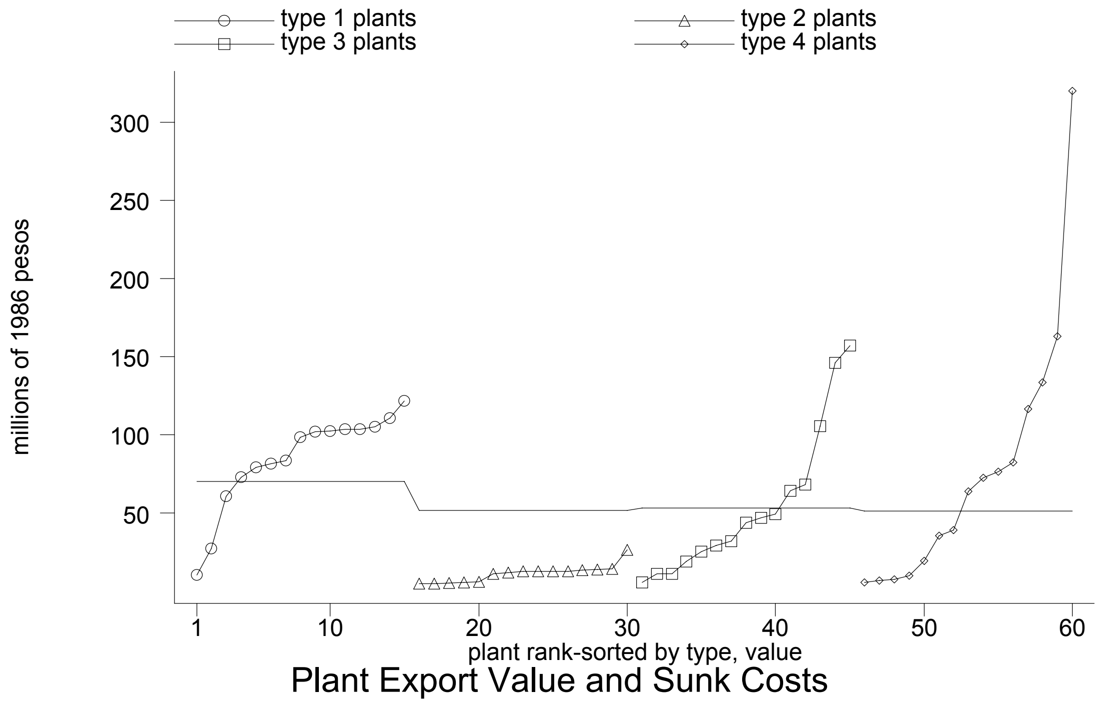

Figure 3b: **Leather Products**

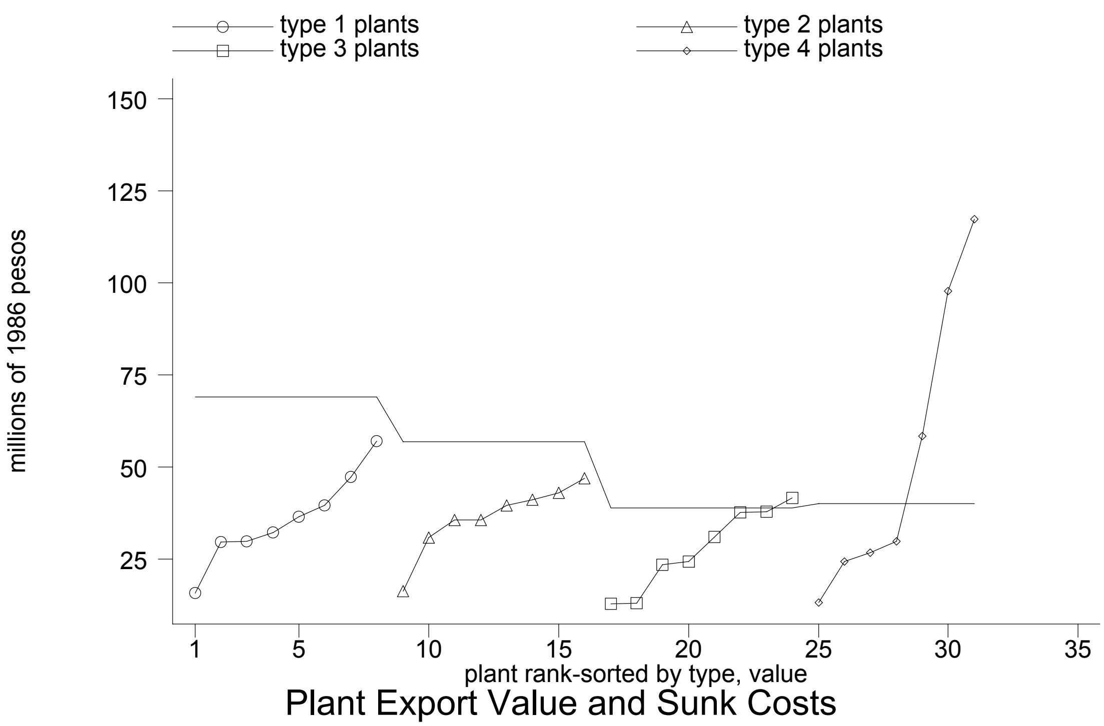

Figure 4a: Industrial Chemicals

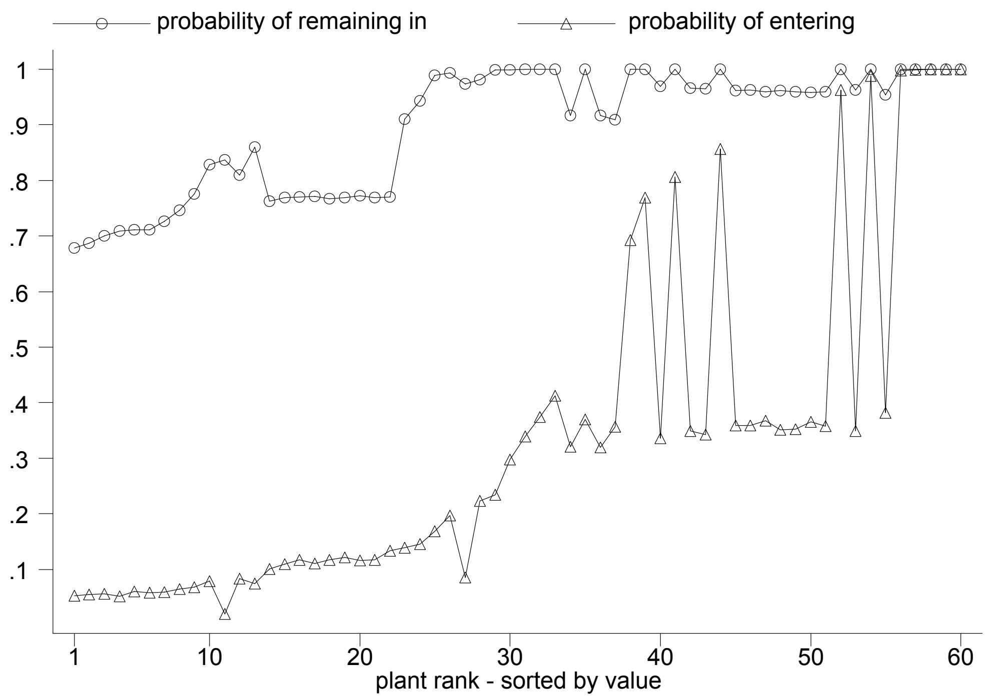

Figure 4b: Leather Products

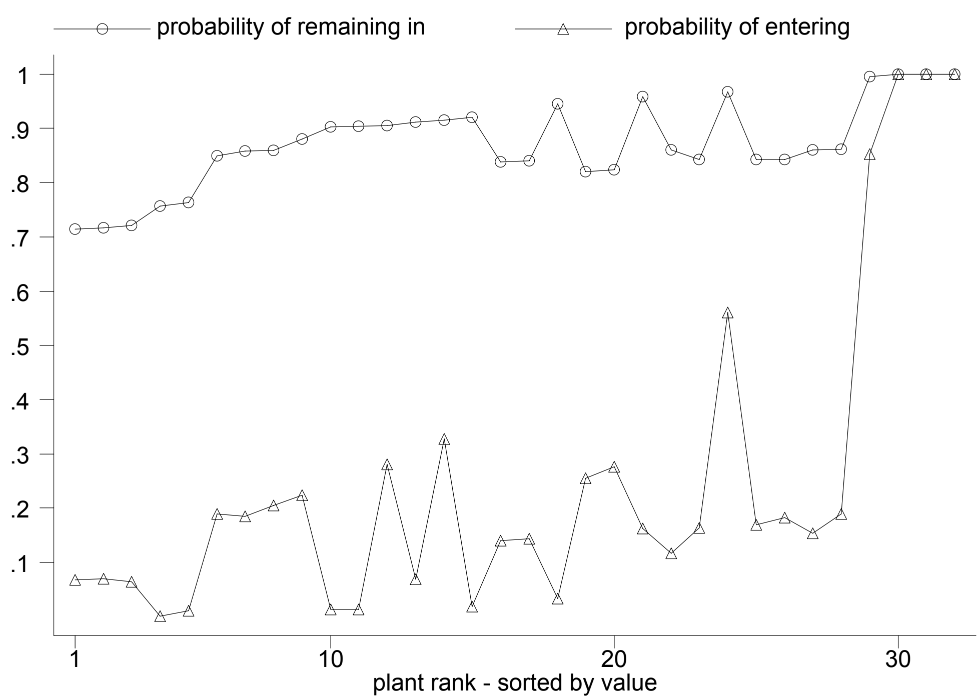

Figure 5a: Industrial Chemicals (non-exporters only)

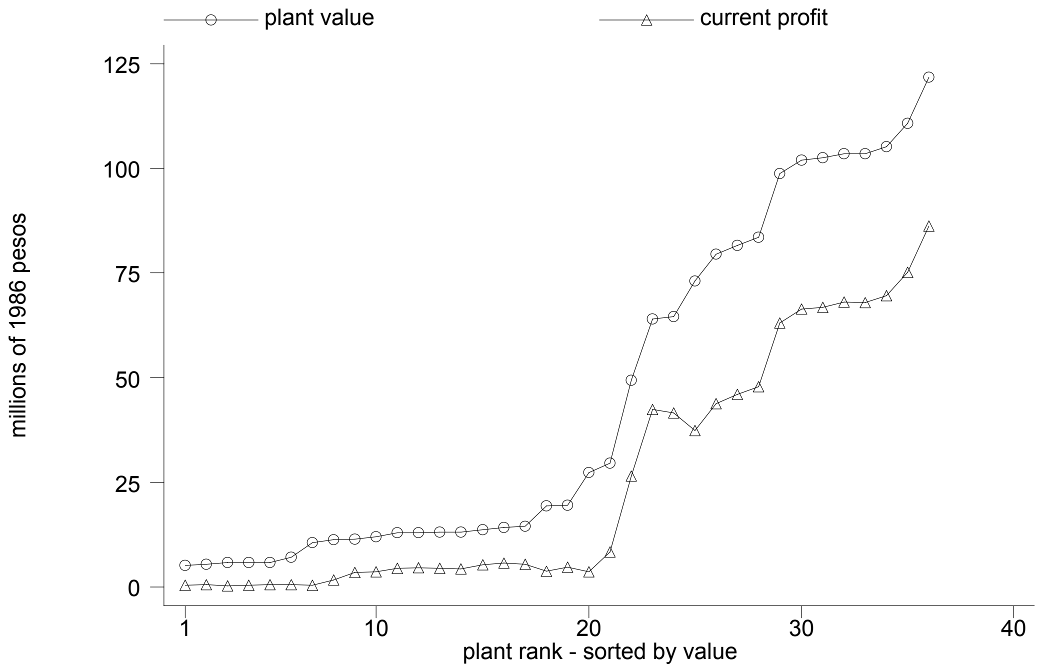

Figure 5b: Leather Products (non-exporters only)

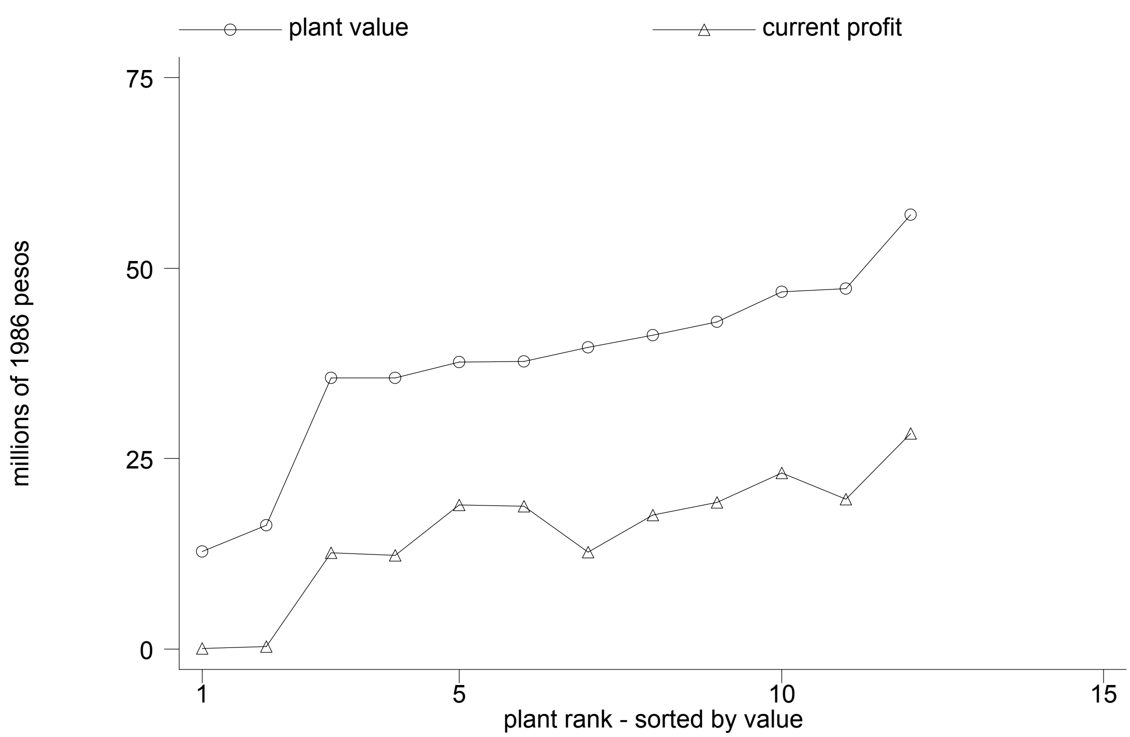

Figure 6a: Industrial Chemicals

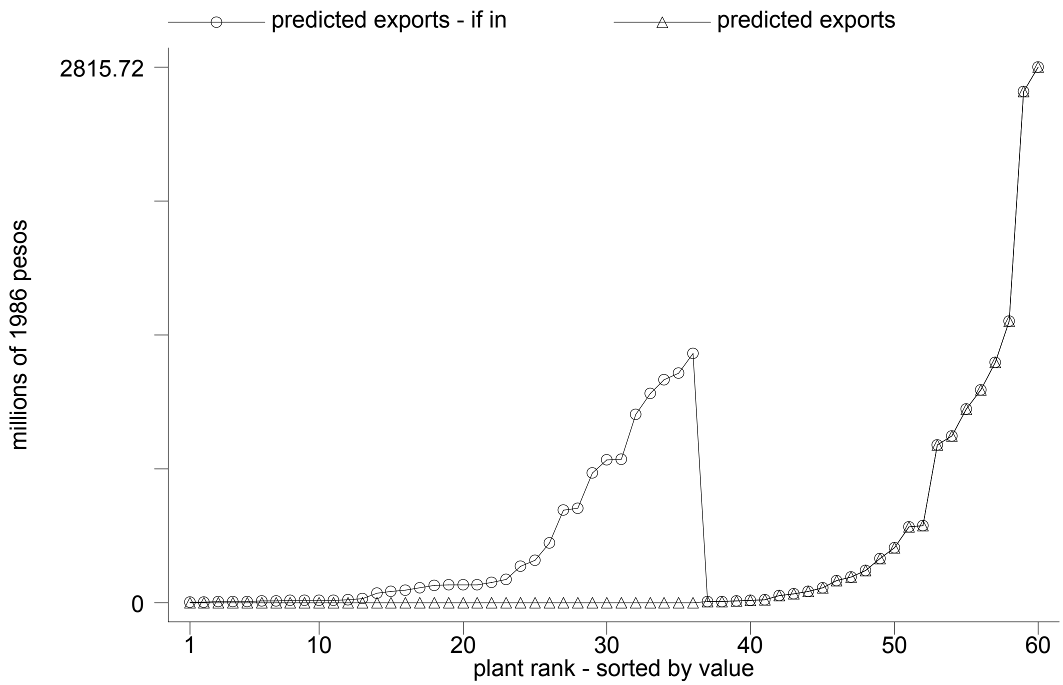

Figure 6b: Leather Products

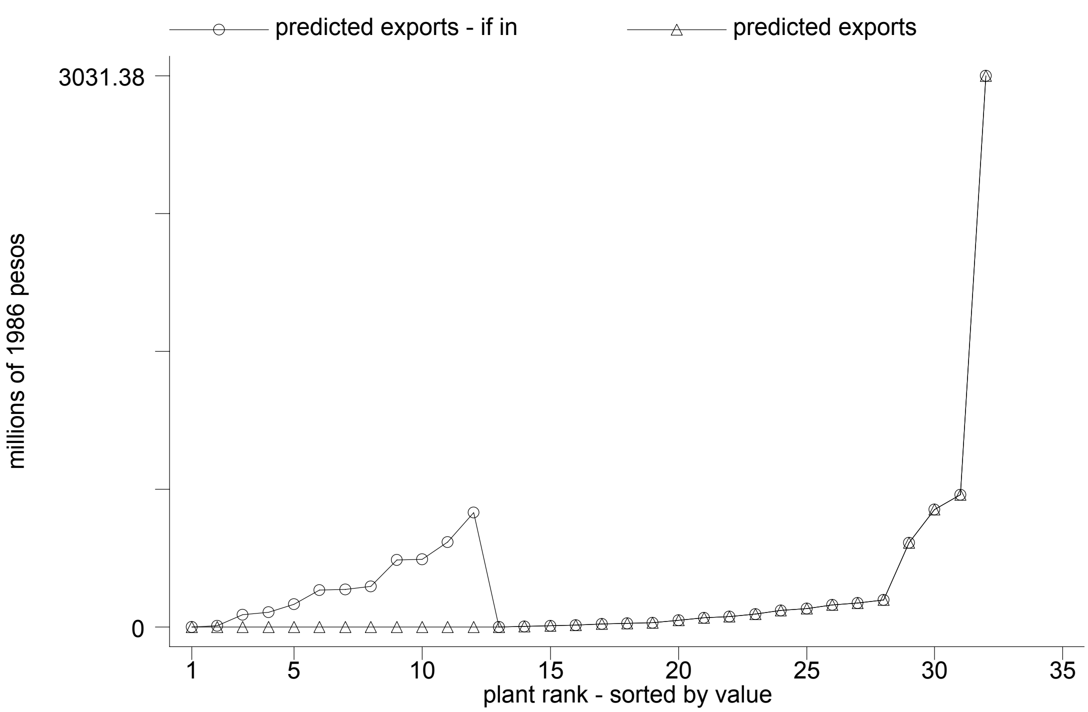

Figure 7a

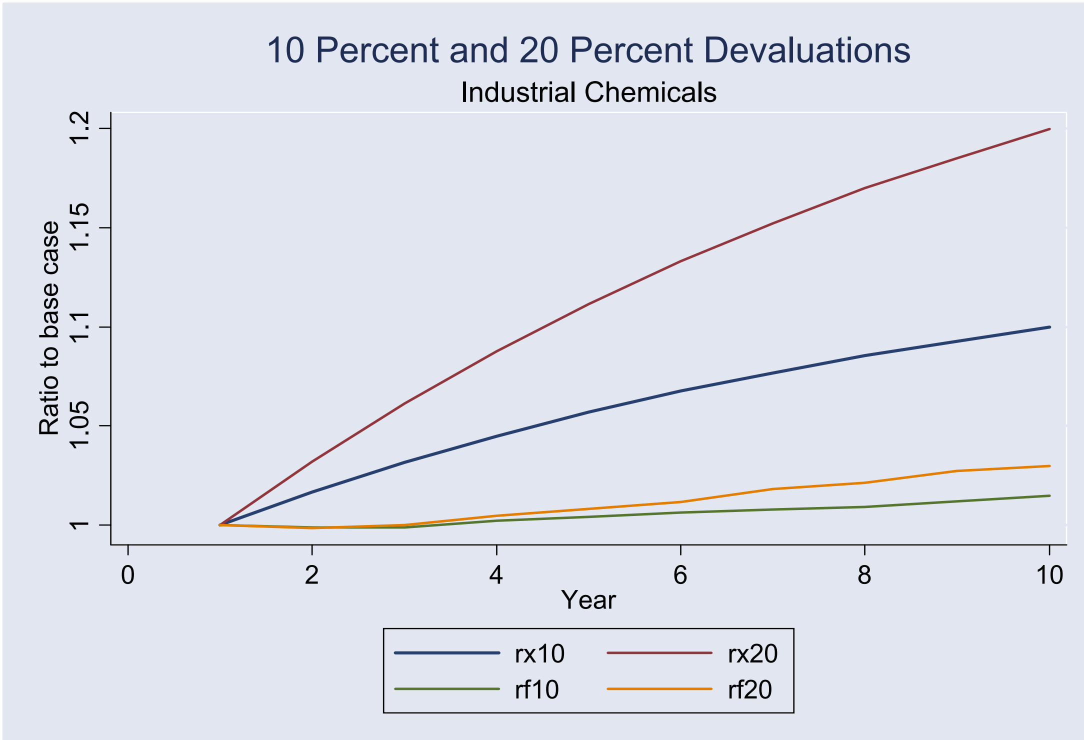

Figure 7b