Trade Dynamics of Colombian Chemical Plants: Productivity and Trade Cost Complementarity

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Abstract

This paper estimates a dynamic model of the firms joint export and import decision process. In the model, participating in trade improves within-period profits and future productivity. In addition, doing one trade activity facilitates the other by reducing the associated fixed/sunk costs. Employing a Bayesian MCMC estimator, I fit the model to Colombian chemical plant panel data from 1981 to 1985. Two findings stand out: (i) importing increases future productivity significantly while exporting does not. (ii) importing facilitates exporting by lowering the sunk costs of entering the foreign market while exporting facilitates importing by decreasing the fixed costs of continuing import. A counterfactual simulation shows that subsidizing the fixed costs of importing is the most effective among trade cost subsidy schemes in improving the average productivity and firm value.

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I Introduction

Many empirical studies have documented that serving foreign markets and using imported inputs have positive impacts on both short-run and long-run performances of firms (For export, Das, Roberts, and Tybout; 2007, Aw, Roberts, and Xu; 2011, Bai, Krishna, and Ma; 2016, Li; 2018, and Grieco, Li, and Zhang 2018. For import, Kashara and Rodrigue; 2008, Halpern, Koren, and Szeidl; 2015, Zhang; 2017). In these studies, participating in trade activities is beneficial to firms in two aspects. First, by joining the global market, a firm can enjoy higher per-period profits than its counterpart in the short-run (static gains from trade). Second, by doing export and import, a firm can boost up its future productivity which is known as learning-by-exporting and learning-by-importing (dynamic gains from trade).

However, evaluation of the benefits of exporting and importing is potentially biased when a researcher does not take both activities into consideration. If export or import has positive effects on future productivity, participating in one activity would drive more firms to self-select into both activities. In this case, it is probable that documented empirical results that export or import boosts up future productivity are actually reflecting the spurious correlation with the other activity. To my knowledge, except for Grieco, Li, and Zhang (2018), most studies ignore other trade activity when they analyze the effects of export and import.

Having this gap in mind, I build a model for the joint import and export decision process of a firm by augmenting a firm dynamic model of Aw, Roberts, and Xu (2011) with production function of Halphern, Koren, and Szeidl (2015). As well established by earlier studies, there are both static and dynamic gains from trade in the model of this paper. Firms can enjoy higher profits and boost up their future productivity by doing import and export. Besides these standard gains, I add one more potential gain from trade: if a firm participates in one trade activity, it will pay different (potentially cheaper) sunk or fixed costs for the other trade activity. Allowing for heterogeneity in sunk/fixed costs across trade history is motivated by the two observed transition patterns that (i) a firm doing one activity is more likely to start the other activity than does its counterpart and (ii) 92% of firms doing both in current period continue doing both activities in next period (See Table 3).

I take the model to panel data of Colombian chemical plants who continuously operated from 1981 to 1985 to back out relevant structural parameters. Since the parameters of the model are too many and constructed likelihood function involves the simulation, the likelihood function is not globally concave. Thus, a conventional optimization algorithm is not suitable for estimating the model of this paper. To bypass non-global concavity, I implement Bayesian Markov Chain Monte Carlo (MCMC) method to characterize the posterior distribution of the structural parameters. Using the estimated model, I conduct two counterfactual exercises. First, I quantify the three proposed gains from trade. Second, I evaluate the anticipated performance and efficiency of policies that subsidize fixed/sunk costs of importing and exporting.

My empirical results reveal several aspects in Colombian chemical industry. First, productivity is endogenously determined; using imported inputs improves future productivity. However, serving a foreign market does not improve future productivity significantly. Notably, when I do not include learning-by-importing in the productivity dynamics, the estimates indicate that Colombian chemical plants are facing learning-by-exporting effect. These empirical results tell that when a researcher finds out learning-by-exporting without including learning-by-importing effect, the estimation result is nothing but a spurious correlation with importing. Second, there are substantial sunk costs for undertaking export and import, and export sunk costs are larger than import sunk costs. It introduces, along with endogenous productivity, an intertemporal trade-off of doing export and import. Third, one activity facilitates the other activity by reducing sunk or fixed costs: Exporting decreases import fixed costs while importing decreases export sunk costs.

The first counterfactual exercise shows that static gains from exporting contribute to 80% of total gains from export, while dynamic gains from importing contribute to 85% of total gains from import. However, gains from the complementarity in costs are not playing a crucial role in shaping total gains from export or import. For export, gains from facilitating importing only account for about 1.8% of total gains, and for import, gains from facilitating exporting account for about 3.78%.

The second counterfactual exercise shows that amongst four possible subsidy policies, subsidizing import fixed costs is the most effective. The simulation result indicates that ten years after the policy, subsidizing import fixed costs increases the average productivity by 0.8% while subsidizing export fixed costs raises the average productivity by 0.2%. The other two policies do not increase productivity. For analyzing the cost and benefit of each policy, I divide the increases in the total values of firms due to a policy by the total subsidy costs paid by the government. Ten years after the policy was implemented, subsidizing import fixed costs outperforms all the other policies. The measured efficiency of subsidizing import fixed costs is about 16, while those of subsidizing export fixed costs, import sunk costs, and export sunk costs are nine, one, 0.5, respectively.

Section II develops the theoretical framework of the firm's joint decision of export and import. Section III describes a two-step estimation strategy for the model. Section IV reports estimates of structural parameters of the model and Section V summarizes the counterfactual results. Finally, Section VI concludes.

II Model

In this section, I introduce a dynamic model to explore the firm's trade participation decision, following the spirit of Aw, Roberts, and Xu (2011), and Halphern, Koren, and Szeidl (2015). These studies analyze the firm's export and import decision, respectively. The model of this paper combines these two models. More specifically, the model of this paper augments the model of Aw, Roberts, and Xu by introducing the production function of Halpern, Koren, and Szeidl. There are two dynamic discrete choices that a firm can make: import and export. A new feature of the model in this paper is that it analyzes both trade activities simultaneously and introduces a complementarity between them by allowing for the fixed and sunk cost parameters are depending on the firm's current trade status. For instance, if an importer would like to start exporting, then it would face the lower sunk cost than the one that its counterpart would have to pay. This feature embodies the possibility that one trade activity could facilitate other activity. Then, armed with the model, I can quantify the three channels through which current trade status improves the values of firms: (i) improving the future productivity, (ii) improving per-period profits, and (iii) reducing the fixed/sunk costs that a firm should pay to undertake the other activity.

II.I Timeline

Following a standard exporter dynamics model, each firm wants to maximize its discounted present value of future profits by choosing the sequence of the optimal decisions. To boil down the firm's lifetime maximization problem into a recursive form, I need to specify the timeline of the decision-making process.

1. At the beginning of the period t, a firm j observes its state vector s_{jt}

$$s_{jt} = (e_{jt}, d_{jt}, k_{jt}, x_{jt}, z_{jt}),$$

where (e_{jt}, d_{jt}) indicates the firm's export and import status, k_{jt} is the logged amount of capital, x_{jt} is the logged productivity, and z_{jt} is the logged foreign market demand shifter.

2. Right after that, the firm j optimally decides its labors and materials and produces the outputs for domestic and foreign markets, respectively. Sales immediately occur so the profits from domestic and foreign markets are realized.

3. The firm j draws the non-convex cost for importing C_{jt}^M from the distribution $F_M(\cdot|s_{jt})$ and then decides whether or not to make an import contract for the next period (d_{jt+1}).

4. Then, the firm j faces the non-convex cost for exporting C_{jt}^X drawn from the distribution $F_X(\cdot|s_{jt})$ and chooses its next period export status e_{jt+1}.

It is noteworthy to point out the crucial assumptions in the model of this paper. First, I assume that one time period is required for making a trade contract with foreigners. These assumptions embody the fact that trade agreement could proceed with the product inspections, search frictions, and negotiations. Second, I abstract from the firm's investment decision given that the data in hand is a short panel.

II.II Technology

The first building block of the model is a production function that converts labors, capital, imported materials, and domestic materials to outputs. In the spirit of Halpern, Koren, and Szeidl (2015), I specify a production function as the following Cobb-Douglas with a nested CES function aggregating the domestic and imported materials:

$$Q_{jt} = \exp(x_{jt}) L_{jt}^{\alpha_l} M_{jt}^{1-\alpha_l} K_{jt}^{\alpha_k}, \tag{1}$$
$$M_{jt} = [(M_{jt}^d)^{\frac{\theta-1}{\theta}} + (A_t M_{jt}^f)^{\frac{\theta-1}{\theta}}]^{\frac{\theta}{\theta-1}}, \ \theta > 1$$

where L_{jt}, K_{jt} are labor and capital inputs, and M_{jt} is the composite basket of domestic materials M_{jt}^d and imported materials M_{jt}^f. θ is the corresponding elasticity of substitution between domestic and imported materials. A_t represents the time-varying relative physical quality measures of imported materials. Note that I assume that the production function is characterized by a CRS technology *in the short-run*. Under this assumption, the short-run marginal cost function is invariant in the amount of produced quantities Q_{jt}.

All firms are a short-run cost minimizer and behave competitively in the factor market. Thus, they take the technology constraint (1) and the prices of composite materials $P_{M,t}$ and the wage rates W_t as given. If a firm is not an importer, then it optimally chooses L_{jt} and M_{jt} to minimize the short-run total costs. If a firm is an importer, it optimally chooses L_{jt} and M_{jt}, and then optimally allocates M_{jt} into M_{jt}^d and M_{jt}^f.

Solving the first order conditions of cost minimization problem yields the following marginal cost functions:

$$C_{import}(K_{jt}, Z_{jt}, W_t, P_t^d, P_t^f) = B(\alpha_l) W_t^{\alpha_l} (P_{M,t}^d)^{1-\alpha_l} K_{jt}^{-\alpha_k} \exp(-x_{jt}) (1 + (A_t \frac{P_t^d}{P_t^f})^{\theta-1})^{\frac{1-\alpha_l}{1-\theta}}, \tag{2}$$

$$C_{non-import}(K_{jt}, Z_{jt}, W_t, P_t^d, P_t^f) = B(\alpha_l) W_t^{\alpha_l} (P_{M,t}^d)^{1-\alpha_l} K_{jt}^{-\alpha_k} \exp(-x_{jt}), \tag{3}$$

where

$$B(\alpha_l) = [(\frac{\alpha_l}{1-\alpha_l})^{1-\alpha_l} + (\frac{1-\alpha_l}{\alpha_l})^{1-\alpha_l}] \tag{4}$$

Note that the cost shifting effect of importing is captured by $(1+(A_t\frac{P_t^d}{P_t^f})^{\theta-1})^{(1-\alpha_l)/(1-\theta)}$ in (2) and this is the only one shifting effect of importing. One can see that when importer and non-importer are with the same level of productivity and capital, the ratio of marginal costs of them is exactly equal to $(1+(A_t\frac{P_t^d}{P_t^f})^{\theta-1})^{\frac{1-\alpha}{1-\theta}}$. This result allows me to specify the logged marginal cost c_{jt} as a linear function of logged level of productivity and capital, and import dummy.

$$c_{jt} = \beta_0 + \alpha_l w_t + (1-\alpha)p_{m,t}^d + \beta_{m,t}d_{jt} + \beta_k k_{jt} - x_{jt} \tag{5}$$

where $w_t, p_{m,t}^d$ are logged wage rates and domestic material prices, k_{jt} is a firm j's logged level of capital at time t, $\beta_k = -\alpha_k$, and $\beta_{m,t}$ is $\frac{1-\alpha_l}{1-\theta}\log(1+(A_t\frac{P_t^d}{P_t^f})^{\theta-1})$.

Note that $\beta_{m,t}$ is time-varying as the relative material price and physical relative quality of imported materials are time-varying. However, in this paper, I am strictly interested in the average advantage of imports due to the reduction in marginal cost. Thus, I simplify $\beta_{m,t}$ as a time-invariant parameter β_m by assuming that the price-adjusted quality of imported materials $A_t\frac{P_t^d}{P_t^f}$ has a constant value, namely κ.

Thus, the logged marginal cost to be used hereafter and to be estimated is as the following:

$$c_{jt} = \beta_0 + \beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}, \tag{6}$$

where β_t captures any time-varying marginal cost shifters including the factor prices and the time-varying components associated with $\beta_{m,t}$ which is abstracted in this specification. This specification is similar to the marginal cost specification of Aw, Roberts, and Xu (2011), except for the inclusion of an indicator of import status as a cost shifter. Given that $\beta_k = -\alpha_k$ and $\beta_m = \frac{1-\alpha_l}{1-\theta}\log(1+(\kappa)^{\theta-1})$, one can see that the sign of β_m and β_k is negative in this framework because $\alpha_k > 0$ and $\theta > 1$. I do not impose this sign restrictions on parameters when I estimate these parameters, rather I will confirm whether this theoretical prediction on the sign of the parameters holds in the data by estimating the parameters without restrictions.

II.III Demand and Static Decision

Market demands in both domestic and foreign markets are characterized by Dixit-Stiglitz CES functions.

$$q_{jt}^D = \Phi_t^D (p_{jt}^D)^{\eta_D}, \tag{7}$$

$$q_{jt}^X = \Phi_t^X (p_{jt}^X)^{\eta_X} \exp(z_{jt}), \tag{8}$$

where q_{jt} the amount of demanded goods in each market, p_{jt} is the price set by a firm j, Φ_t represents the time-varying aggregate industry demand shifter, and η represents the demand elasticity of both markets. Note that for the foreign demand, I incorporate foreign market demand shifter z_{jt} which is time-varying and firm-specific. Here, the domestic market demand does not include any firm-specific factor, except for p_{jt}^D. Thus, z_{jt} essentially captures the relative differences between domestic and foreign market demand shifters.

In both markets, a firm j behaves as a monopolistic competitor, so sets the good price in order to maximize the static profits. Then, it is straightforward to derive the logged revenue functions.

$$r_{jt}^D = (\eta_D + 1) \log \frac{\eta_D}{1+\eta_D} + \log \Phi_t^D + (\eta_D + 1)(\beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}), \tag{9}$$

$$r_{jt}^X = (\eta_X + 1) \log \frac{\eta_X}{1+\eta_X} + \log \Phi_t^X + (\eta_X + 1)(\beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}) + z_{jt}. \tag{10}$$

Finally, by CES demand property, the operating profits are proportional to the revenues.

$$\pi_{jt}^D = -\frac{1}{\eta_D} \exp(r_{jt}^D) = \Pi_D(k_{jt}, x_{jt}, d_{jt}), \tag{11}$$

$$\pi_{jt}^X = -\frac{1}{\eta_X} \exp(r_{jt}^X) = \Pi_X(k_{jt}, x_{jt}, d_{jt}, z_{jt}). \tag{12}$$

Two important features of the model need to be pointed out. First, the relative foreign market demand shifter z_{jt} does not serve any role in shaping firms' domestic market revenues. This feature comes from the model assumption that the short-run marginal cost function is invariant in the amount of produced quantities. The assumption that the marginal cost is constant makes the output levels in domestic and foreign markets are independent and it allows me to disentangle firm-specific productivity x_{jt} and foreign market demand shifter z_{jt}. More specifically, x_{jt} will capture all the firm-specific variations that could affect both domestic and export revenues, while z_{jt} will capture the between-exporter heterogeneity in export revenues which were not explained by the size, import status, and productivity x_{jt}. Second, both domestic and foreign operating profits are a function of import status d_{jt}. That is, due to the cost reduction effect of importing, an importer would enjoy the higher profits than it's counterpart.

II.IV Productivity and Foreign Market Demand Shifter Evolution

I specify the evolution of the firm's productivity x_{jt} as a stationary Markov process depending on the firm's trade participation status in the previous period. Specifically, the productivity x_{jt} evolves as the following:

$$x_{jt} = \rho_0 + \sum_{p=1}^{3} \rho_p x_{jt-1}^p + g_e e_{jt-1} + g_m d_{jt-1} + u_{jt}, \tag{13}$$

where e_{jt-1} and d_{jt-1} are indicating whether a firm j was a exporter and an importer at time $t-1$, respectively. One can see that previous experience in exporting and importing would improve the productivity. This specification allows for the possibility of learning-by-trading. For instance, a firm could access to technical support from trading partner or improve the quality of their product by experiencing a foreign market or using imported materials with higher quality.

The firm's foreign market shock is specified as a stationary AR(1) process:

$$z_{jt} = \rho_z z_{jt-1} + \epsilon_{jt}. \tag{14}$$

The persistence of z is capturing all the other possible driving forces associated with exporting such as the quality of product or the contractual relationship between foreign importers.

II.V Dynamic Decision

Given profits that a firm earns from the market, the firm would decide whether or not to participate in trade in order to maximize its value after observing realized fixed and sunk costs. However, it is probable that each firm faces heterogeneous fixed and sunk costs for participating in trade because of the difference in trade experience or the connection to foreign partner. To characterize this heterogeneity, I specify that non-convex costs for importing and exporting C_{jt}^{M} and C_{jt}^{X} are identically and independently drawn from the state-specific distributions:

$$
\begin{aligned}
C_{jt}^{M}|s_{jt} &\sim iid\ Exp(\lambda_M(e_{jt}, d_{jt})) \\
C_{jt}^{X}|s_{jt} &\sim iid\ Exp(\lambda_X(e_{jt}, d_{jt}))
\end{aligned}
$$

where

$$
\begin{aligned}
\lambda_M(e_{jt}, d_{jt}) &= (1-d_{jt})(1-e_{jt})\gamma^{SM} + (1-d_{jt})e_{jt}\nu^{SM} + d_{jt}(1-e_{jt})\gamma^{FM} + d_{jt}e_{jt}\nu^{FM} \\
\lambda_X(e_{jt}, d_{jt}) &= (1-d_{jt})(1-e_{jt})\gamma^{SX} + (1-d_{jt})e_{jt}\gamma^{FX} + d_{jt}(1-e_{jt})\nu^{SX} + d_{jt}e_{jt}\nu^{FX}.
\end{aligned}
$$

Note that the trade status in current period affects the cost distribution that a firm will face. First, if a firm j is currently serving foreign market ($e_{jt} = 1$) then it pays only fixed costs (ν^{FX} or γ^{FX}) to continue its export status in the next period, and so is it for the case of importing. Second, this specification allows for complementarity between two trade activities. If a firm j was an importer but not an exporter at time t, the firm's sunk cost for exporting would be drawn from $Exp(\nu^{SX})$. Meanwhile, if it was not participating in any trade activity, it's sunk cost for exporting would be drawn from $Exp(\gamma^{SX})$. This specification allows me to investigate whether one trade activity facilitates other activity.

Given state vector s_{jt}, the value of a firm at the beginning of the period is given by

$$
V(s_{jt}) = \Pi_D(k_{jt}, x_{jt}, d_{jt}) + e_{jt}\Pi_X(k_{jt}, x_{jt}, d_{jt}, z_{jt}) + \int \max_{d_{jt+1}}\{V_M(s_{jt}) - C_{jt}^{M}, V_{NM}(s_{jt})\} dF_M(C_{jt}^{M}|s_{jt}) \tag{15}
$$

where V_M is the value of an importer given the optimal choice for its export status and V_{NM} is the value of a non-importer given the optimal choice for its export status. The optimal values of an importer and non-importer are given by

$$V_M(s_{jt}) = \int \max_{e_{jt+1}}\{\delta EV(e_{jt+1}=1, d_{jt+1}=1|s_{jt}) - C^X_{jt}, \delta EV(e_{jt+1}=0, d_{jt+1}=1)|s_{jt})\} dF_X(C^X_{jt}|s_{jt}) \tag{16}$$

$$V_{NM}(s_{jt}) = \int \max_{e_{jt+1}}\{\delta EV(e_{jt+1}=1, d_{jt+1}=0|s_{jt}) - C^X_{jt}, \delta EV(e_{jt+1}=0, d_{jt+1}=0)|s_{jt})\} dF_X(C^X_{jt}|s_{jt}) \tag{17}$$

Note that depending on the current trade status, the firm's future productivity would change in way characterized by (13). Thus, the future value of firms will be depending on both future and current trade status. Finally, the expected future value conditional on the trade status is defined as following:

$$EV(e_{jt+1}, d_{jt+1}|s_{jt}) = \int V(e_{jt+1}, d_{jt+1}, k_j, x_{jt+1}, z_{jt+1}) dF_x(x_{jt+1}|x_{jt}, e_{jt}, d_{jt}) dF_z(z_{jt+1}|z_{jt}). \tag{18}$$

In this framework, the marginal returns to exporting is depending on the future import status due to the assumption on timeline. Thus, the margin is defined as following:

$$MBX_{jt}(d_{jt+1}, s_{jt}) = \delta[EV(e_{jt+1}=1, d_{jt+1}|e_{jt}, d_{jt}) - EV(e_{jt+1}=0, d_{jt+1}|e_{jt}, d_{jt})]. \tag{19}$$

However, the margin on importing is only relying on the current state vector s_{jt} and it is defined by

$$MBM_{jt}(s_{jt}) = V_M(s_{jt}) - V_{NM}(s_{jt}). \tag{20}$$

Hence, a given state s_{jt}, a firm decides to import if and only if $MBM_{jt}(s_{jt}) \leq C^M_{jt}$, and then given s_{jt} and d_{jt+1}, the firm decides to export if and only if $MBX_{jt}(d_{jt+1}, s_{jt}) \leq C^X_{jt}$. Since I assume that the costs are drawn from the exponential distribution, I can back out the conditional choice probability of exporting and importing in a closed form, which allows me to construct a likelihood function easily.

III Estimation Strategy

I estimate the structural model described in the previous section through the two step approach. In the model, the structural parameters include the demand elasticities (η_D, η_X), the cost shifters (β_k, β_m), the productivity parameters ($\rho_0, \rho_1, g_e, g_m, \sigma_u$), the foreign market demand parameters (ρ_z, σ_z), the average logged export revenue Φ_0^X, and the parameters on the sunk and fixed costs (γ, ν).

III.I Static Parameters

I start with recovering the parameters involved in firm's static decision. Augmenting the domestic revenue function (9) with measurement error ξ_{jt}, I obtain

$$\begin{aligned} r_{jt}^D &= (\eta_D + 1)\log\frac{\eta_D}{1+\eta_D} + \log\Phi_t^D + (\eta_D+1)(\beta_t + \beta_k k_{jt} + \beta_m d_{jt} - x_{jt}) + \xi_{jt} \\ &= \tilde{\Phi}_t^D + (\eta_D+1)(\beta_k k_{jt} + \beta_m d_{jt} - x_{jt}) + \xi_{jt}. \end{aligned} \tag{21}$$

Here, ξ_{jt} is uncorrelated with the right hand side variables. Note that I abandon identifying the time shifts in the revenue and cost functions separately for the sake of a simplified estimation procedure. Thus, the composite term of time variations in revenues and costs is captured by $\tilde{\Phi}_t^D$.

The equation (21) cannot be consistently estimated through ordinary least squares. The error term in this regression equation is the composite of unobserved productivity x_{jt} and measurement error ξ_{jt}. By (13), x_{jt} is correlated with x_{jt-1} and d_{jt} is also correlated with x_{jt-1} because d_{jt} is determined in the previous period. Therefore, a typical simultaneity problem arises if one does not control for x_{jt}.

To deal with simultaneity problem emerging in (21), I employ the insight of Olley and Pakes (1996) and Levinsohn and Petrin (2003)'s proxy approach. That is to control the unobserved productivity, one can use observed variables correlated with the firm's productivity. Note that in the theoretical model described in the previous section, it is straightforward to see that the composite of domestic and imported materials M_{jt} is associated with the firm's productivity x_{jt} in a monotonic manner. Furthermore, with the assumption that the price-adjusted relative quality of imported materials is constant, the factor demand for domestic material M_{jt}^d is constantly proportional to the composite of materials. Therefore, conditional on the level of capital and the import status, I can utilize the logged domestic material expenditure m^d_{jt} as a control function for the firm's productivity. Therefore, I can rewrite the productivity as $x_{jt} = g(k_{jt}, d_{jt}, m^d_{jt})$. Plugging it into the equation (15), I get

$$\begin{aligned} r^D_{jt} &= \Phi^D_t + (\eta_D + 1)(\beta_t + \beta_k k_{jt} + \beta_m d_{jt} - g(k_{jt}, d_{jt}, m^d_{jt})) + \xi_{jt} \\ &= m_0 + m_t + h(k_{jt}, d_{jt}, m^d_{jt}) + v_{jt}. \end{aligned} \tag{22}$$

where the function h is combined effect of the function arguments. I specify h as a cubic function of its arguments and estimate (22) through ordinary least squares. Let $\hat{h}_{jt}$ be the fitted values of h. This term is estimates of $(\eta_D + 1)(\beta_k k_{jt} + \beta_m d_{jt} - x_{jt})$. Given the cost parameters (β_k, β_m), the productivity is defined by the following: $x_{jt} = -\frac{1}{1+\eta_D}\hat{h}_{jt} + \beta_k k_{jt} + \beta_m d_{jt}$. Plugging this term into (13), I obtain the nonlinear equation characterizing the productivity evolution.

$$\begin{aligned} \hat{h}_{jt} = &-(\eta_D + 1)\rho_0 \\ &+ \rho_1(\hat{h}_{jt} - (\eta_D + 1)\beta_k k_{jt-1} - (\eta_D + 1)\beta_m d_{jt-1}) \\ &- (\rho_2/(\eta_D + 1))(\hat{h}_{jt-1} - (\eta_D + 1)\beta_k k_{jt-1} - (\eta_D + 1)\beta_m d_{jt-1})^2 \\ &+ (\rho_3/(\eta_D + 1)^2)(\hat{h}_{jt-1} - (\eta_D + 1)\beta_k k_{jt-1} - (\eta_D + 1)\beta_m d_{jt-1})^3 \\ &+ (\eta_D + 1)\beta_k k_{jt} + (\eta_D + 1)\beta_m d_{jt} \\ &- (\eta_D + 1)g_e e_{jt-1} - (\eta_D + 1)g_m d_{jt-1} \\ &- (\eta_D + 1)u_{jt} \end{aligned} \tag{23}$$

Equation (23) can be consistently estimated through nonlinear least squares. By the timeline of the model, all the explanatory variables in the right-hand side are uncorrelated with the innovation in the firm's productivity. k_{jt} is subsumed to be constant over time and d_{jt} is determined in the previous period. Also, the variables with subscript $t-1$ are obviously uncorrelated with the innovation occurring at time t.

Upon recovering the demand elasticity of domestic market η_D, I can identify the whole structural parameters associated with marginal cost and the productivity evolution path. One can be doubt about identifying β_m and g_m separately because both are associated with d_{jt-1} in the equation because the effect of d_{jt-1} on $\hat{h}_{jt}$ is the composite of three parameters: $(g_m + \rho_1 \beta_m)$. However, since the correlation between $\hat{h}_{jt}$ and $\hat{h}_{jt-1}$ pins down ρ_1 and the response of $\hat{h}_{jt}$ to d_{jt} pins down β_m, I could separately identify g_m. That is, I could tease out the learning-by-importing effect from the cost reduction effect of importing.

The remaining first stage parameters are the demand elasticities of domestic and foreign markets (η_D, η_X). To back out the elasticities, I follow Aw, Roberts, and Xu (2011)'s approach. Notice that the demands are CES and the marginal cost does not depend on the amount of quantities produced. Thus, the total variable costs TVC_{jt} are the weighted sum of domestic and foreign market revenues:

$$TVC_{jt} = (1 + \frac{1}{\eta_D})R^D_{jt} + (1 + \frac{1}{\eta_X})R^X_{jt} + \zeta_{jt},$$

where ζ_{jt} is the associated measurement error. I regress this equation by ordinary least squares to obtain the estimates of η_D and η_X.

III.II Identification of Dynamic Parameters and Associated Issues

The remaining parameters are the ones associated with the firm's dynamic decision of importing and exporting. I exploit the time variations in the trade participation rates and the transition patterns of the firm's trade status to identify the fixed and sunk cost parameters (ν, γ). For example, the transition rates from the trade status $(e_{jt} = 1, d_{jt} = 0)$ to the status $(e_{jt} = 0, d_{jt} = 1)$, and the transition rates from $(e_{jt} = 1, d_{jt} = 0)$ to $(e_{jt} = 1, d_{jt} = 1)$ will be involved in identifying the ν^{SM}. Furthermore, conditioning on the firm's export status, the observed variations in the export revenues can provide me with the information on the parameters Φ^X_0, ρ_z and σ_z.

Estimating dynamic parameters is not a trivial problem. The associated numerical issues in estimating the dynamic parameters of the model are in order. First, while foreign market demand shifter z_{jt} is observed by firms, it is not observed by the researcher. Second, the conditional choice probabilities based on the equations (19) and (20) are not relevant to the initial period trade status because there is no information on the previous trade status. Third, the likelihood function would be subject to non-global concavity problem. I will discuss these issues and the methodologies employed to tackle them in the following three subsections.

III.III Dealing with Unobserved z_{jt}: Das, Roberts, and Tybout (2007)

The estimation of the dynamic parameters is based on the likelihood for the observed trade participation and the logged level of export revenues $\{(e_{jt+1}, d_{jt+1}, r^X_{jt+1})\}_{j=1,t=1}^{N,T-1}$. The likelihood that I have to construct is as the following.

$$\prod_{j=1}^{N}\prod_{t=1}^{T-1} f(e_{jt+1}, d_{jt+1}, r^X_{jt+1}|x_{jt}, k_j, e_{jt}, d_{jt}, r^X_{jt}).$$

By the construction of the model of this paper, conditioning on x_{jt}, k_j, e_{jt}, d_{jt}, and r^X_{jt}, the variations in r^X_{jt+1} is only governed by z_{jt+1}. Also, the conditional choice probabilities of (e_{jt+1}, d_{jt+1}) are depending on the state vector at time t: s_{jt}. Thus, the likelihood value of firm j at time $t+1$ can be represented as the following.

$$\begin{aligned} &P(e_{jt+1}, d_{jt+1}|x_{jt}, k_j, e_{jt}, d_{jt}, z_{jt}) f(z_{jt+1}|z_{jt}). \\ =&P(e_{jt+1}, d_{jt+1}|s_{jt}) f(z_{jt+1}|z_{jt}) \end{aligned} \tag{24}$$

This likelihood cannot be evaluated immediately given that only exporters report r^X_{jt}, which turns in that econometricians can only observe z_{jt} of exporters. However, it is true that even non-exporting firms also observes z_{jt} and then decides whether or not to export. Thus, to construct the likelihood function, I need to back out latent z_{jt} for non-exporting firms. To do so, I follow Das, Roberts, and Tybout (2007)'s simulation approach. More specifically, given the observed z_{jt} and the parameters Φ^X_0, ρ_z, and σ_z, I can simulate K's many time series datasets of foreign market demand shifter $\{z^k_{jt}\}_{j,t,k}^{N,T,K}$ which is serially correlated in a manner of the AR(1) process characterized by the equation (14):

1. Notice that given marginal cost parameters and firm-specific productivity, I attain the adjusted exported revenues for exporters.

$$\tilde{r}^X_{jt} = r^X_{jt} - (\hat{\eta}_X + 1)\hat{\beta}_k k_{jt} - (\hat{\eta_X} + 1)\hat{\beta_m} d_{jt} + (\hat{\eta_X} + 1)\hat{x}_{jt}.$$

2. Next, given $(\Phi^X_0, \rho_z, \sigma_z)$, I can back out observed z_{jt} for exporters through the fol-

lowing equation

$$z_{jt} = \tilde{r}^X_{jt} - \Phi^X_0.$$

3. For firm j who at least has served the foreign market at once, define $z^+_j = \{z_{jt} : \tilde{r}^X_{jt} \text{ is observed}\}$ and let $q_j = \sum_{t=1}^T e_{jt}$. Then, q_j is the number of periods in that firm j exports and z^+_j is a $q_j \times 1$ vector. With the assumption that z_{jt} is in the long-run stationary process, I obtain

$$z^+_j \sim N(0, \Sigma_+),$$

where the diagonal components of Σ_+ are $v_z \equiv \frac{\sigma_z^2}{1-\rho_z^2}$ and off-diagonal components are $\rho_z^{|p|} v_z$ for $p \neq 0$.

4. Note that z^+_j and $\mathrm{z}_j = (z_{j1}, z_{j2}, \cdots, z_{jT})'$ are both normal random vectors. By using the property of Normal random vector, I can represent z_j as a linear combination of z^+_j and some normal random vector:

$$\mathrm{z}_j = Az^+_j + B\epsilon_j,$$

where ϵ_j is T by 1 standard Normal random vector, $A = \Sigma_{z+}\Sigma_+^{-1}$, and B satisfies $BB^{'} = \Sigma_{zz} - \Sigma_{z+}\Sigma_+^{-1}\Sigma^{'}_{z+}$. Here, Σ_{z+} is a T by q_j matrix $E[\mathrm{z}_j z^{+'}_j]$ and Σ_{zz} is T by T matrix $E[\mathrm{z}_j \mathrm{z}^{'}_j]$.

5. Draw $\{\epsilon^k_j\}_{k=1}^K$ from standard Normal distribution. Then, given observed z_{jt}, (ρ_z, σ_z), I can simulate $\{\mathrm{z}^k_j\}_{k=1}^K$ by following the linear representation:

$$\mathrm{z}^k_j = Az^+_j + B\epsilon^k_j.$$

6. For firm j who has never exported during the sample period, I simulate $\{\mathrm{z}^k_j\}_{k=1}^K$ from the long-run stationary distribution of z_{jt}. That is,

$$\mathrm{z}^k_j = chol(\Sigma_{zz})\epsilon^k_j,$$

where $chol(\cdot)$ refers to the Cholesky decomposition of a positive semi-definite matrix.

Two important features of the method stand out. First, as the first term Az_j^+ implies, the simulation method exploits the entire information in the periods in which firm j exports, which incorporates the fact that z_{jt} is serially correlated stochastic process. Furthermore, by the construction of A, a row of A corresponding to the period in which firm j exports is a row vector that consists of one and $q_j - 1$'s many zeros so that A can always pick up the observed z_{jt} for exporting periods. Second, the dimension of kernel (or null space) of $BB^{'}$ is q_i, thus B contains q_i's many zero rows. These rows are corresponding to the periods in which the firm j exports. Therefore, ϵ_j is not involved in constructing z_{jt} for exporting periods. Carrying over the two features, one can see that (i) simulated shifters can be serially correlated with observed demand shifters and (ii) the elements of z_j in rows corresponding to exporting periods do not vary across simulations. [1]

For each simulation $k = 1, 2, \cdots, K$, I can observe state vector $s_{jt}^k = (x_{jt}, k_j, e_{jt}, d_{jt}, z_{jt}^k)$, and then construct the conditional choice probabilities of exporting and importing:

$$P(e_{jt+1}, d_{jt+1}|s_{jt}^k) = P(e_{jt+1}|d_{jt+1}, e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k)P(d_{jt+1}|e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k), \tag{25}$$

where

$$P(e_{jt+1}|d_{jt+1}, e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k) = P(C_{jt}^X \leq MBX_{jt}(d_{jt+1}, s_{jt}^k)|s_{jt}^k), \tag{26}$$
$$P(d_{jt+1}|e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k) = P(C_{jt}^M \leq MBM_{jt}(s_{jt}^k)|s_{jt}^k). \tag{27}$$

The conditional choice probabilities are depending on the continuation values driven from the fixed point problem characterized by (15), (16), (17), and (18). Given the candidate dynamic parameters, I can compute the continuation values by iterating the equations (15), (16), (17), and (18) backward and then evaluate the likelihood value.

Given the specification that z_{jt} follows AR(1) process as (14), I have

$$f(z_{jt+1}^k|z_{jt}^k) = \frac{1}{\sigma_z}\phi(\frac{z_{jt+1}^k - \rho_z z_{jt}^k}{\sigma_z}), \tag{28}$$

[1] Appendix A describes how the method works with a simple example.

for $k = 1, 2, \cdots, K$. Here ϕ refers to the pdf of standard Normal distribution.

Using (25) and (28), I construct the individual contribution to the full likelihood:

$$\prod_{t=1}^{T-1} P(e_{jt+1}, d_{jt+1} | s_{jt}^k) f(z_{jt+1}^k | z_{jt}^k) \tag{29}$$

in each simulation k. Note that the equation (29) conveys the information for the years $(2, 3, \ldots, T)$ so this formula is not a complete form of the individual likelihood function.

III.IV Constructing the Likelihood of the Initial Period: Heckmann (1981)

I need $P(e_{j1}, d_{j1}) f(z_{j1}^k)$ to complete the individual likelihood function. Incorporating the likelihood of the initial period is essential. Notice that z_{jt}^k and x_{jt} are evolving over time. Thus, z_{j1}^k and x_{j1} are correlated with the variations in s_{jt}^k in the subsequent periods. Given this feature, I cannot treat the choice behavior in the initial period as exogenous process. This is so-called "Initial Period Problem" raised by Heckmann (1981). I follow the method proposed by Heckmann. Specifically, I approximate the expected margins of exporting and importing at the initial period as the following representations:

$$\begin{aligned} \text{Export: } & w_{j1}^{'} \alpha_e - \zeta_j^X, \\ \text{Import: } & w_{j1}^{'} \alpha_m - \zeta_j^M, \end{aligned}$$

where ζ_j^X and ζ_j^M are mutually independent standard Normal distributed random variables. Thus, I obtain the choice probabilities of exporting and importing at the initial period:

$$P(e_{j1}, d_{j1}) = \Phi(w_{j1}^{'} \alpha_e) \Phi(w_{j1}^{'} \alpha_m), \tag{30}$$

where Φ refers to the cdf of standard Normal distribution. The crucial job done for correcting initial period problem is that when I approximate the margins of exporting and importing at the initial period, I should include the variations correlated with the variations in every subsequent periods. By doing so, I can treat the initial period choices as endogenous process. Hence, w_{j1} includes constant, z_{j1}, x_{j1}, and k_j.

The initial period density of z_{j1}^k is simply defined as the following:

$$f(z_{j1}^k) = \frac{1}{v_z}\phi(\frac{z_{j1}^k}{v_z}), \tag{31}$$

where $v_z = \sqrt{\frac{\sigma_z}{1-\rho_z^2}}$. Thus, by multiplying $P(e_{j1}, d_{j1})f(z_{j1}^k)$ and (29), I complete the individual likelihood in generic k-th simulation:

$$P(e_j, d_j|s_j^k)f(z_j^k), \tag{32}$$

where $e_j = (e_{j1}, e_{j2}, \cdots, e_{jT})$, $d_j = (d_{j1}, d_{j2}, \cdots, d_{jT})$, and $z_j^k = (z_{j1}^k, z_{j2}^k, \cdots, z_{jT}^k)$.

Finally, averaging out (32) over the K simulations, I obtain the final individual contribution to the full likelihood, and multiply the contributions over the all firms, I construct the full likelihood function.

$$\mathscr{L}(\Theta_D|D) = \prod_{j=1}^{N}\frac{1}{K}[\sum_{k=1}^{K}P(e_j, d_j|s_j^k)f(z_j^k)], \tag{33}$$

where $\Theta_D = (\Phi_0^X, \rho_z, \sigma_z, \gamma, \nu, \alpha_e, \alpha_m)$ and D is the dataset in my hand. In practice, I choose $K = 10$ to simulate z_{jt}. Given a structural parameter Θ_D, it takes about 0.1 to 0.3 seconds using MATLAB to evaluate the likelihood value (33) on a standard PC with 4.0 GHz processor.

III.V Circumventing non-Global Concavity of Likelihood: Bayesian MCMC

Since the likelihood function is not globally concave, a conventional algorithm would have difficulty in finding the global maximum. Thus, rather than maximizing the likelihood, I employ Bayesian Markov Chain Monte Carlo (MCMC) to estimate the dynamic parameters. This approach allows me to circumvent the multiple local optima problems and manage the non-global concavity of the likelihood function. To do so, I construct the random-walk Metropolis-Hastings Markov chain to draw the samples from the posterior distribution of the dynamic parameters. To construct a posterior distribution, I need to specify the prior distribution of the dynamic parameters. I rely on the diffuse prior distribution to rule out the possibility that the estimates are highly depending on the prior distribution.[2]

The main goal of Bayesian MCMC is characterizing the posterior distributions of the parameters of interest. With the random-walk Metropolis-Hastings chain, I can draw B's many dynamic parameter vectors $(\Theta_{D,1}, \Theta_{D,2}, \cdots, \Theta_{D,b}, \cdots, \Theta_{D,B})$ from the posterior distribution $\pi(\Theta_D|D) = \mathscr{L}(\Theta|D)p(\Theta)$. Then I construct the mean and 95% credible intervals as $\bar{\Theta}_D = \frac{1}{B}\sum_{b=1}^{B}\Theta_{D,b}$ and the corresponding percentiles of MCMC draws

In practice, since I should estimate 19 dynamic parameters, implementing the random-walk Metropolis-Hasting algorithm without breaking Θ_D into multiple blocks is highly inefficient (low acceptance rates). To obtain reasonable acceptance rates, I break parameter vectors into seven blocks.

$$
\begin{aligned}
\Theta_D^1 &= (\rho_z, \log\sigma_z), \\
\Theta_D^2 &= (\Phi_0^X, \alpha_e^{'}), \\
\Theta_D^3 &= \alpha_m^{'}, \\
\Theta_D^4 &= (\gamma^{SM}, \gamma^{SX}), \\
\Theta_D^5 &= (\nu^{SM}, \nu^{SX}), \\
\Theta_D^6 &= (\gamma^{FM}, \gamma^{FX}), \\
\Theta_D^7 &= (\nu^{FM}, \nu^{FX}).
\end{aligned}
$$

The random-walk Metropolis-Hasting algorithm used in this paper involves the following steps.

1. Start with $b = 0$ and $j = 1$.

2. Draw a candidate parameter vector $\Theta_{D,b}^{j*} = \Theta_{D,b}^{j} + \varphi_b^j$, where $\varphi_b^j \sim N(0, \Sigma^j)$

3. Define

$$\alpha_b^j = \min\{0, \log\frac{\pi(\Theta_{D,b+1}^1, \cdots, \Theta_{D,b}^{j*}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7|D)}{\pi(\Theta_{D,b+1}^1, \cdots, \Theta_{D,b}^{j}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7|D)}\}$$

[2] A posterior distribution, through Bayes' rule, boils down to the scaled likelihood function when the prior distribution is diffuse. Thus, the mean or mode of the posterior distributions drawn from MCMC is numerically not different from the maximum likelihood estimates.

4. Draw $u \sim Unif(0,1)$ and update the parameters

$$(\Theta^1_{D,b+1}, \cdots, \Theta^j_{D,b+1}, \Theta^{j+1}_{D,b}, \cdots, \Theta^7_{D,b}) = \begin{cases} (\Theta^1_{D,b+1}, \cdots, \Theta^{j*}_{D,b}, \Theta^{j+1}_{D,b}, \cdots, \Theta^7_{D,b}), & \text{if } \log u \leq \alpha^j_b \\ (\Theta^1_{D,b+1}, \cdots, \Theta^j_{D,b}, \Theta^{j+1}_{D,b}, \cdots, \Theta^7_{D,b}). & \text{otherwise} \end{cases}$$

5. If $j < 7$, $j = j+1$, and go to step 2. If $j = 7$, and $b < B$, let $b = b+1$, and go to step 2. If $j = 7$ and $b = B$, the chain is over.

The most important parameters in MCMC are the covariance matrices $(\Sigma^1, \cdots, \Sigma^7)$ which are governing acceptance rates of the chain. In practice, I can consider that the chain steps over the support of the posterior distribution quickly if acceptance rates are ranging in the reasonable interval $(0.15, 0.7)$. Given this discussion, I specify Σ^j as a diagonal matrix and choose variances ensuring that acceptance rates are in the reasonable range.

Another crucial issue is the choice of initial parameter vector to generate the chain. If one chooses initial parameter which is too far away from the posterior maximizer, she would generate many draws for being confident that the chain has converged to a stationary region. I search over the parameter space using Simulated Annealing algorithm to find a point which is close to the posterior maximizer. Start with that point, I draw 60,000 MCMC draws and burn-in the first 10,000 draws to annihilate the initial choice effect. On a standard PC with 4.0GHz processor, MCMC took around 24 hours.

IV Empirical Results

This section first describes the dataset used for the empirical analysis and then reports the estimates of structural parameters in the model. I first report the estimates of the demand, cost, and productivity dynamics in the chemical industry. I then report the estimates of the fixed and sunk costs and the foreign market demand shifter dynamics.

IV.I Data

I take the model to the Colombian plant-level data. The dataset is from the Colombian manufacturing plant survey which is collected by Colombia Departamento Administrativo Nacional de Estadistica (DANE) for 1977 to 1991. The dataset contains detailed information about both domestic and export sales, domestic and imported materials, the number of employees, book values of plants' fixed properties such as land or building, investments, and any other plant's characteristics. I clean the data and construct the capital using perpetual inventory approach which is described in Roberts and Tybout (1996).

I particularly focus on 236 chemical plants[3] who were continuously operating in the domestic market from the year 1981 to 1985. I choose this industry because the industry is not only an export-oriented but an import-oriented industry. As seen in Table 2, the industry exhibits the foreign market entry and exit, and the import startup and turnover during the sample period.

I focus on the period spanning from 1981 to 1985. The selection of the sample period reveals two considerations. First, in the model, I abstract the capital accumulation decision in order to simplify the model and focus only on the dynamic trade decision. To rationalize this simplification, I use the short panel, so that the capital accumulation cannot play a crucial role in computing the values of plants. Second, there was a change in import tariff policy in the year 1985. If I use the whole sample period to estimate the model, this policy change would mislead to wrong estimates and thus the counterfactual results become unreliable. To rule out this possibility, I choose the period prior to the policy change in the year 1985. Notice that I include the observations in the year 1985. In the model specification, the current trade status has been determined by firms one period ahead. Under this structure, the trade status of the year 1985 is determined in the year 1984 which is prior to the policy change. Thus, I include observations of the year 1985.

Table 1 provides summary statistics of firm sales. The upper panel reports the median sales of plants in each year and the lower panel summarizes the average sales of plants in each year. Notice that regardless of export status, importers enjoy larger domestic sales. While the median domestic sales of firms doing neither are around 20,000 Million in 1981 Pesos, the median domestic sales of firms doing only import increases from 62,000 Million to 106,000 Million. Similarly, the median sales of firms doing only export are substantially smaller than the one of firms doing both. The similar patterns are also observed when I compare the average sales. This pattern indicates that even after con-

[3] 3-digit ISIC classifier code is 351 or 352

trolling for the firm size, any possible time-varying factors, and the self-selection, there could be a systematic difference between non-importers and importers, which indicates the possibility of learning-by-importing. The similar pattern arises when I compare sales of non-exporters and exporters, which implicitly indicates the possibility of learning-by-exporting. Motivated by these patterns, I model the productivity process to depend on the previous trade status.

Furthermore, as reported in Table 3, there is a significant persistence in the trade status, which is possibly driven by a combination of fixed and sunk costs. Note that among firms doing nothing at the period t, about 87% of them remain as firms doing nothing in the adjacent period. The ratios of both, only export, and only import groups are 92%, 58%, and 82%, respectively. These patterns will allow me to identify the fixed and sunk costs for both exporting and importing. Also, firms engaging in at least one trade activity is more likely to start the other activity than does its counterpart in the next period. About 5% of firms doing only importing start to serve the foreign market in the next period and about 20% of firms doing only export start to use imported intermediates in the next period. In contrast, among firms not engaging in any activity, about 11% of them start to import and about 1% of them participate in serving the foreign market. Motivated by this pattern, I model the fixed/sunk costs to be trade-history dependent.

IV.II Demand, Cost, and Productivity Dynamics

Tables 4 reports the estimates of the demand, cost, and productivity dynamics drawn from the equations (22) and (23). I add dummies of 4-digit industry codes to control for 4-digit industry-specific effects on the firm's domestic revenues. For the robustness check, I also estimate the productivity dynamics with a variety of specifications. The estimates from the benchmark specification are reported in the first column of Table 4 and the estimates from the other specifications are reported in the remaining columns. I will use the estimates of the parameters and estimated productivity from the benchmark specification in the second stage. The estimation results are summarized as follow.

First, the estimates of demand elasticities imply that an exporter could enjoy the larger market power than its counterpart. Notice that the demand elasticities of domestic and foreign markets are approximately -6.47 and -4.72, respectively. The estimates imply that a plant in Colombian chemical industry charges about 18% and 26% markups over marginal costs for domestic and foreign markets, respectively.

Second, both capital and import status are decreasing the marginal cost that a firm should pay and this result is consistent with the prediction drawn from the theoretical framework that I discussed in Section II. In equation (6), the sign of the parameters associated with import status and the level of capital is expected to be negative. The estimation results confirm this theoretical prediction, indicating that (i) as the level of capital increase by 1%, a firm could produce a good by paying 5.26% lower marginal costs than its counterpart, and (ii) an importer would face the 6.8% lower marginal costs than a firm who is using only domestic materials.

Third, the firm-specific productivity evolves over time and it is highly persistent. The estimated coefficient on the lagged productivity is 0.9155 and this implies that one deviation increase in the productivity innovation term u_{jt} will persistently affect the future productivity path for about 50 years. Furthermore, there is a strong nonlinear relationship between the current and past productivities. Notice that both coefficients on the squared and cubic terms of x_{jt-1} are statistically significant and quantitatively large.

Fourth, the experience in trade improves upon the current level of productivity but the learning-by-importing is about five times larger than learning-by-exporting. In particular, holding everything, the productivity of a firm who has exported is about 0.45% higher than the counterpart's one. But this is not statistically significant. In contrast, the gains from importing are about 2% and these are significantly larger than the gains from exporting. This result indicates that when a firm has participated in both activities, it would enjoy much larger productivity in the current period. Furthermore, carrying over the high persistence in the productivity dynamics, the long-run impacts of exporting and importing become substantially large. Relative to a firm who will never do trade, a firm who will continuously do both exporting and importing will have long-run mean productivity that is about 35% higher. However, this long run gain is mostly accounted for by learning-by-importing. Notice that a firm always participating in exporting will be only 5% more productive, while an always importer becomes 29% more productive in the long-run.

IV.III Fixed and Sunk Costs, and Foreign Market Demand

Given the first stage estimates, I recover the remaining dynamic parameters through the method of MCMC. Table 5 reports the means and 95% credible intervals of the dynamic parameters. Since the 95% credible intervals never cover zero, I can conclude that the posterior distribution is quite tight and consider the means of the posterior distributions as credible estimates of the dynamic parameters. The estimation results are summarized as follow.

First, the estimate of the average export market revenue Φ_0^X is substantially lower than the estimate of the average domestic market revenue (0.5107 and 3.12, respectively. The average domestic market revenue is not reported in any table). This implies that even a firm exports its product, it sells less in the foreign market than in the domestic market.

Second, the foreign market demand shifter is highly persistent and it is highly volatile. The autoregressive coefficient is 0.9029 and the standard deviation of the innovation term is $\exp(0.2153) = 1.15$. These estimates are quite larger than the estimates from the previous studies (Aw, Roberts, and Xu 2011; Bai and Krishna 2016) but qualitatively in line with them. Aw, Roberts, and Xu report that the estimates of these parameters are 0.77 and -0.287, respectively, and Bai and Krishna report that they are 0.83 and -0.176, respectively. The persistence in z_{jt} also contributes to the persistence in export status and export revenues.

Finally, the implication from the estimates of the cost parameters are summarized as follow.

Import Costs Both exporters and non-exporters will draw similar sunk costs for importing, while a firm doing both activities can continue importing more easily than only importers. These estimates imply that exporting seems to facilitate importing through the reduction in the fixed costs for importing. Note that the estimates of γ^{FM} and ν^{FM} are substantially different: the 95% credible intervals for both parameters never overlap each other. One can see that the lower bound of the 95% credible interval for γ^{FM} is larger than the upper bound of 95% credible interval for ν^{FM}. That is, to continue importing, a firm who is doing both is likely to draw the smaller fixed costs associated with import than its counterparts. In contrast, the estimates of γ^{SM} and ν^{SM} are also similar and the 95% credible interval for γ^{SM} is nested to the one for ν^{SM}. This result indicates that a firm doing neither and a firm doing only exporting are supposed to pay a similar amount of money to start importing foreign materials.

Export Costs In contrast to the case of import costs, an importer is likely to pay less money to start serving the foreign market than a domestic counterpart does. Note that though both firms are expected to pay high entry costs for exporting (ν^{SX} and γ^{SX} are 25.42 and 64.23, respectively), an importer would pay about 3.5 times smaller entry costs to enter the foreign market. The substantial difference in sunk costs for exporting is intuitive: an importer has experienced the foreign market by interacting with foreign exporters, and they learned the foreign customs, which reduce the startup costs that the importer should have to pay. But doing importing does not complement continuing firms' foreign business. Note that the estimates of ν^{FX} and γ^{FX} are not much different and surprisingly the ν^{FX} is larger than γ^{FX}. One possible explanation is that firms participating in both activities are way larger than their counterparts in terms of the level of capitals.[4] Aw, Roberts and Xu (2011) show that large firms in Taiwanese electric industry would like to pay larger fixed and sunk costs for exporting than the smaller ones due to the larger scale of operation for larger firms. This story could also come in the Colombian chemical industry. Thus, I expect that I could get the more intuitive estimates of ν^{FX} and γ^{FX} if I control for the size of capital in estimating the fixed and sunk cost parameters. However, due to the computational burden, I do not take it into account in this paper.

IV.IV Model Fit

Armed with the estimates in the Tables 4 and 5, I assess the model's in-sample fitting power. To do so, I start with the year 1981's the firms' productivity and trade status and then simulate the firms' productivity and trade status in the subsequent years. Since the dynamics of a firm's productivity is endogenously determined by the firm's dynamic decision, it is necessary to check whether the simulated trajectory tracks the realized average productivity well. Table 6 compares the realized moments and the model mo-

[4] In Colombian chemical industry, firms doing both activities are almost six to seven times larger than firms participating in only one activity in terms of the level of capital. Also, those firms are 24 times larger than firms serving only the domestic market without using imported materials.

ments. Though it underpredicts the import participation rates in the first few years, the model does a good job at matching the moments overall.

Table 7 summarizes the transition patterns from the data and the model. The simulated data performs quite well in matching the transition patterns of firms engaging in both or engaging in nothing, while it does not do a good job at tracking the transition patterns of firms doing only one activity. In particular, the model overpredicts the transition from only export to both (35% vs 18%). The model captures, however, the interdependence between exporting and importing. In the data, a firm undertaking at least one activity is more likely to start the other activity than a firm that does not undertake anything. For example, in the model, a firm doing neither at the current period would translate to an exporter in the next period with a probability of 0.0054, while an importer would start exporting with a probability of 0.0640. These patterns are similar to the observations in the data.

V Counterfactual

V.I Quantifying Benefits from Trade

This section quantifies the impacts of import and export in more details. The model of this paper is constructed to quantify the three possible channels through which import and export can boost up the firm's performance. For import, the proposed three channels are (i) improving the future productivity, (ii) reducing the current short-run marginal cost, and (iii) reducing the sunk costs that a firm should pay to start serving the foreign market. For export: (i) improving the future productivity, (ii) earning additional profits from the foreign market, and (iii) reducing the fixed costs that a firm should pay to continue importing foreign materials. To quantify the impact of each channel, I follow the decomposition exercise conducted by Zhang (2017). This exercise allows me to isolate the contribution of each channel to the industry average of the firm values in 1981 Colombian Pesos.

V.I.1 Gains from Import

I begin with defining the total gains from importing. Let $V(s_{jt})$ be the simulated industry average of the firm values in the benchmark specification and $V_{No-Import}(s_{jt})$ be the simulated industry average of the firm in the economy where importing is not allowed. Then, the gains from importing in the model is defined by the difference between $V(s_{jt})$ and $V_{No-Import}(s_{jt})$:

$$\text{Gains from importing} = V(s_{jt}) - V_{No-Import}(s_{jt})$$

Follow Zhang (2017), I compute $V_{No-Import}$ by letting $\gamma^{SM} = \gamma^{FM} = \nu^{SM} = \nu^{FM} = \infty$.

The gains from importing can be exactly decomposed into three parts: gains from learning-by-importing, gains from facilitating export, and gains from reducing the short-run marginal costs. First, the gains from learning-by-importing can be computed by the difference between $V(s_{jt})$ and $V(s_{jt}|g_m = 0)$:

$$\text{Gains from learning-by-importing} = V(s_{jt}) - V(s_{jt}|g_m = 0),$$

where $V(s_{jt}|g_m = 0)$ is the simulated industry average of the firms in the economy where there is no learning-by-importing channel. Second, I compute the gains from facilitating exporting by the difference between $V(s_{jt}|g_m = 0)$ and $V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX})$:

$$\text{Gains from facilitating exporting} = V(s_{jt}|g_m = 0) - V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX}),$$

where $V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX})$ is the simulated industry average of the firms in the economy where there are no learning-by-importing and facilitating exporting channels. Finally, the remaining term would account for the gains from reducing the short-run marginal costs:

$$\text{Gains from reducing the short-run marginal costs} = V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX}) - V_{No-Import}(s_{jt}).$$

Table 8 displays the gains from importing, and the gains from three channels spanning through the year 1982 to 1985. The first panel reports the total gains from importing in 100 millions of 1981 Colombian Pesos. The second to fourth panels report the gains from (i) learning-by-importing, (ii) facilitating exporting, and (iii) reducing short-run marginal costs, respectively. Notice that the learning-by-importing channel accounts for about over 80% of the gains from importing. In the year 1985, the total gains are 383 millions of 1981 Pesos and 85% of the gains are attributed by the learning-by-importing. This result is not surprising because as shown in Table 4, importing was playing a crucial role in boosting up the future level of productivity, which translates to the larger values of firms. Also, 13% of the gains are explained by the reduction in short-run marginal costs. This result is also consistent with the static estimates indicating that an importer could enjoy higher profits than its counterpart as it can produce a product with the cheaper costs. However, the facilitating exporting channel does not attribute to the total gains from importing. The channel only accounts for 1.8% of the total gains. That is, even though an importer could access to the foreign market easily, it does not translate to the increase in the values of the firm.

V.I.2 Gains from Export

I decompose the total gains from exporting in the same manner. Again, let $V(s_{jt})$ be the simulated industry average of the firm values in the benchmark specification and $V_{No-Export}(s_{jt})$ be the simulated industry average of the firm in the economy where exporting is not allowed. The value can be computed by letting $\gamma^{FX} = \gamma^{SX} = \nu^{FX} = \nu^{SX} = \infty$. I also define the firm values used to isolate the effect of each channel: $V(s_{jt}|g_e = 0)$ is the simulated industry average of firms in the economy where no learning-by-exporting channel exists, and $V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM})$ is the simulated average in the economy where there are no learning-by-exporting and facilitating importing channels. Then, the total gains of exporting can be decomposed into the following three gains:

$$\text{Gains from learning-by-importing} = V(s_{jt}) - V(s_{jt}|g_e = 0),$$
$$\text{Gains from facilitating exporting} = V(s_{jt}|g_m = 0) - V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM}),$$
$$\text{Gains from earning profits from the foreign market} = V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM}) - V_{No-Export}(s_{jt}).$$

Table 9 reports the gains from exporting, and the gains driven from the three channels, respectively. The first panel reports the total gains in 100 millions of 1981 Colombian Pesos. The second to fourth panels are displaying the gains from each channel. Notice that in the year 1985, unlike the case of importing, the learning-by-exporting only accounts for 18% of the total gains. In contrast, the gains from earning profits from the foreign market were playing a significant role in shaping the total gains from exporting. Note that this channel explains about 79% of the total gains from exporting. In line with the case of importing, facilitating the other activity plays a minor role in accounting for the total gains. The gains account for only about 3% of the total gains.

V.II Policy Counterfactual

In this section, I use the estimated model to conduct counterfactual experiments to evaluate the government policy that subsidizes the sunk or fixed costs for trade, which is a typical policy encouraging firms to participate in international trade. In this exercise, I consider four possible subsidy plans: subsidizing (1) import fixed, (2) export fixed, (3) import sunk, and (4) export sunk costs. I choose subsidy rates of each policy such that firm's expected subsidized grants are equal to 1,500,000 1981 Colombian Pesos.[5] To quantify the effects, I simulate the model for 10 years and report the differences between the outcomes from the counterfactual world and the benchmark. I particularly investigate differences in (i) the industry average of productivity, (ii) import participation rates, (iii) export participation rates, and (iv) the industry average of firm values.

Figures 1 to 3 display the results of all the four policies. Amongst all the four policies, subsidizing import fixed costs is the most effective to boost up the industry average productivity. Ten years after the import fixed cost subsidy policy, the average productivity is about 0.4% higher than the benchmark case. This result is driven by the fact that import fixed cost subsidy could boost up the import participation rates dramatically (Figure 2) and the learning-by-importing effect is significant. Notice that in the long-run, subsidizing export/import sunk costs will not increase the average productivity. Given that the learning-by-importing is crucial and subsidizing export/import sunk costs would not boost up the import participation rate in the long-run, the decrease in the average productivity is not a surprising result. Subsidizing export fixed costs also improves the average productivity but the improvement is quantitatively small.

Subsidizing fixed trade costs is expected to promote trade participation rates (Figure

[5] This amount is equivalent to about 10% subsidy of export fixed costs.

?? and 3). First, not surprisingly, subsidizing import fixed costs improves import participation rates by 4% points ten years after the policy, and a similar result emerges in the case of export fixed cost subsidy. Second, along with the estimation result that export and import facilitate each other, I find that subsidizing import/export fixed costs also promotes other activity participation rates. In particular, subsidizing import fixed costs would increase the export participation rates by 1.5% points and subsidizing export fixed costs encourages more firms to engage in using foreign intermediate inputs.

Contrary to the fixed cost subsidy case, subsidizing sunk costs, which is equivalent to encouraging non-trade-participants to engage in international trade, is not a good policy plan in terms of improving productivity and trade participation rates. This result is similar to Peters et al. (2017) and Peters, Roberts, and Vuong (2018), who document that subsidizing R&D startup costs is not helpful for both German high- and low-tech industries. Of course, a domestic firm could start export or import with the cheaper costs and it will increase the participation rates. However, the policy also could encourage firms who are currently doing export or import to stop now and plant to restart the activity later. Under the parameter values in Tables 4 and 5, the later effect offsets the former one and thus the participation rates remain unchanged or changed very slightly. This result also translates to no change in average productivity.

Finally, subsidizing import fixed costs is the most effective amongst the proposed subsidy plans according to the cost-benefit analysis displayed in Figure 4. The figure displays the gains from the subsidy which is measured by the difference between the industry firm values in the benchmark and counterfactual worlds. Ten years after the policies, the gains from the policy subsidizing import fixed costs are about 5,300 millions of 1981 Pesos which is the largest one amongst the gains from other policies. This is because subsidizing import fixed costs improves the industry average productivity, and this large improvement translates into an increase in the average firm values. Export fixed cost subsidy is also beneficial to Colombian chemical firms, but the benefits are not as large as the ones from import fixed cost subsidy. Given that sunk cost subsidy plans do a poor job at promoting productivity and trade participation rates, benefits of sunk cost subsidy plans are quite small: 150 and 70 millions of 1981 Pesos from import and export sunk cost subsidies, respectively.

VI Conclusion

I propose a dynamic structural model of endogenous importing and exporting decisions with fixed and sunk costs to explore the effects of import and export on the productivity and the values of firms. The model allows me to decompose the gains from trade into the gains from three channels: (i) learning-by-trade, (ii) increasing the current profits, and (iii) facilitating the other activities, and to evaluate the trade cost subsidy policies.

Estimation results drawn from Colombian chemical industry indicate that a firm has an incentive to import because it will face the lower marginal cost and boost up its own productivity through the learning-by-importing channel. A firm also has an incentive to export as it will enjoy more profits from the foreign market but exporting does not affect the future level of productivity as much as importing does. In line with the previous studies, startup costs for both importing and exporting are significantly larger than continuation costs for trade. A novel result is that an importer could access to the foreign market more easily than domestic firm due to the reduction in sunk costs for exporting, and an exporter can pay less money in order to continue its import status due to the reduction in fixed costs for importing.

Decomposition of the gains from trade implies that the most of gains from importing are explained by the gains from learning-by-importing, while the gains from exporting are mostly explained by the static gains from earning more profits from the foreign market. Learning-by-importing effects explain about 85% of the total gains from importing in the year 1985. In the same year, static gains from earning more profits account for 80% of the total gains from exporting.

Counterfactual results indicate that subsidizing the import fixed costs is the most efficient policy plan amongst the four proposed plans. The gains from this policy are about 16 times larger than the subsidy costs that the Colombian government should pay. In contrast, no matter what the trading activity is, subsidizing sunk costs is not a good way to promote international trade participation and improving the values of firms.

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Tables and Figures

Table 1: Median and Mean Sales: 1981-1985

		1981	1982	1983	1984	1985
		Median Sales				
Neither	Domestic	21.4	24.6	20.0	22.3	26.1
Only Import	Domestic	62.9	79.9	93.7	115	106
Only Export	Domestic	75.1	87.4	90.5	58.6	41.8
	Export	11.5	24.7	3.84	2.09	3.64
Both	Domestic	508	500	514	496	512
	Export	14.3	11.3	10.5	12.0	13.3
		Mean Sales				
Neither	Domestic	37.3	43.6	39.4	39.1	52.8
Only Import	Domestic	211	211	209	277	286
Only Export	Domestic	195	200	178	66	234
	Export	38.5	40.9	34.3	3.65	30.5
Both	Domestic	896	885	908	959	1021
	Export	49.6	47.8	64.1	65.0	84.3

Note. 100 Millons in 1981 Pesos

Table 2: Trade Participation Rates: 1982-1985

1982	1983	1984	1985
Export Participation Rates			
0.3008	0.3136	0.3093	0.3051
Import Participation Rates			
0.6186	0.6483	0.6568	0.6398

Table 3: Transition Pattern: 1981-1985

Status in Year t	Status in Year $t+1$			
	Both	Only Export	Only Import	Neither
Both	0.9258	0.0156	0.0547	0.0039
Only Export	0.1818	0.5758	0.0303	0.2121
Only Import	0.0479	0.0056	0.8212	0.1257
Neither	0.0067	0.0101	0.1145	0.8687

Table 4: Estimated Static Parameters

Parameters	Benchmark	No Learning by Importing	No Cost Reduction	$d_{jt} = \frac{M_{jt}^f}{M_{jt}}$	Linear
η_D	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)
η_X	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)
const.	0.001 (0.0036)	0.0091^{**} (0.0028)	0.0074^{**} (0.0036)	0.0177^{**} (0.0080)	0.0080^{**} (0.0036)
x_{jt-1}	0.9155^{***} (0.0290)	0.9533^{***} (0.0107)	0.9295^{***} (0.0310)	0.9215^{***} (0.0619)	0.9341^{***} (0.0107)
x_{jt-1}^2	0.2702^{**} (0.1146)	0.1984^{*} (0.1121)	0.2667^{***} (0.1067)	0.1298 (0.1361)	–
x_{jt-1}^3	-0.4047^{***} (0.1129)	-0.3553^{***} (0.1129)	-0.3589^{***} (0.0956)	-0.0974 (0.0868)	–
g_m	0.0201^{***} (0.0045)	–	0.0032 (0.0049)	0.0259^{***} (0.0076)	0.0216^{***} (0.0045)
g_e	0.0045 (0.0044)	0.0083^{**} (0.0043)	0.0091^{**} (0.0046)	0.0038 (0.0044)	0.0080^{*} (0.0045)
β_k	-0.0526^{***} (0.0065)	-0.0543^{***} (0.0069)	-0.0543^{***} (0.0094)	-0.0365^{***} (0.0083)	-0.0326^{***} (0.0094)
β_m	-0.0679^{***} (0.0061)	-0.0589^{***} (0.0058)	–	-0.0739^{***} (0.0134)	-0.0689^{***} (0.0062)

Note. Standard errors are in parenthesis. Asterisks mark rejection at the 1%(***), 5%(**), and 10%(*) significant level, respectively.

Table 5: Estimated Dynamic Parameters

Parameters	Mean	95% Credible Interval	Prior Dist.
γ^{FM}	0.8959	[0.897, 1.0108]	$N(0,500^2)$
γ^{SM}	6.1272	[4.1943, 8.8647]	$N(0,500^2)$
ν^{FM}	0.6648	[0.5992, 0.7359]	$N(0,500^2)$
ν^{SM}	6.5011	[3.051, 10.2651]	$N(0,500^2)$
γ^{FX}	0.6931	[0.5868, 0.8079]	$N(0,500^2)$
γ^{SX}	64.2326	[62.2998, 66.9702]	$N(0,500^2)$
ν^{FX}	0.7642	[0.6986, 0.8353]	$N(0,500^2)$
ν^{SX}	25.4269	[22.8308, 29.1909]	$N(0,500^2)$
Φ_0^X	0.5107	[0.4821, 0.5405]	$N(0,100^2)$
ρ_z	0.9029	[0.8926, 0.9117]	$U[-1,1]$
$\log\sigma_z$	0.2153	[0.2050, 0.2241]	$N(0,10^2)$

Note. Mean and 95% Credible interval of parameters are drawn from the posterior distribution. I draw 60,000 parameters through Metropolis-Hastings random walk chain, and burn-in the first 10,000 draws to rule out the effect of the starting value. I choose the starting value of parameters as the maximizer of log kernel which was found by Simulated Annealing algorithm.

Table 6: In-Sample Model Fits: Productivity and Trade Participation Rates

	1982	1983	1984	1985
	Productivity			
Data	0.2985	0.2944	0.3086	0.3220
Model	0.2989	0.2957	0.2929	0.2931
	Export Participation Rates			
Data	0.3008	0.3136	0.3093	0.3051
Model	0.3008	0.3016	0.3045	0.3101
	Import Participation Rates			
Data	0.6186	0.6483	0.6568	0.6398
Model	0.6220	0.6136	0.6094	0.6161

Note. Simulation reports average results from fifty simulations.

Table 7: In-Sample Model Fits: Transition Pattern

Status in Year t		Status in Year $t+1$			
		Both	Only Export	Only Import	Neither
Both	Data	0.9258	0.0156	0.0547	0.0039
	Model	0.9203	0.0057	0.0676	0.0064
Only Export	Data	0.1818	0.5758	0.0303	0.2121
	Model	0.3497	0.4931	0.0200	0.1372
Only Import	Data	0.0479	0.0056	0.8212	0.1257
	Model	0.0640	0.0038	0.7528	0.1794
Neither	Data	0.0067	0.0101	0.1145	0.8687
	Model	0.0026	0.0054	0.1245	0.8675

Note. Simulation reports average results from fifty simulations.

Table 8: Accounting for Gains from Importing

	1982	1983	1984	1985
Total Gains				
Firm Values	3.2939	3.4843	3.7381	3.8321
Gains from Learning-by-Importing				
Firm Values	2.6846	2.8951	3.1321	3.2654
%	(81.50)	(83.09)	(83.79)	(85.21)
Gains from Facilitating Exporting				
Firm Values	0.0594	0.0628	0.0656	0.0681
%	(1.80)	(1.80)	(1.75)	(1.78)
Gains from Reducing Short-Run Marginal Costs				
Firm Values	0.5499	0.5264	0.5404	0.4986
%	(16.69)	(15.11)	(14.46)	(13.01)

Note. Simulation reports average results from fifty simulations. Firm values are in 100 millions of 1981 Pesos. The numbers in brackets are the percentage ratio of each gains to the total gains.

Table 9: Accounting for Gains from Exporting

	1982	1983	1984	1985
	Total Gains			
Firm Values	3.2304	3.4686	3.8278	3.9018
	Gains from Learning-by-Exporting			
Firm Values	0.5400	0.5858	0.6420	0.6729
%	(16.72)	(16.89)	(16.77)	(17.25)
	Gains from Facilitating Importing			
Firm Values	0.1347	0.1404	0.1456	0.1475
%	(4.17)	(4.05)	(3.80)	(3.78)
	Gains from Earning Profits from Foreign Market			
Firm Values	2.5557	2.7424	3.0402	3.0814
%	(79.11)	(79.06)	(79.42)	(78.97)

Note. Simulation reports average results from fifty simulations. Firm values are in 100 millions of 1981 Pesos. The numbers in brackets are the percentage ratio of each gains to the total gains.

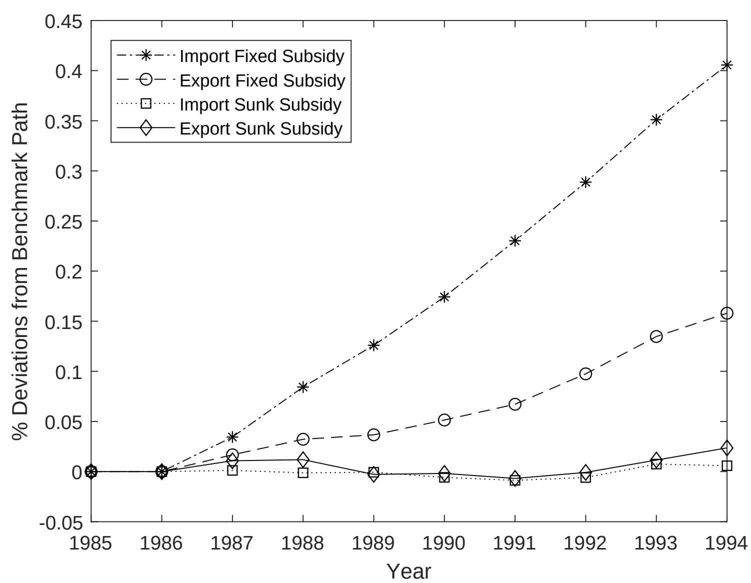


Figure 1: Effect of Trade Cost Subsidy Policies: Productivity

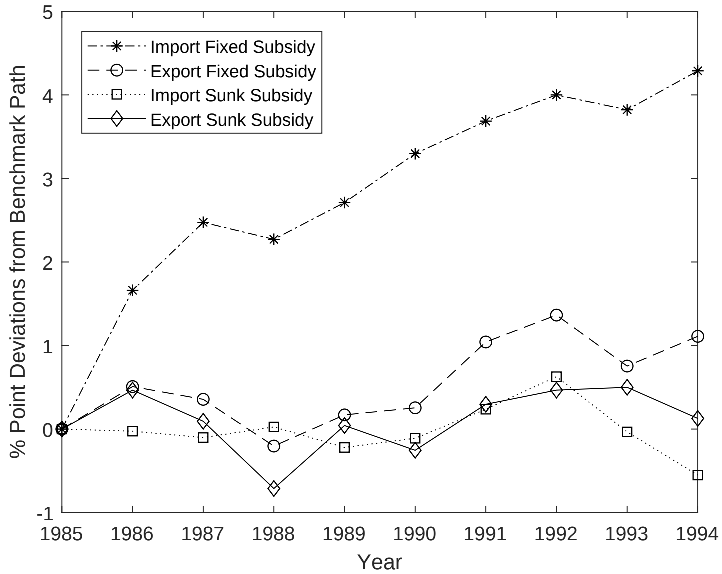


Figure 2: Effect of Trade Cost Subsidy Policies: Import Participations

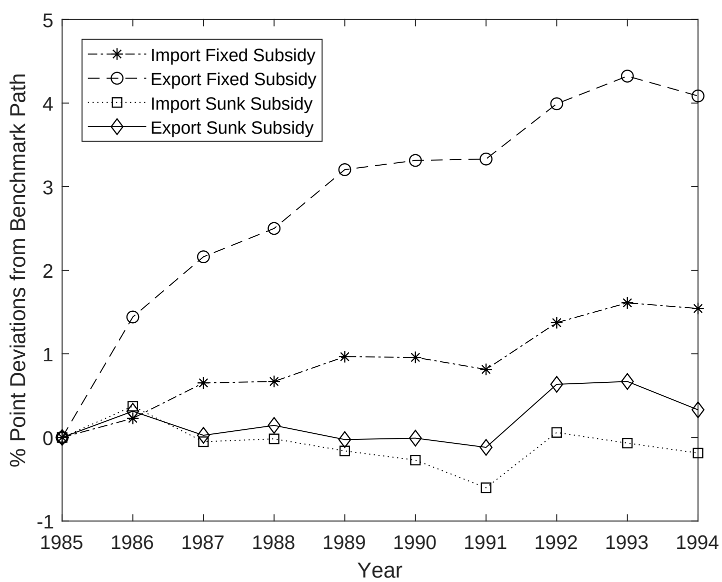


Figure 3: Effect of Trade Cost Subsidy Policies: Export Participations

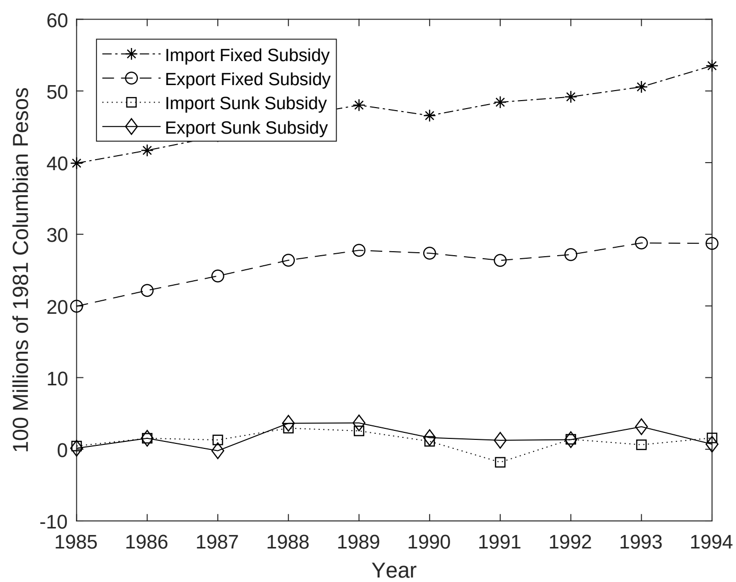


Figure 4: Effect of Trade Cost Subsidy Policies: Ratio of Benefits to Costs

Appendix A: Example of Das, Roberts, and Tybout (2007)'s Simulation Method

This appendix describes how the method allows observed z_{it} and simulated z_{is} to be correlated with a simple example.

Consider a case in which $T = 3$, and $(e_{j1}, e_{j2}, e_{j3}) = (1, 0, 1)$. Then, by the definition of z_j^+ and Σ_+, I obtain

$$z_j^+ = \begin{bmatrix} z_{j1} \\ z_{j3} \end{bmatrix},$$

and

$$z_j^+ \sim N(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} v_z & \rho_z^2 v_z \\ \rho_z^2 v_z & v_z \end{bmatrix}),$$

where $v_z = \frac{\sigma_z^2}{1-\rho_z^2}$. Furthermore, by the definition of Σ_{z+} and Σ_{zz}, I can construct A and B which are essential to simulate the z_j:

$$\Sigma_{z+} = E(\begin{bmatrix} z_{j1} \\ z_{j2} \\ z_{j3} \end{bmatrix} \begin{bmatrix} z_{j1} & z_{j3} \end{bmatrix}) = \begin{bmatrix} v_z & \rho_z^2 v_z \\ \rho_z v_z & \rho_z v_z \\ \rho_z^2 v_z & v_z \end{bmatrix}$$

and

$$\Sigma_{zz} = \begin{bmatrix} v_z & \rho_z v_z & \rho_z^2 v_z \\ \rho_z v_z & v_z & \rho_z v_z \\ \rho_z^2 v_z & \rho_z v_z & v_z \end{bmatrix}.$$

Hence,

$$A = \Sigma_{z+}\Sigma_+^{-1} = \begin{bmatrix} 1 & 0 \\ \frac{\rho_z}{1+\rho_z^2} & \frac{\rho_z}{1+\rho_z^2} \\ 0 & 1 \end{bmatrix},$$

$$BB' = \Sigma_{zz} - \Sigma_{z+}\Sigma_+^{-1}\Sigma_{z+}' = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{\sigma_z^2}{1+\rho_z^2} & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

and

$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{\sigma_z}{\sqrt{1+\rho_z^2}} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

Thus, in generic simulation k, the constructed z_j^k is defined as the following:

$$\mathrm{z}_j^k = \begin{bmatrix} z_{j1} \\ \frac{\rho_z}{1+\rho_z^2} z_{j1} + \frac{\rho_z}{1+\rho_z^2} z_{j3} + \frac{\sigma_z}{\sqrt{1+\rho_z^2}} \epsilon_{j2}^k \\ z_{j3} \end{bmatrix}.$$

Notice that along with simulations, z_{j1}^k and z_{j3}^k do not vary and fixed at the observed values (z_{j1}, z_{j3}).

The important feature is that in simulations, z_{j2}^k is a linear combination of observed values z_{j1} and z_{j3}. This feature allows for simulated z_{j2}^k to be serially correlated with observed values z_{j1} and z_{j3}.

Also, it is necessary to check whether z_{j2}^k is drawn from AR(1) specification. To do so, I first show that autocorrelations between z_{j1} and simulated z_{j2}^k, and between z_{j3} and simulated z_{j2}^k remain fixed at ρ_z in simulations. Notice that

$$\begin{aligned}
COV(z_{j1}, z_{j2}^k) &= \frac{\rho_z}{1+\rho_z^2} COV(z_{j1}, z_{j1}) + \frac{\rho_z}{1+\rho_z^2} COV(z_{j1}, z_{j3}) \\
&= \frac{\rho_z}{1+\rho_z^2} v_z + \frac{\rho_z}{1+\rho_z^2} \rho_z^2 v_z \\
&= \rho_z v_z,
\end{aligned}$$

and

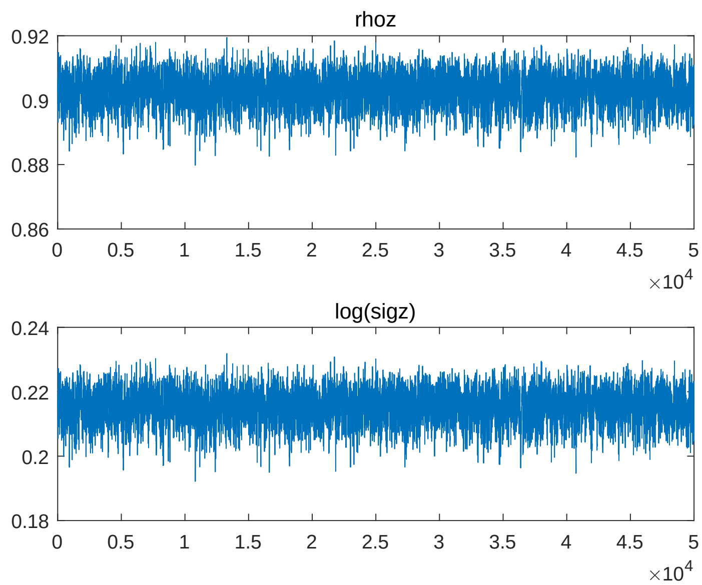
$$\begin{aligned}
COV(z_{j2}^k, z_{j2}^k) &= COV\left(\frac{\rho_z}{1+\rho_z^2} z_{j1} + \frac{\rho_z}{1+\rho_z^2} z_{j3} + \frac{\sigma_z}{\sqrt{1+\rho_z^2}} \epsilon_{j2}^k, \frac{\rho_z}{1+\rho_z^2} z_{j1} + \frac{\rho_z}{1+\rho_z^2} z_{j3} + \frac{\sigma_z}{\sqrt{1+\rho_z^2}} \epsilon_{j2}^k\right) \\
&= 2\left(\frac{\rho_z}{1+\rho_z^2}\right)^2 v_z + 2\left(\frac{\rho_z}{1+\rho_z^2}\right)^2 \rho_z^2 v_z + \frac{1-\rho_z^2}{1+\rho_z^2} v_z \\
&= v_z.
\end{aligned}$$

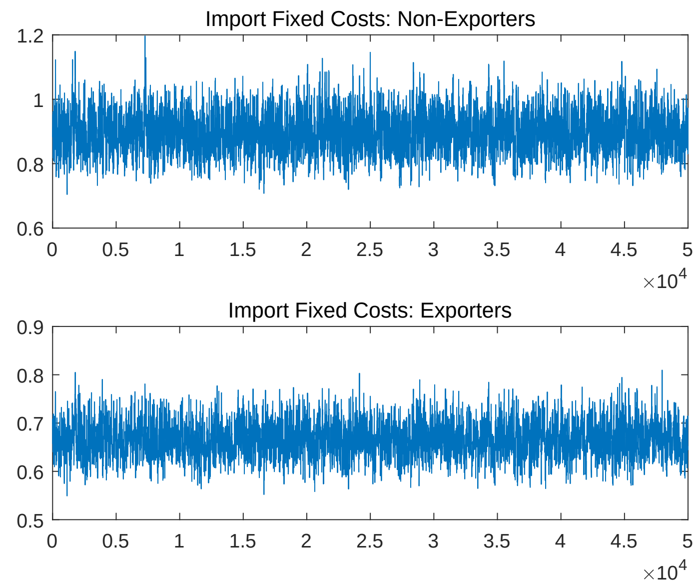
Hence, in simulations, the autocorrelation between z_{j1} and z_{j2}^k is fixed at ρ_z. Analogously, the autocorrelation between z_{j2}^k and z_{j3} is also fixed at ρ_z. Second, by showing that the conditional variance of z_{j2}^k conditioning on z_{j1} is σ_z^2, I can confirm that the simulated value z_{j2}^k is also following the same AR(1) specification that the observed values follow. Notice that

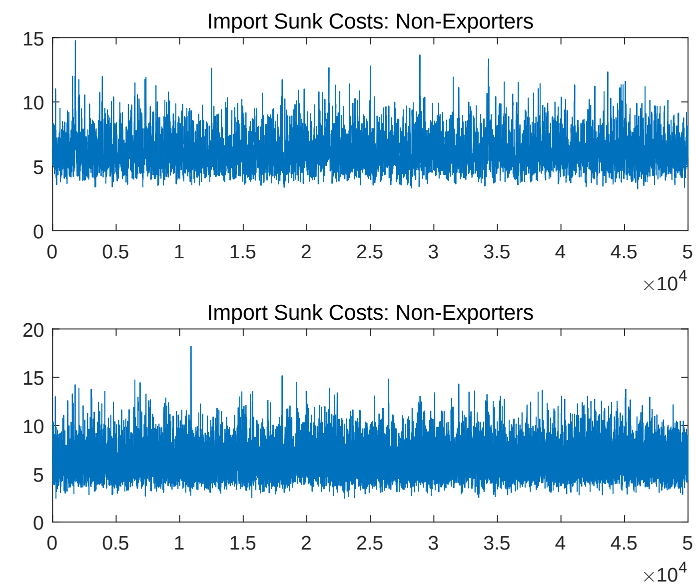
$$\begin{aligned}
E((z_{j2}^k - \rho_z z_{j1})^2) &= E((z_{j2}^k)^2 - 2\rho_z z_{j2}^k z_{j1} + \rho_z^2 z_{j1}^2) \\
&= v_z - \rho_z^2 v_z \\
&= \sigma_z^2.
\end{aligned}$$

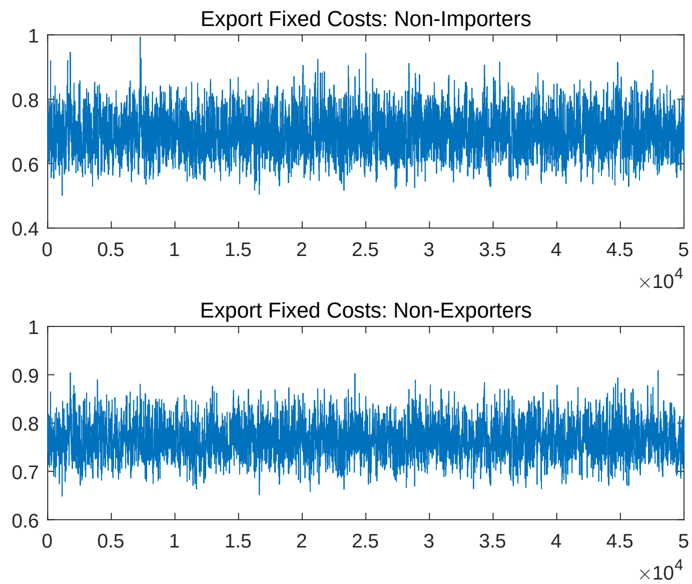
Therefore, the simulated values drawn from the proposed method follow the same AR(1) process.

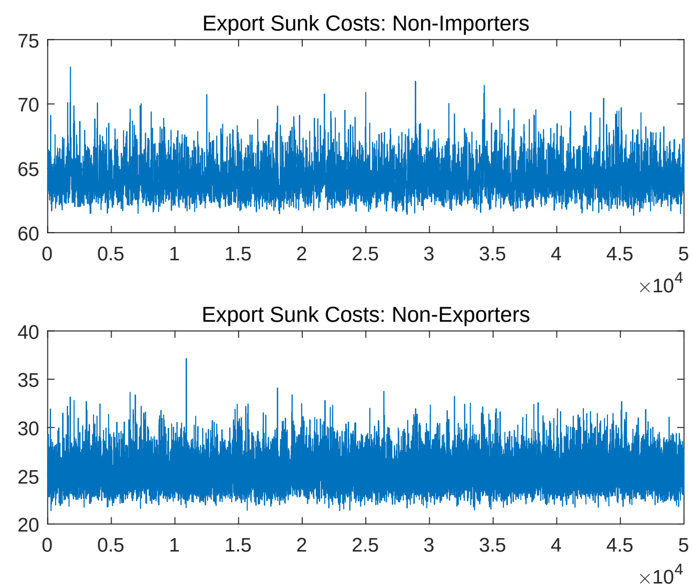
Appendix B: MCMC Trace Plots and Posterior Histograms

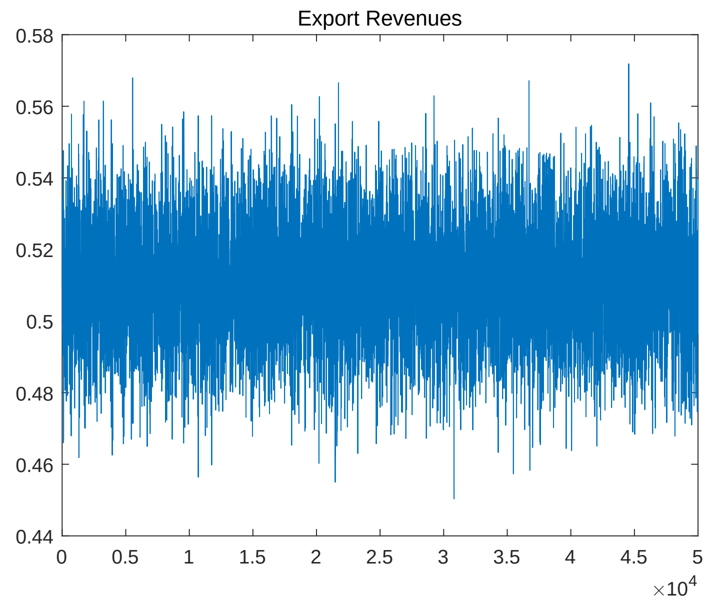


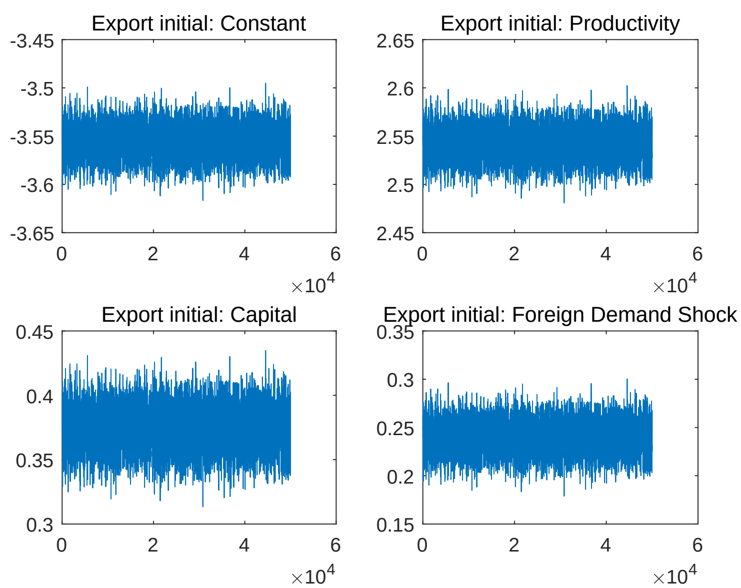

Import Fixed Costs: Non-Exporters
1.2
1
0.8
0.6
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4
Import Fixed Costs: Exporters
0.9
0.8
0.7
0.6
0.5
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4

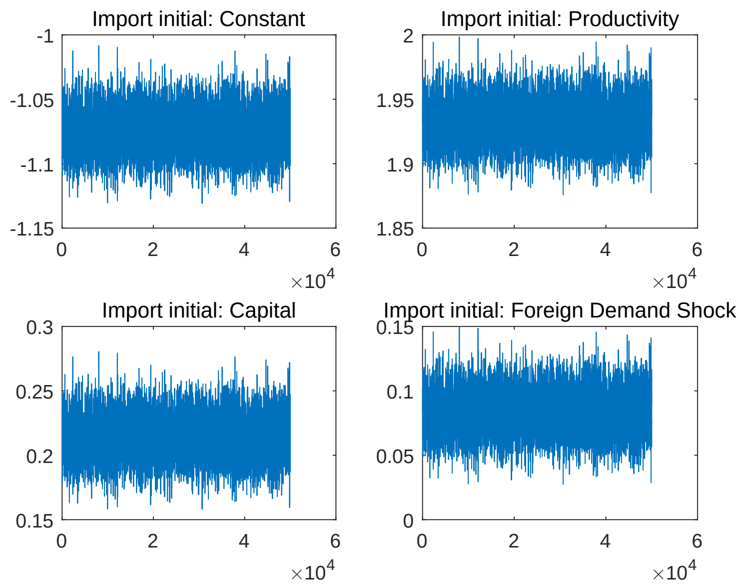

Import Sunk Costs: Non-Exporters
15
10
5
0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4
Import Sunk Costs: Non-Exporters
20
15
10
5
0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4


Export Fixed Costs: Non-Importers
1
0.8
0.6
0.4
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4
Export Fixed Costs: Non-Exporters
1
0.9
0.8
0.7
0.6
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4

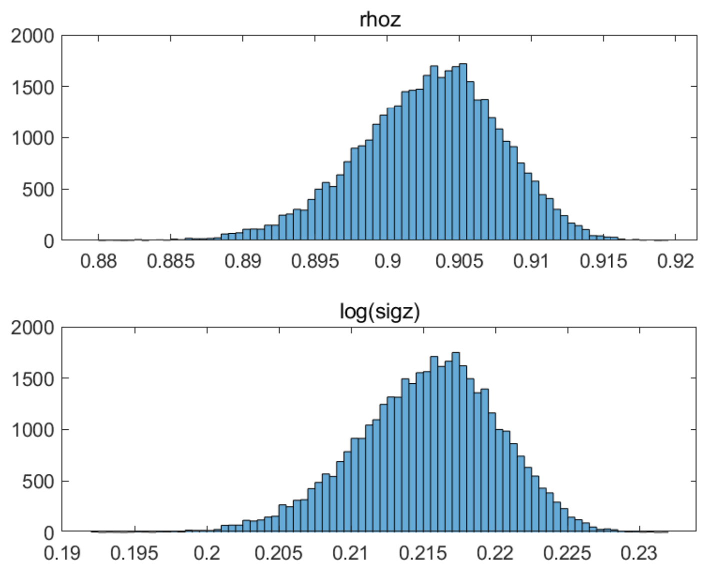

Export Sunk Costs: Non-Importers
75
70
65
60
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4
Export Sunk Costs: Non-Exporters
40
35
30
25
20
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
×10^4


Export Revenues
0.58
0.56
0.54
0.52
0.5
0.48
0.46
0.44
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
$\times 10^4$

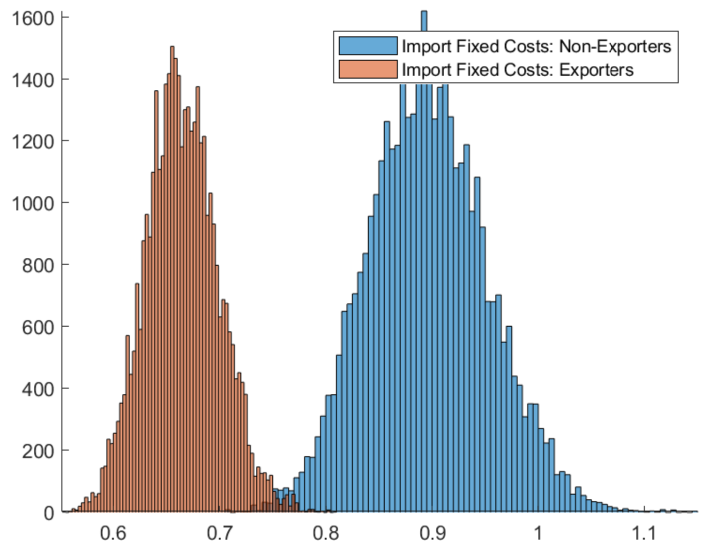

Export initial: Constant
-3.45
-3.5
-3.55
-3.6
-3.65
0
2
4
6
$\times 10^4$
Export initial: Productivity
2.65
2.6
2.55
2.5
2.45
0
2
4
6
$\times 10^4$
Export initial: Capital
0.45
0.4
0.35
0.3
0
2
4
6
$\times 10^4$
Export initial: Foreign Demand Shock
0.35
0.3
0.25
0.2
0.15
0
2
4
6
$\times 10^4$

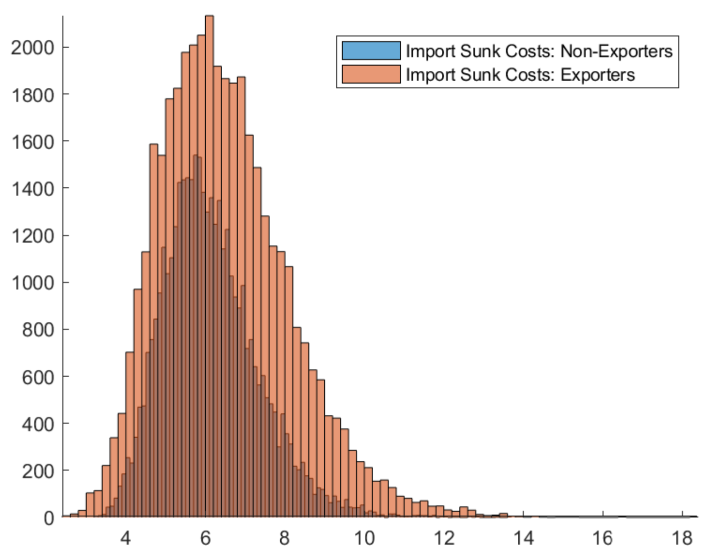


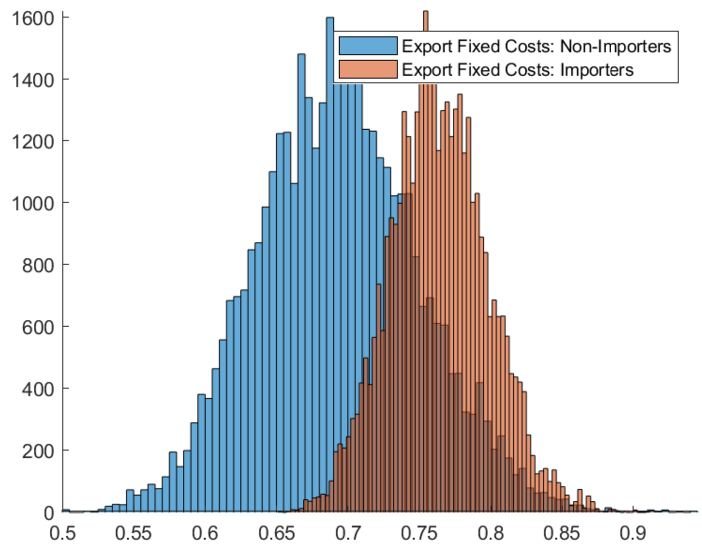
Import initial: Constant
Import initial: Productivity
Import initial: Capital
Import initial: Foreign Demand Shock
-1
-1.05
-1.1
-1.15
2
1.95
1.9
1.85
0.3
0.25
0.2
0.15
0.1
0.05
0
0 2 4 6
×10^4



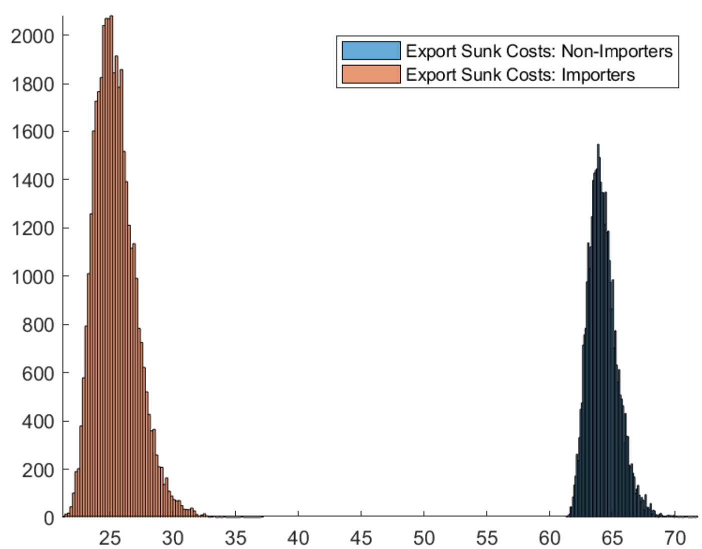
rhoz
2000
1500
1000
500
0
0.88 0.885 0.89 0.895 0.9 0.905 0.91 0.915 0.92
log(sigz)
0.19 0.195 0.2 0.205 0.21 0.215 0.22 0.225 0.23


Import Fixed Costs: Non-Exporters
Import Fixed Costs: Exporters
1600
1400
1200
1000
800
600
400
200
0
0.6
0.7
0.8
0.9
1
1.1

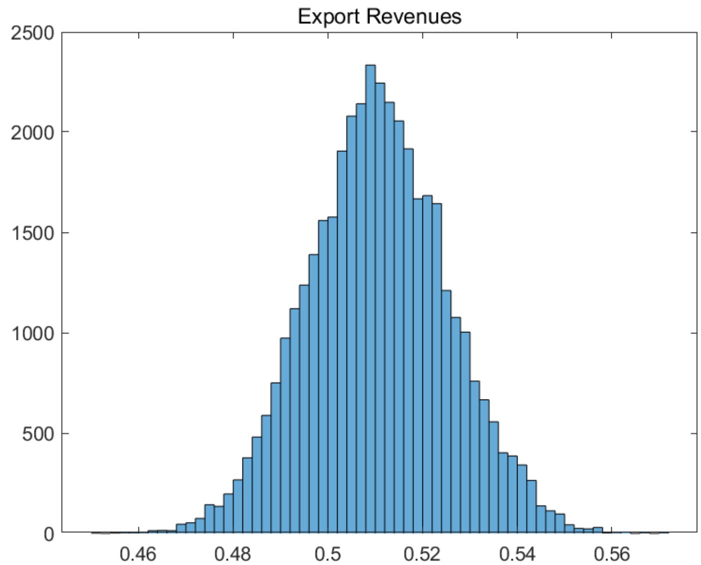

Import Sunk Costs: Non-Exporters
Import Sunk Costs: Exporters
2000
1800
1600
1400
1200
1000
800
600
400
200
0
4
6
8
10
12
14
16
18

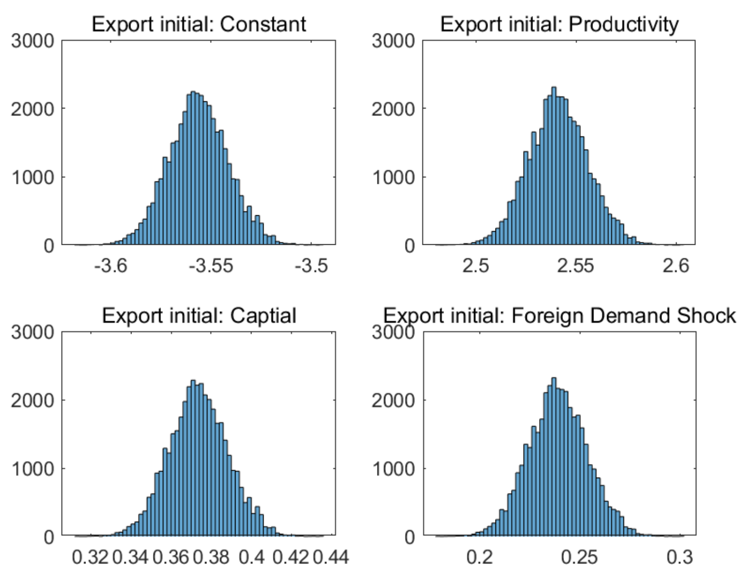


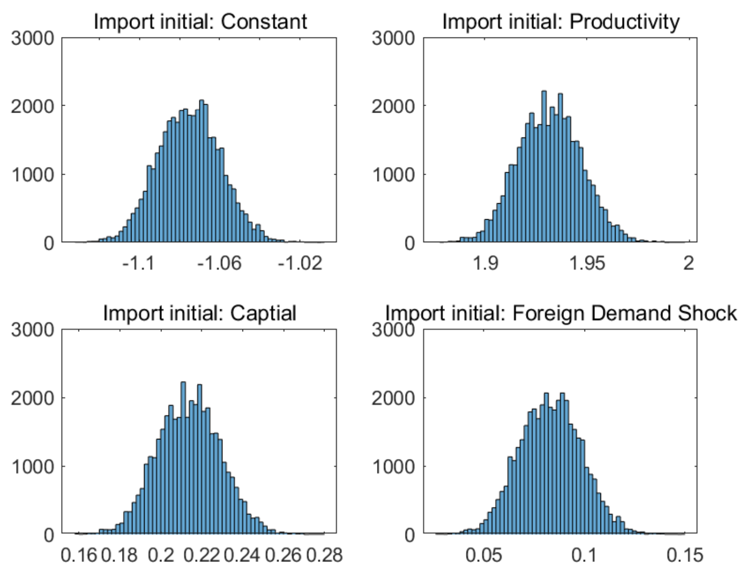
Export Fixed Costs: Non-Importers
Export Fixed Costs: Importers



Export Sunk Costs: Non-Importers
Export Sunk Costs: Importers


Export Revenues
2500
2000
1500
1000
500
0
0.46
0.48
0.5
0.52
0.54
0.56


Export initial: Constant
Export initial: Productivity
Export initial: Captial
Export initial: Foreign Demand Shock
3000
2000
1000
0
-3.6
-3.55
-3.5
2.5
2.55
2.6
0.32 0.34 0.36 0.38 0.4 0.42 0.44
0.2
0.25
0.3


Import initial: Constant
Import initial: Productivity
Import initial: Captial
Import initial: Foreign Demand Shock
3000
2000
1000
0
-1.1
-1.06
-1.02
1.9
1.95
2
0.16
0.18
0.2
0.22
0.24
0.26
0.28
0.05
0.1
0.15