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

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Abstract

This paper estimates a dynamic model of the firm's 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 export market, while exporting facilitates importing by decreasing the fixed continuation costs of importing. 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

[1] A vast literature at the intersection of industrial organization and international trade documents the short-run and long-run benefits of trade participation at the firm level. First, by serving the foreign market (exporting), firms can make additional profits from the foreign market (Das, Roberts, and Tybout (2007); Li (2018)). Second, importers can access a broader selection of high-quality inputs at lower prices (Halpern, Koren, and Szeidl (2015); Grieco, Li, and Zhang (2022)). In addition, firms can improve their productivity in the long run via technical support or expertise from their foreign buyers, which is known as "learning-by-exporting" and "learning-by-importing" (Kasahara and Rodrigue (2008); Aw, Roberts, and Xu (2011); Bai, Krishna, and Ma (2017); Zhang (2017); Grieco, Li, and Zhang (2022)).

However, the evaluation of the benefits of exporting and importing is potentially biased when a researcher does not consider both activities. For instance, exporting and importing might be interdependent: participating in one activity alters the incentive to engage in the other activity. Hence, models ignoring either exporting or importing can incorrectly measure the benefits of trade participation and the impacts of hypothetical trade subsidy schemes. Yet, to the best of my knowledge, except for Grieco et al. (2022), empirical studies tend to analyze these two trade activities individually.

Having this gap in mind, I build a structural model for the joint import and export decision process by augmenting the dynamic model of Aw et al. (2011) with the production function of Halpern et al. (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 their future productivity by importing and exporting. 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) start-up or continuation costs for the other trade activity. Allowing for the dependence of sunk start-up and fixed continuation costs of trading on the trade status is motivated by the two observed transition patterns: (i) a firm doing one activity is more likely to start the other activity than its counterpart; (ii) 92% of firms doing both in current period continue doing both activities in next period (Table 2).

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I take the model to panel data of Colombian chemical plants that 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. A conventional optimization algorithm is thus inappropriate for estimating the model. I bypass such a non-global concavity by using the Bayesian Markov Chain Monte Carlo (MCMC) method to characterize the posterior distribution of the structural parameters.

I use the estimated model to conduct two counterfactual simulations: (1) I quantify the three proposed gains from trade; (2) I evaluate the anticipated performance and efficiency of policies that subsidize start-up/continuation costs of importing and exporting.

My empirical results reveal several aspects of international trade in the Colombian chemical industry. First, productivity is endogenously determined; using imported material purchases enhance future productivity. However, serving the export market does not improve future productivity significantly. Notably, in the specification with learning-by-exporting alone, I observe that researchers may incorrectly interpret the productivity effects of trading as if Chemical plants in Colombia enjoyed the substantial learning-by-exporting effect. This biased positive productivity effect of exporting thus reflects a spurious correlation with importing. Second, there are substantial sunk start-up costs for undertaking exporting and importing. Third, one trading decision facilitates the other decision by reducing start-up/continuation costs: exporting decreases the continuation costs of importing, while importing reduces the start-up costs of exporting.

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 the continuation costs of importing is the most effective. The simulation result indicates that ten years after the policy, subsidizing the continuation costs of importing 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 the continuation costs of importing is about 16, while those of subsidizing the start-up costs of importing, the continuation costs of exporting, and the start-up costs of exporting are one, nine, and 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

This section constructs a dynamic model of the firm's joint export and import decision process. Specifically, I expand upon Aw et al. (2011) by incorporating the production function of Halpern et al. (2015) in the spirit of Zhang (2017). Firms produce outputs using labor, domestic and imported materials, and capital and sell their outputs to the domestic and export markets, which are monopolistically competitive. Firms make two dynamic discrete choices: importing and exporting.[2] In addition, I introduce trade cost complementarity between these two activities: the fixed continuation and sunk start-up cost parameters depend on the firm's current trade status. For instance, if an importer would like to start exporting, then it would face the lower start-up costs of exporting 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.

[2] I abstract away the decision to invest in physical capital following Aw et al. (2011); Zhang (2017), and Grieco et al. (2022). This abstraction is justified by the fact that my empirical analysis utilizes a short panel. Since the decisions to invest in the capital are lumpy, it is unlikely that there would be a rapid change in the firm's stock of capital within the sample periods.

II.I Timeline

Times are discrete, and firms seek to maximize its present value of future profits, discounted with common discount factor δ, by choosing the sequence of the optimal trading decisions. The timeline of the production and trading decision processes is as follow:

1. At the beginning of period t, firm j takes its state vector s_{jt} as given:

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

   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. The firm makes the inputs decision for production and earns variable profits by selling their products to the domestic and export markets.

3. The firm draws the start-up (continuation) costs of importing C^M_{jt} from the distribution $F_M(\cdot|s_{jt})$ and then decides whether or not to start (continue) importing in the next period (d_{jt+1}).

4. The firm subsequently draws the start-up (continuation) costs of exporting C^X_{jt} from the distribution $F_X(\cdot|s_{jt})$ and decides to start (continute) exporting in the next period (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 lumpy investment decision given that the data spans five years.

II.II Technology

The first building block of the model is a production function that converts labors, capital, and material purchases (domestic and imported) to outputs. Following Halpern et al.

(2015) and Zhang (2017), I consider the following Cobb-Douglas production function with a nested CES basket which aggregates domestic and imported materials:

$$
\begin{aligned}
Q_{jt} &= \exp(x_{jt}) L_{jt}^{\alpha_l} M_{jt}^{1-\alpha_l} K_{jt}^{\alpha_k}, \\
M_{jt} &= [(M_{jt}^d)^{\frac{\theta-1}{\theta}} + (A_t M_{jt}^f)^{\frac{\theta-1}{\theta}}]^{\frac{\theta}{\theta-1}}, \ \theta > 0
\end{aligned} \tag{1}
$$

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 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 constant return to scale (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.

The first order conditions of the short-run cost minimization problem imply the following marginal cost functions:

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

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

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 $(1 + (A_t \frac{P_{M,t}^d}{P_{M,t}^f})^{\theta-1})^{(1-\alpha_l)/(1-\theta)}$ 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 $(1+(A_t\frac{P^d_{M,t}}{P^f_{M,t}})^{\theta-1})^{\frac{1-\alpha}{1-\theta}}$. 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.

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

where $w_t, p^d_{m,t}$ 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 $\frac{1-\alpha_l}{1-\theta}\log(1+(A_t\frac{P^d_{M,t}}{P^f_{M,t}})^{\theta-1})$.

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 strictly focus on the average advantage of importing due to the reduction in marginal cost. Thus, I simplify $\beta_{m,t}$ as time-invariant parameter β_m by assuming that the price-adjusted quality of imported materials $A_t\frac{P^d_{M,t}}{P^f_{M,t}}$ has a constant value, namely κ: $\beta_m \equiv (1+(\kappa)^{\theta-1})^{\frac{1-\alpha}{1-\theta}}$.

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 analogous to the marginal cost specification of Aw et al. (2011), except for the inclusion of an indicator of import status as a cost shifter.

Two features of β_m merits comments. First, the impact of importing on short-run marginal costs hinges on the substitutability between domestic and imported materials. For instance, when imported materials are substitutes for domestic counterparts ($\theta > 1$), importers can enjoy lower short-run marginal costs than non-importers. In addition, imported materials with better quality (i.e., $\kappa > 0$) amplify such a cost-reduction effect of importing.

II.III Demand and Static Profits

In the domestic and export markets, each firm faces iso-elastic demand curves:

$$Q^D_{jt} = \Phi^D_t (P^D_{jt})^{\eta_D}, \tag{7}$$
$$Q^X_{jt} = \Phi^X_t (P^X_{jt})^{\eta_X} \exp(z_{jt}), \tag{8}$$

where Q^m_{jt} are the amount of demanded goods in market m; P^m_{jt} is market m's prices set by firm j; Φ^m_t represents the time-varying aggregate industry demand shifter for market m; and η_m represents the demand elasticity of market m. Note that for the export demand, I incorporate export market demand shifter z_{jt} which varies across firms and periods. Here, z_{jt} essentially captures the relative differences between domestic and foreign market demand shifters.

The domestic and export markets are assumed to be monopolistically competitive. Thus, firm j charges constant mark-up $\frac{\eta_m}{1+\eta_m}$, and the logged revenue functions are given by

$$r^D_{jt} = (\eta_D + 1)\log\frac{\eta_D}{1+\eta_D} + \log\Phi^D_t + (\eta_D + 1)(\beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}), \tag{9}$$
$$r^X_{jt} = (\eta_X + 1)\log\frac{\eta_X}{1+\eta_X} + \log\Phi^X_t + (\eta_X + 1)(\beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}) + z_{jt}. \tag{10}$$

In addition, operating profits of each market are proportional to revenues:

$$\pi^D_{jt} = -\frac{1}{\eta_D}\exp(r^D_{jt}) = \Pi_D(k_{jt}, x_{jt}, d_{jt}), \tag{11}$$
$$\pi^X_{jt} = -\frac{1}{\eta_X}\exp(r^X_{jt}) = \Pi_X(k_{jt}, x_{jt}, d_{jt}, z_{jt}). \tag{12}$$

Two important features of the model need to be pointed out. First, importers would make higher domestic and export profits than non-importers if domestic and imported materials are substitutes (i.e., $\beta_m < 0$), capturing the cost-reduction effect of importing. Second, export market demand shifter z_{jt} is the only firm-level heterogeneity that shapes between-exporter variations in revenues. That is z_{jt} will capture differences in revenues across exporters which are unexplained by capital, productivity, and import status. In addition, this feature allows me to distinguish between productivity x_{jt} and export market demand shifter z_{jt}, which prevents from conflating "learning-by-exporting" effect and export market specific shocks (Aw et al. (2011)).

II.IV Evolution of Productivity and Export Market Demand Shifter

Firm's productivity x_{jt} evolves according to 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 in period $t-1$, respectively. The specification allows for the possibility of learning-by-trading. For instance, a firm could access to technical support from trading partners or improve the quality of their product from an interaction with their partners.

Export market demand shifter z_{jt} follows 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 Trading Decisions

When deciding whether or not to partake in trade activities (exporting & importing), a firm seeks to maximize its presented discounted values of future domestic and export profits after observing realized continuation and start-up costs. However, it is probable that each firm faces heterogeneous continuation and start-up costs of partaking in trade. For instance, firms can be different in trade experience or a connection to a foreign partner. I capture this potential heterogeneity by assuming that costs of importing and exporting C_{jt}^M and C_{jt}^X are identically and independently drawn from exponential distributions whose scale parameters depend on the trade status:

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

where

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

Note that the trade status in current period affects the cost distribution that a firm will face. First, if firm j is an exporter ($e_{jt} = 1$), it would pay only the continuation costs of exporting (ν^{FX} or γ^{FX}) to become an exporter in the next period, and so is it for the case of importing. Second, the model allows for the potential cost complementarity between two trade activities. For instance, if firm j is an importer but not an exporter in time t, the firm's export start-up costs would be drawn from $Exp(\nu^{SX})$. Meanwhile, if it has not participated in any trade activity, it's start-up costs of exporting would be drawn from $Exp(\gamma^{SX})$. If there is the cost complementarity, the estimation results would indicate that $\gamma^{SX} < \nu^{SX}$.

Given state vector s_{jt}, the firm's value before the realization of trade costs is given by

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

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

$$V_M(s_{jt}) = \int \max_{e_{jt+1}} \Big\{ \delta EV(e_{jt+1} = 1, d_{jt+1} = 1 | s_{jt}) - C_{jt}^X,$$

$$\delta EV(e_{jt+1} = 0, d_{jt+1} = 1) | s_{jt}) \Big\} dF_X(C_{jt}^X | s_{jt}) \tag{16}$$

$$V_{NM}(s_{jt}) = \int \max_{e_{jt+1}} \Big\{ \delta EV(e_{jt+1} = 1, d_{jt+1} = 0 | s_{jt}) - C_{jt}^X,$$

$$\delta EV(e_{jt+1} = 0, d_{jt+1} = 0) | s_{jt}) \Big\} dF_X(C_{jt}^X | s_{jt}) \tag{17}$$

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 $MBM_{jt}(s_{jt}) \leq C_{jt}^M$, and then given s_{jt} and d_{jt+1}, the firm decides to export if and only if $MBX_{jt}(d_{jt+1}, s_{jt}) \leq C_{jt}^X$.

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 not correlated with the explanatory 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 $\tilde{\Phi}_t^D$.

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}.

I address the simultaneity problem emerging in (21) by following Olley and Pakes (1996), Levinsohn and Petrin (2003), and Aw et al. (2011)'s proxy approach. In the theoretical model, the factor demand for composite of domestic and imported materials M_{jt} is monotone in productivity x_{jt}. In addition, 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_{jt}^d as a control function for the firm's productivity: $\tilde{h}(k_{jt}, d_{jt}, m_{jt}^d)$. Hence, equation (21) can be written by

$$
\begin{aligned}
r_{jt}^D &= \Phi_t^D + (\eta_D + 1)(\beta_t + \beta_k k_{jt} + \beta_m d_{jt} - \tilde{h}(k_{jt}, d_{jt}, m_{jt}^d)) + \xi_{jt} \\
&= m_0 + m_t + h(k_{jt}, d_{jt}, m_{jt}^d) + v_{jt}. \qquad (22)
\end{aligned}
$$

where the function h is a complex unknown function of capital, import status, and domestic material purchases. Following Aw et al. (2011), I approximate h as a cubic polynomial and conduct ordinary least squares to estimate (22). 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.

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

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 et al. (2011). 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)

To estimation the structural parameters, I maximize the likelihood for the observed trade participation and the logged level of export revenues $\{(e_{jt+1}, d_{jt+1}, r^X_{jt+1})\}^{N,T-1}_{j=1,t=1}$. 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 et al. (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 $\{z^k_{jt}\}^{N,T,K}_{j,t,k}$ 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 $z^+_j = \{z_{jt} : \tilde{r}^X_{jt}$ 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 $v_z \equiv \frac{\sigma^2_z}{1-\rho^2_z}$ and off-diagonal components are $\rho^{|p|}_z v_z$ 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 $\{\epsilon^k_j\}^K_{k=1}$ from standard Normal distribution. Then, given observed z_{jt}, (ρ_z, σ_z), I can simulate $\{\mathrm{z}^k_j\}^K_{k=1}$ 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 $\{\mathrm{z}^k_j\}^K_{k=1}$ 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.

There are two important features of this method. 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. Given these, 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. [3]

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:

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

where

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

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

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

[3] 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: Heckman (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 Heckman (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:

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

where G is a cdf of the 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:

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

where g is a pdf of the standard Normal distribution, and $\nu_z = \sqrt{\frac{\sigma_z}{1-\rho_z^2}}$. 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, by averaging out (32) over the K simulations, I obtain the final individual contribution to the full likelihood. By multiplying these contributions across all the 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}.

III.V 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. Following Das et al. (2007) and Aw et al. (2011), I address this issue using Bayesian Markov Chain Monte Carlo (MCMC). Specifically, I construct the random-walk Metropolis-Hastings Markov chain to draw the samples from the posterior distribution of the dynamic parameters. When characterizing a posterior distribution, I use the diffuse prior distribution to prevent the estimates from being influenced by an arbitrary choice of prior distributions.[4]

The main goal of Bayesian MCMC is to characterize the posterior distributions of

[4] 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.

model parameters. Using the random-walk Metropolis-Hastings chain, I 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.[5]

One 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.[6]

IV Empirical Results

This section first describes the dataset used for the empirical analysis and then reports the estimates of demand, marginal cost, productivity dynamics, and trade costs in the Colombian chemical industry.

IV.I Data

I estimate the model using a firm-level panel dataset, collected by the Colombian manufacturing plant survey which is collected by Colombia Departamento Administrativo Nacional de Estadistica (DANE) for periods from 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 (1996). I focus on periods after 1981 because DANE began to track export sales since then.

I look at 236 chemical plants (SIC codes are 351 and 352) that continuously operated in the domestic market from 1981 to 1985, reflecting two considerations. First, the industry is trade-oriented as shown in Table 3. During the sample periods, approximately 61% of plants purchased imported materials, and 30% of of plants sold their products

[5] Appendix B describes the details about the random-walk Metropolis-Hastings algorithm.
[6] Appendix C reports the MCMC diagnostics.

to the export market. Second, the stringent import tariffs of Colombia were liberalized in 1985, which might affect the margins of trading decisions (Roberts (1996)). Hence, I focus on periods from 1981 to 1985 to avoid a potential bias in structural estimates due to this regime shift.

Table 1: 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 4 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 the 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 those of firms doing both. Similar patterns stand out when it comes to average sales. This pattern indicates that even after controlling for the firm size, any possible time-varying factors, and self-selection, there could be a systematic difference between non-importers and importers, which indicates the possibility of learning-by-importing. A similar pattern arises when I compare sales of non-exporters and exporters, suggesting the possibility of learning-by-exporting. The empirical model of this paper allows me to disentangle such effects of learning-by-trading from other factors shaping the trading decisions: firm size, productivity, and trade costs.

IV.II Demand, Cost, and Productivity Dynamics

Tables 5 reports the parameter estimates of the demand, cost, and productivity dynamics in equations (22) and (23). I add dummies of SIC 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 5 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 follows.

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

Second, both capital and import status decrease 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 increases 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, firm-specific productivity evolves and 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 that has exported is about 0.45% higher than the counterpart's one. However, 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, due to the high persistence in the productivity dynamics, the long-run impacts of exporting and importing become substantially large. Relative to a firm that will never do trading, a firm that 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 6 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 follows.

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 difference indicates that Colombian chemical exporters sell less in the foreign market than they do 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 σ_z is $\exp(0.2153) = 1.15$. These estimates are quite larger than the estimates from the previous studies but qualitatively in line with them. Aw et al. (2011) report that the estimates of these parameters are 0.77 and -0.287, respectively, and Bai et al. (2017) 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 implications from the estimates of the cost parameters are summarized as follows.

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 that is doing both is likely to draw 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 reduces 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 capital.[7] Aw et al. (2011) show that large firms in the 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 be the case 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.

[7] In the 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.

IV.IV Model Fit

Armed with the estimates in Tables 5 and 6, 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 are endogenously determined by the firm's dynamic decision, it is necessary to check whether the simulated trajectory tracks the realized average productivity well. Table 7 compares the realized moments and the model moments. Though it underpredicts the import participation rates in the first few years, the model tracks the overall trend well.

Table 8 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 Counterfactuals

V.I Quantifying Benefits from Trade

This section quantifies the impacts of importing and exporting in the Colombian chemical industry. The model of this paper is constructed to quantify the three possible channels through which import and export can boost the firm's performance. For importing, the proposed three channels are (i) improving 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 exporting, there are analogous three channels: (i) improving 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 Importing

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 are defined by the difference between $V(s_{jt})$ and $V_{No-Import}(s_{jt})$:

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

Following 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:

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

Table 9 displays the gains from importing, and the gains from three channels spanning from 1982 to 1985. The first panel reports the total gains from importing. All units are expressed in 100 million 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 million of 1981 Pesos and 85% of the gains are attributed to the impact of learning-by-importing. This result is not surprising because as shown in Table 5, importing was playing a crucial role in boosting 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 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 the export market easily, it does not translate to an increase in the firm values.

V.I.2 Gains from Exporting

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. Thus, the total gains of exporting can be decomposed analogously:

$$\text{Gains from learning-by-importing} = V(s_{jt}) - V(s_{jt}|g_e = 0),$$
$$\text{Gains from facilitating exporting} = V(s_{jt}|g_m = 0) - V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM}),$$
$$\text{Gains from making an export profit} = V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM}) - V_{No-Export}(s_{jt}).$$

Table 10 reports the decomposition of the gains from exporting. The first panel displays the total gains from exporting. The second to fourth panels display the gains from the three channels. Notice that in the year 1985, unlike the case of importing, the impact of learning-by-exporting only accounts for 18% of the total gains. In contrast, the gains from short-run export profits are central to shaping the total gains from exporting. This short-run gain 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

Using the estimated model, I conduct counterfactual experiments to evaluate trade-cost subsidy schemes, which are typical policy instruments to encourage firms' international trade activities. 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 the firm's expected subsidized grants are equal to 1,500,000 1981 Colombian Pesos.[8] 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 four policies. Amongst all the four policies, subsidizing import fixed costs is the most effective to boost 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 reflects the fact that import

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

fixed cost subsidy could boost 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 learning-by-importing is crucial and subsidizing export/import sunk costs would not boost 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 2 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, Roberts, Vuong, and Fryges (2017) and Peters, Roberts, and Vuong (2022), 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 exporting or importing at cheaper costs, and it will raise 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 5 and 6, the latter 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 among the proposed subsidy plans according to the cost-benefit analysis displayed in Figure 4. The figure displays the gains from the subsidy. Ten years after the policies, the gains from the policy subsidizing import fixed costs are about 5,300 million 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, the benefits of sunk cost subsidy plans are quite small: 150 and 70 million of 1981 Pesos from import and export sunk cost subsidies, respectively.

VI Conclusion

I propose a dynamic model of the joint decisions to export and import to quantify the gains from partaking in trade activities. Using the model, I decompose the gains from partaking in trade activities into the gains from three channels: (i) learning-by-trading, (ii) increasing the short-run profits, and (iii) trade cost complementarity. In addition, I use the model to evaluate trade cost subsidy schemes, which are common policy instruments in many developing countries.

Estimation results drawn from the Colombian chemical industry indicate that a firm has the incentive to import because it will face the lower marginal cost and boost its productivity through the learning-by-importing channel. A firm also has the 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 the foreign market more easily than a 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 among 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 improve the firm values.

Tables and Figures

Table 2: Transition Rates for Trade Status: 1981-1985

Trade Status in Year t	Trade 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 3: 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 4: 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. Units are in 100 Millons of 1981 Pesos

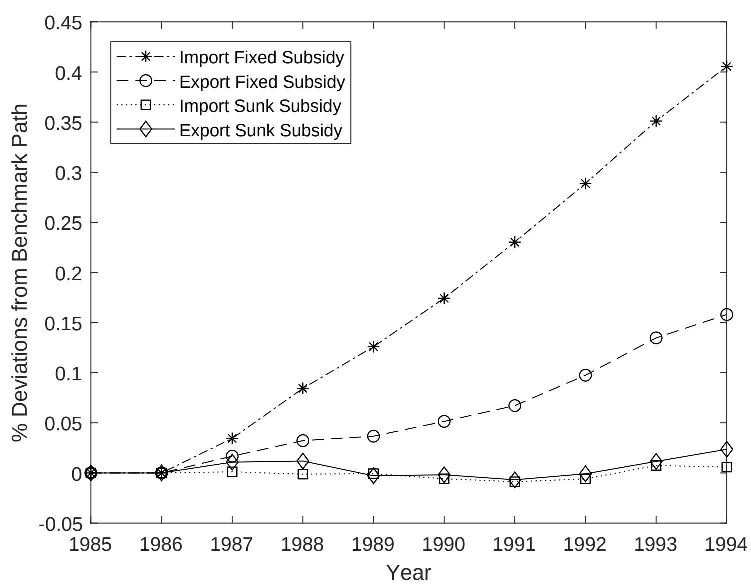

Figure 1: Effect of Trade Cost Subsidy Schemes: Productivity

Table 5: Estimated Static Parameters

Parameters	Benchmark	No Learning-by-Importing	No Cost Reduction	$d_{jt} = \frac{M^f_{jt}}{M_{jt}}$	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^2_{jt-1}	0.2702^{**} (0.1146)	0.1984^{*} (0.1121)	0.2667^{***} (0.1067)	0.1298 (0.1361)	–
x^3_{jt-1}	-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 6: 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. MCMC diagnostics are reported in Appendix C. The starting point of an MCMC is the maximizer of log kernel, which was found by Simulated Annealing algorithm.

Table 7: 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 8: In-Sample Model Fits: Transition Rates for Trade Status

Trade Status in Year t		Trade 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 9: Accounting for Benefits from Importing

	1982	1983	1984	1985
	Total Benefits			
Firm Values	3.2939	3.4843	3.7381	3.8321
	Long-run Benefits			
Firm Values	2.6846	2.8951	3.1321	3.2654
%	(81.50)	(83.09)	(83.79)	(85.21)
	Benefits from Complementarity			
Firm Values	0.0594	0.0628	0.0656	0.0681
%	(1.80)	(1.80)	(1.75)	(1.78)
	Short-run Benefits			
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. Long-run Benefits are the gains from learning-by-importing; Benefits from Complementarity are the gains from reducing the costs of exporting; and Short-run Benefits are the gains from reducing short-run marginal costs.

Table 10: Accounting for Benefits from Exporting

	1982	1983	1984	1985
	Total Gains			
Firm Values	3.2304	3.4686	3.8278	3.9018
	Long-run Benefits			
Firm Values	0.5400	0.5858	0.6420	0.6729
%	(16.72)	(16.89)	(16.77)	(17.25)
	Benefits from Complementarity			
Firm Values	0.1347	0.1404	0.1456	0.1475
%	(4.17)	(4.05)	(3.80)	(3.78)
	Short-run Benefits			
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. Long-run Benefits are the gains from learning-by-exporting; Benefits from Complementarity are the gains from reducing the costs of importing; and Short-run Benefits are the gains from making short-run profits in the foreign market.

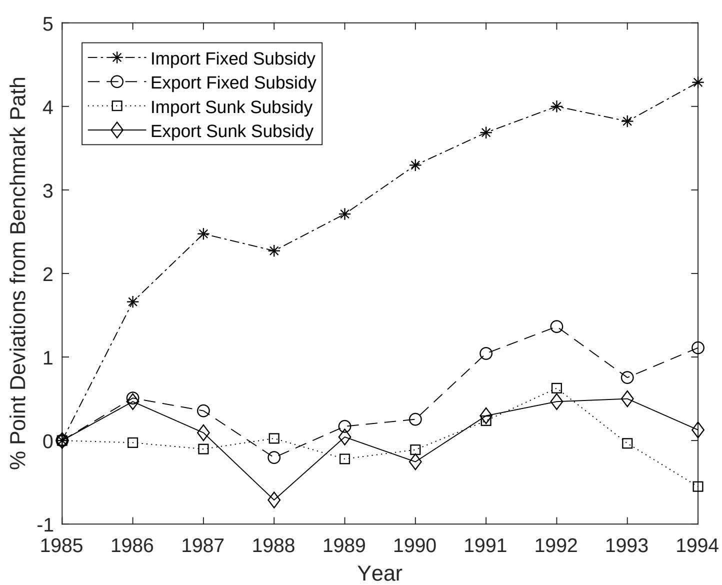

Figure 2: Effect of Trade Cost Subsidy Schemes: Import Participations

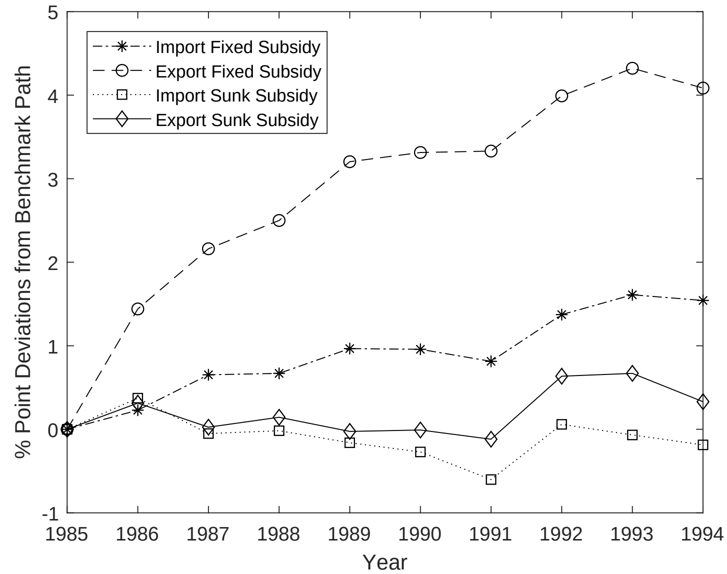

Figure 3: Effect of Trade Cost Subsidy Schemes: Export Participations

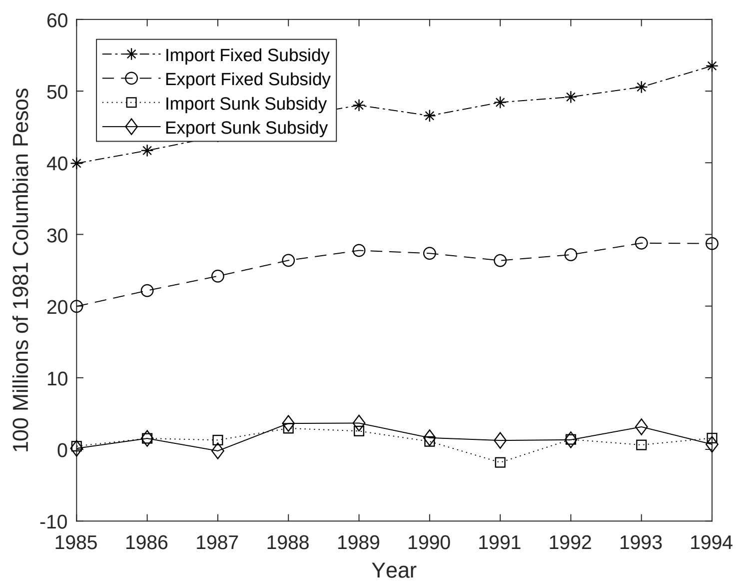

Figure 4: Effect of Trade Cost Subsidy Schemes: Ratio of Benefits to Costs

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Appendices

A Example of Das et al. (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

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

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.

B Detail of the random-walk Metropolis-Hastings Algorithm

This appendix describes how I design the random-walk Metropolis-Hastings algorithm in practice.

Since I should estimate 19 dynamic parameters, implementing the 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

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

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

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

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.

C MCMC Diagnostics

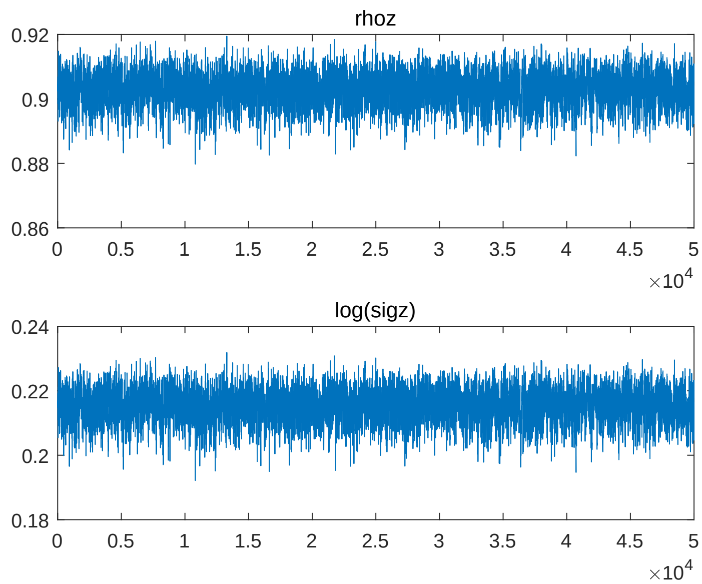

Figure 5: MCMC Trace Plot: Export Demand Parameters

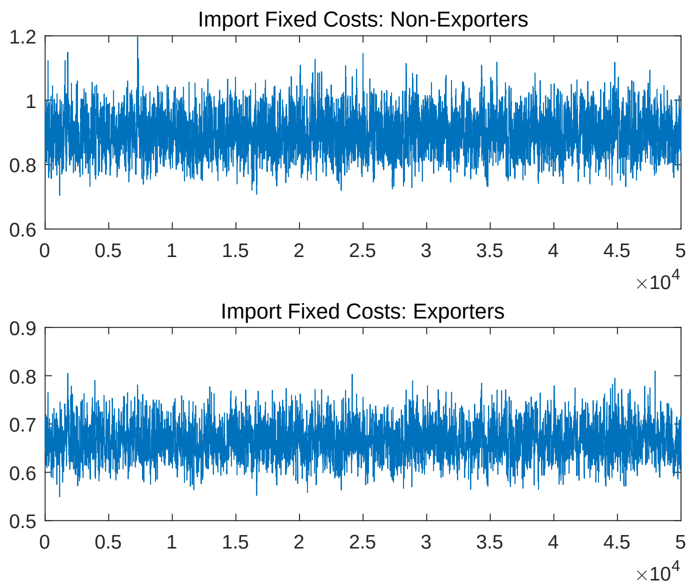

Figure 6: MCMC Trace Plot: Fixed Costs of Importing

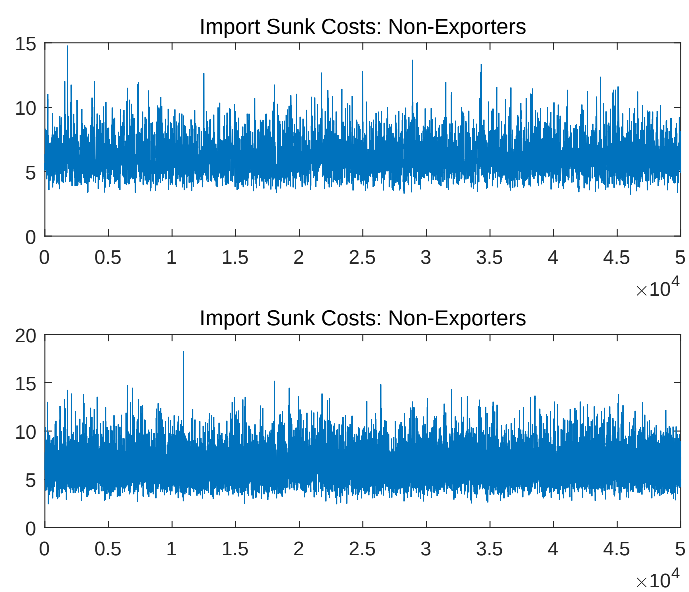

Figure 7: MCMC Trace Plot: Sunk Costs of Importing

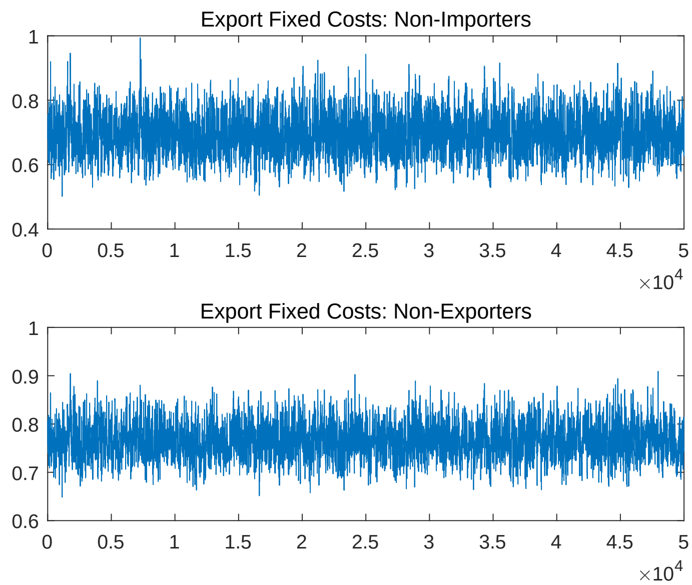

Figure 8: MCMC Trace Plot: Fixed Costs of Exporting

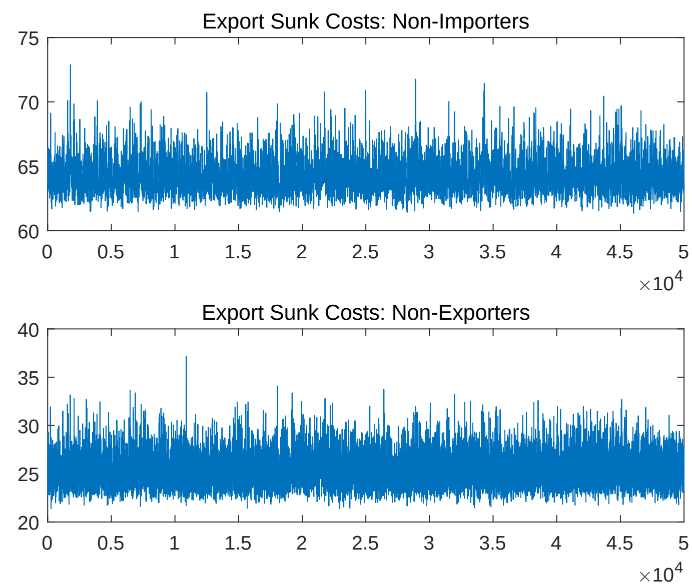

Figure 9: MCMC Trace Plot: Sunk Costs of Exporting

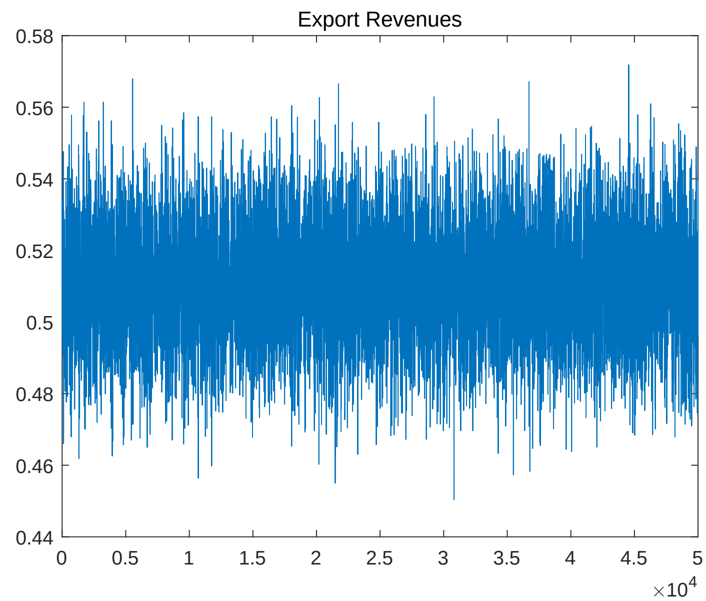

Figure 10: MCMC Trace Plot: Baseline Export Revenue

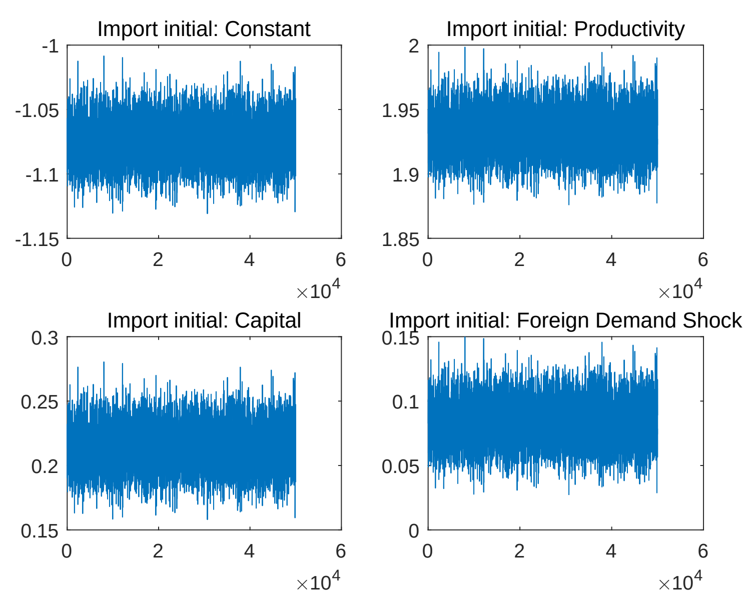

Figure 11: MCMC Trace Plot: Initial Condition Parameters for Import

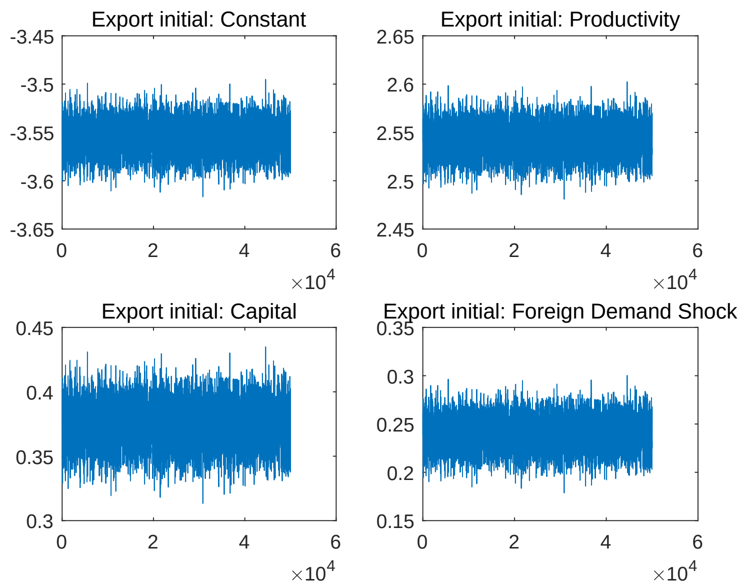

Figure 12: MCMC Trace Plot: Initial Condition Parameters for Export

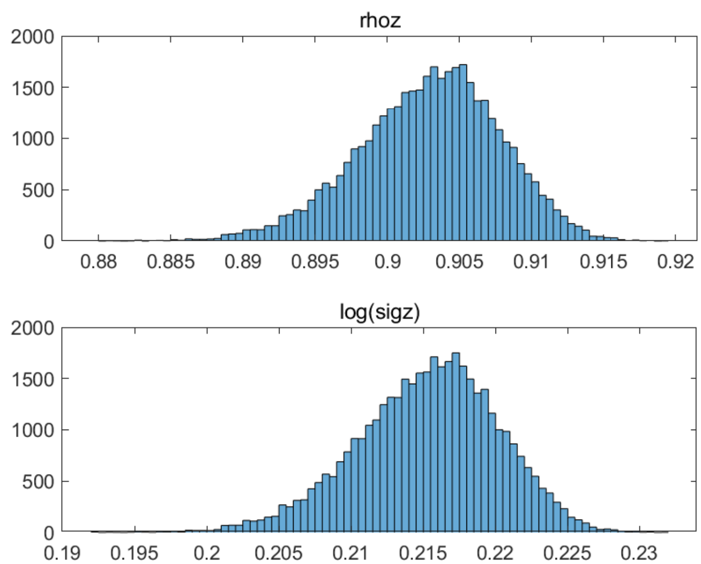

Figure 13: MCMC Histogram: Export Demand Parameters

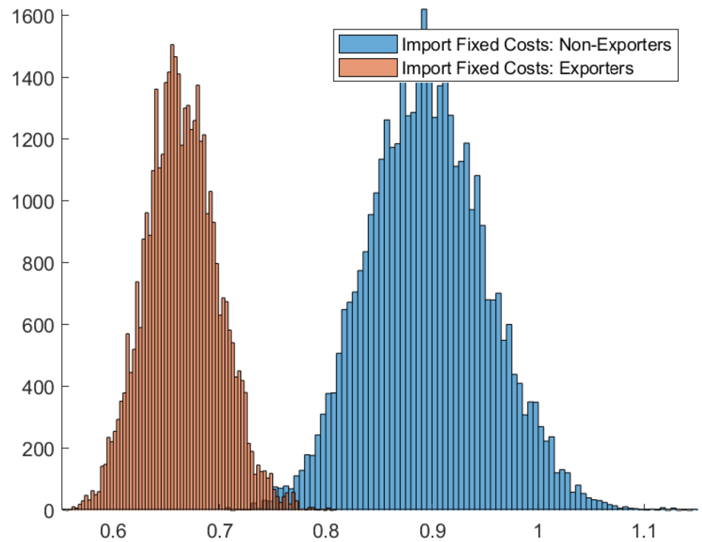

Figure 14: MCMC Histogram: Fixed Costs of Importing

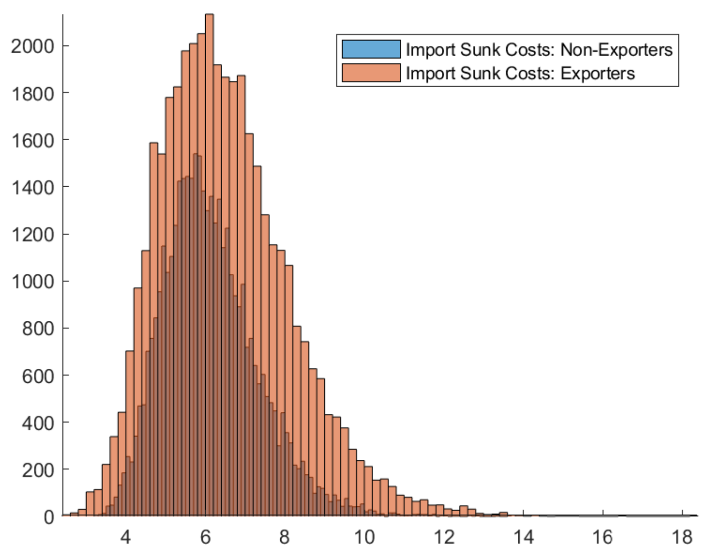

Figure 15: MCMC Histogram: Sunk Costs of Importing

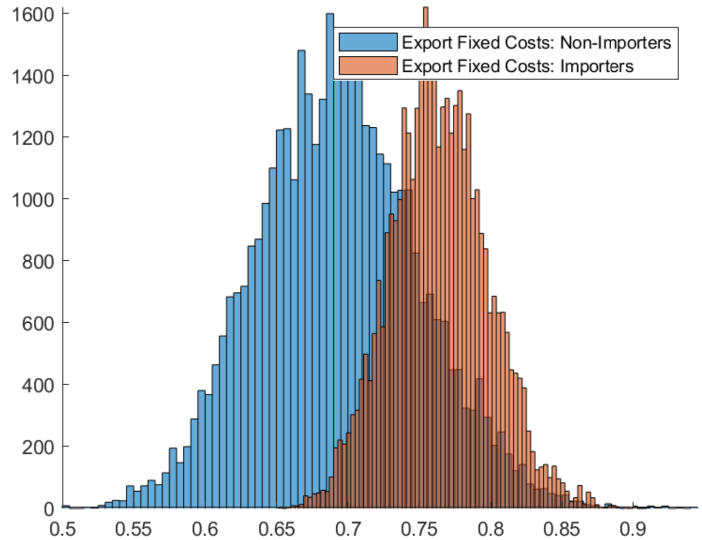

Figure 16: MCMC Histogram: Fixed Costs of Exporting

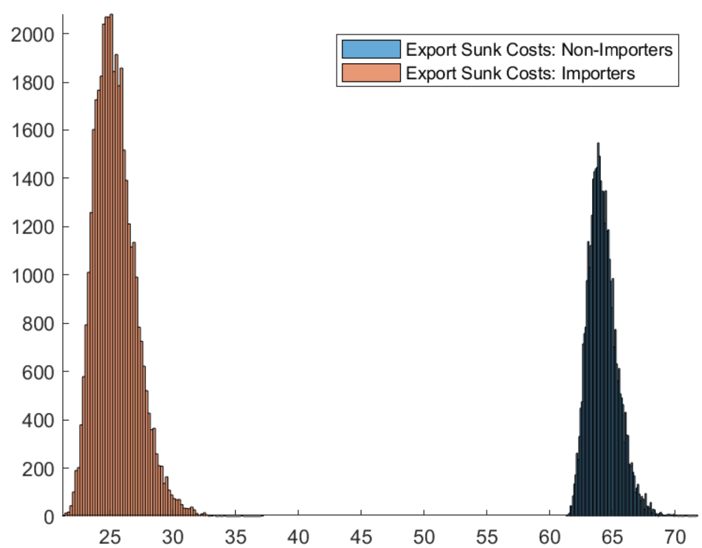

Figure 17: MCMC Histogram: Sunk Costs of Exporting

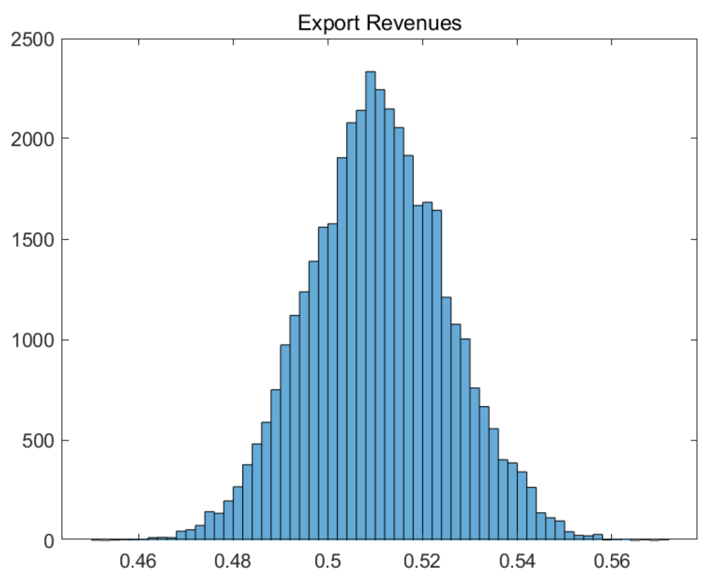

Figure 18: MCMC Histogram: Baseline Export Revenue

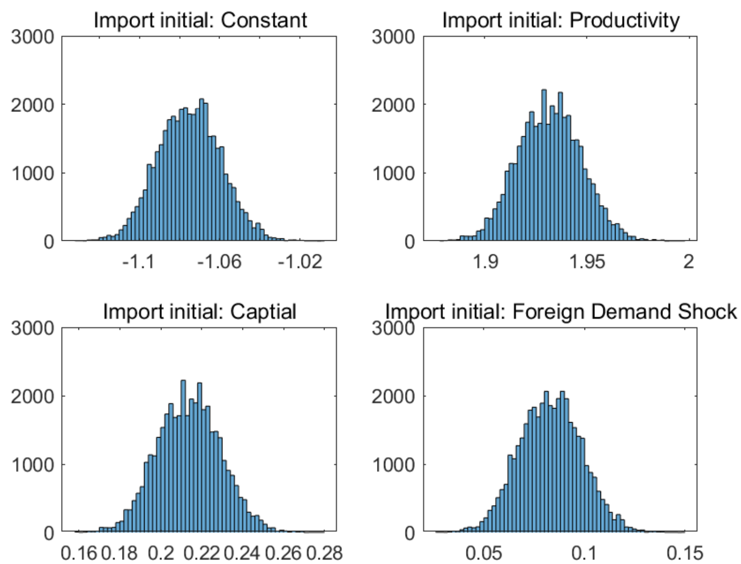

Figure 19: MCMC Histogram: Initial Condition Parameters for Import

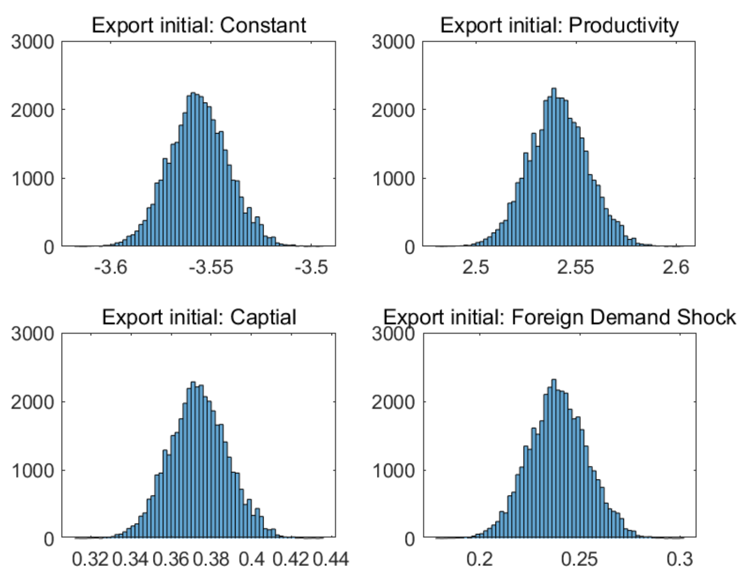

Figure 20: MCMC Histogram: Initial Condition Parameters for Export