Are Sunk Costs to Entry in International Agricultural Markets Important?

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Abstract

Theoretical models of market entry imply that sunk costs are an important source of exports persistence in international markets. Motivated by this observation, we propose a Bayesian method to estimate a dynamic gravity model with unknown threshold of agricultural trade. We extend Eaton and Tamura's (1994) static gravity model with unknown threshold to a dynamic panel data gravity model with lagged censored dependent variable and unknown threshold and estimate it with data on 86 trading partners from 1971 to 1997. We find that entry costs are economically and statistically important for global trade in agriculture. In particular, our results imply that it is much more difficult to break into developing country markets than developed ones and developing exporters are much less likely than developed exporters to break into foreign markets. Additionally, we estimate that Meat and Dairy export markets have larger sunk entry costs than Vegetable and Fruits markets.

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1 Introduction

Theoretical models of export market entry predict that current exports depend on export history when sunk start-up costs are present (Baldwin, 1988; Baldwin and Krugman, 1989; Dixit, 1989). Much of the recent theoretical advances in modeling firm's export behavior hinge on sunk foreign market entry costs as well (Melitz, 2003). Gopinath et al. (2007) provide an excellent survey of this literature along with its implications for agricultural and food industries. Empirically, Roberts and Tybout (1997) have shown that such entry costs are an important source of export persistence in Colombian manufacturing. While foreign market participation of local producers is an important decision for industrial firms, it is even more important for agricultural producers, especially those from developing nations (see Aksoy and Beghin, 2005).

In this paper, we develop a methodology to evaluate the magnitude of sunk entry costs into foreign agricultural markets. Motivated by the theoretical observation that in the presence of sunk costs to export market entry, current exports depend on prior export performance, we propose a Bayesian method to estimate a dynamic gravity model with unknown threshold of agricultural trade. We extend Eaton and Tamura's (1994) static gravity model with unknown threshold to a dynamic panel data gravity model with lagged censored dependent variable and unknown threshold. Using a balanced panel data that follows 86 trading partners for 27 years from 1971 to 1997, we estimate our model and calculate the export market entry probability, which reflects the magnitude of the sunk costs. We find that entry costs are economically and statistically important for global trade in agriculture.

Because foreign market entry costs for agricultural commodities are likely to be quite different based on exporter and importer development status, we split our sample into three groups – developed, emerging and developing countries. Two important conclusions emerge from our results. First, for any type of exporter, it is most difficult to enter a developing foreign agricultural market while it is easiest to enter a developed one. Second, for any foreign agricultural market, entry probabilities are lowest for a developing exporter and highest for a developed one. Our findings are quite intuitive given that it is easier to identify distribution channels and learn about bureaucratic procedures in a developed country than it is in a developing nation due to, among other reasons, better legal institutions and lower corruption rates (see Barrett, 1997; Barrett and Mutambatsere, 2007). This makes entry costs into developing foreign agricultural markets higher than the entry costs into developed markets. Additionally, as developed producers have easier access to financial institutions and credit they may be better able to afford to pay the entry costs into foreign markets compared to their counterparts from developing nations. Furthermore, we estimate foreign market entry probabilities for the 6 most traded agricultural commodities – Meat, Dairy, Fish, Cereals, Vegetables and Fruits, as well as Sugar. For any type of exporter and market (developed, emerging , and developing), we find evidence of high sunk costs to entry in the Meat and Dairy industries, while Vegetables and Fruits markets have considerably lower entry costs, perhaps because consumers' tastes in Meat and Dairy differ substantially across markets, making it more expensive for foreign producers to cater to local tastes.

Our results have policy implications as well. Trade subsidy policies will be most effective if certain potential export producers are targeted. For example, for U.S., which is a developed country, if the government wants to increase agricultural exports, it should help producers pay sunk costs for developing markets because sunk costs are not very large for developed markets. Also, the government should help meat and dairy producers more than vegetable and fruits producers, because the former international markets are much harder to enter.

The contribution of this paper to the literature is twofold. First, to the best of our knowledge, this is the first paper that evaluates the magnitude of sunk entry costs into foreign agricultural markets in a systematic and thorough way. Previous studies have analyzed entry costs into international manufacturing markets alone; additionally, they consider only a handful of developing countries (eg. Roberts and Tybout, 1997; Tybout et al., 1998)[1]. Second, we develop an estimation strategy for the dynamic gravity model with unknown threshold, which handles two prominent features of international trade data, namely, state dependence and 0 trade flow observations, at the same time. Though different variants of

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[1] Note that Food processing industries are included in the set of manufacturing industries.

the gravity models have been widely used in the international trade studies (e.g. Stein and Daude, 2007), no empirical model so far has addressed these two issues at the same time.

The rest of the paper is organized as follows. In the following section, we provide the theoretical framework for our analysis. The third section describes our data; the fourth, details our econometric strategy of identifying the magnitude of the sunk export market entry costs. We present our estimates and discuss the results in the fifth section. The last section concludes.

2 The Conceptual Framework

The following dynamic model of export market entry with sunk start-up costs serves to motivate our empirical work. Using data on merchandise exports from Colombia, Roberts and Tybout (1997) find sunk costs to be a significant source of export market persistence. Such start-up costs arise for example from the need to identify distribution channels, learn bureaucratic procedures, and modify products to better suit foreign consumers' tastes. Denote the difference between firm i's expected gross profits when exporting $y_{it} > 0$ and expected gross profits when not exporting $(y_{it} = 0)$ in period t by $\pi_{it}(y_{it})$. Let F_i^0 to be the firm's export market entry cost which is borne in the first year of exporting. Following Baldwin (1989) and Roberts and Tybout (1997), we assume that once the firm enters the foreign market, it can freely adjust its export quantity. Also, following Das et al. (2007), it is further assumed that firms lose their investment in start-up costs if they are absent from the export market for a single year. This is reasonable based on the evidence in Robert and Tybout (1997) who estimate that start-up investments depreciate very quickly as firms that exported two years ago must pay nearly as much to reenter export markets as firms that never exported. Hence, current export profits net of sunk entry costs for firm i in year t are given by

$$R_{it}(y_{it}, y_{it-1}) = \pi_{it}(y_{it}) \quad F_i^0 1(y_{it-1} = 0) \tag{1}$$

where $1(\cdot)$ is the indicator function which takes the value of 1 if its argument is true and 0 otherwise.[2] (1) can also be written as

$$R_{it}\left(y_{it}, y_{it-1}\right) = \begin{cases} \pi_{it}\left(y_{it}\right) \text{ if } y_{it} > 0 \text{ and } y_{it-1} > 0 \\ \left(\pi_{it}\left(y_{it}\right) \quad F_i^0 \text{ if } y_{it} > 0 \text{ and } y_{it-1} = 0 \\ 0 \text{ if } y_{it} = 0 \end{cases} . \tag{2}$$

Firms choose the infinite sequence of values $y_{it}^{+} = \{y_{it+j} | j \geq 0\}$ that maximizes the expected present value of net profits:

$$V_{it}\left(y_{it-1}\right) = \max_{y_{it}^{+}} E_t\left(\sum\nolimits_{k=t}^{\infty} \delta^{j-t} R_{ik} | y_{it-1}\right), \tag{3}$$

where δ is the one-period discount rate and the expectation is taken with respect to the firm i's export decision last period y_{it-1}. The following Bellman's equation then implies that firm i's current exporting decision can be represented as the value of y_{it} that satisfies

$$V_{it}\left(y_{it-1}\right) = \max_{y_{it} \geq 0} \left\{R_{it}\left(y_{it}, y_{it-1}\right) + \delta E_t\left[V_{it+1}\left(y_{it}\right) | y_{it-1}\right]\right\}. \tag{4}$$

Hence, firm i's optimal decision regarding exporting in period t, y_{it}^{*} is a function of its exports quantity last period, that is, y_{it-1}.

On the other hand, the model implies that in the absence of sunk entry cost, R_{it} and hence the optimal exporting decision y_{it}^{*} is independent of past exporting history, or y_{it-1}. Therefore, one can empirically test the sunk entry cost hypothesis by checking if exporting history helps explain current exports. This implies that we need a panel data set in order to estimate the potential effects of entry costs into international agricultural markets. Because there is no multi-country firm-level panel data set that incorporates firms trading agricultural commodities in international markets, we have to use industry-level agricultural trade data instead. Though the theoretical model above is a micro-level model for individual firms,

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[2] Throughout, π_{it} and hence R_{it} also depend on firm-specific information set in period t, Ω_{it}. This dependence is suppressed for brevity purpose.

its implications apply to industry-level data as well. If individual exporters of a particular industry in country i face high entry costs to break into a foreign market j, then we expect to see a strong export persistence at the industry level data since in such a scenario, not many potential exporters are able to break into the market and/or not many old exporters can easily exit and then re-enter the market some time later.

At the industry-level, the appropriate empirical specification for explaining bilateral agricultural trade flows is the gravity equation. The basic form of the equation states that exports from country i to country j, EXP_{ij}, are proportional to the product of each country's economic mass, usually proxied by GDP, and inversely proportional to the distance (a proxy for trade costs), $DIST_{ij}$, between the two nations. The equation is then augmented to include other factors, Z_{ij} (such as common language, past colonial relationship, and existence of regional free trade agreement), that may enhance or impede trade:

$$EXP_{ij} = \frac{GDP_i^{\gamma_1} \cdot GDP_j^{\gamma_2} \exp \left(Z_{ij}^{\gamma_z} \right)}{DIST_{ij}^{\gamma_3}}. \tag{5}$$

The theoretical literature that has developed the micro-foundations of the gravity equation includes Anderson (1979), Helpman and Krugman (1985), who develop a model of imperfect competition and trade, and Deardorff (1998), who shows that the gravity equation is also consistent with the neoclassical trade theory based on factor endowments. Typically the gravity equation above is log-linearized and then estimated via OLS, but such a procedure may be problematic due to the existence of bilateral trade flows with a value of zero. Often researchers simply do not include those observations in the estimation, which may lead to biased coefficients. While Santos-Silva and Tenreyro (2006) show that the omission of the zero trade flows is unlikely to lead to biases, given that we place a special importance on estimating the effect of foreign market entry costs, incorporating the zero trade observations is crucial in our empirical analysis. To accommodate for zero trade flows, instead of estimating the log-linearized version of the gravity equation, we follow Eaton and Tamura (1994) and use a threshold specification. To estimate the effects of sunk entry costs into foreign markets, we augment the Eaton and Tamura's gravity model with unknown threshold by including a lagged exports term as an explanatory variable, making the empirical gravity equation dynamic.[3] As we already discussed, in this set-up, we can test the sunk cost hypothesis by checking if exporting history helps explain current exports. Additionally, given the estimates from our dynamic model, we construct transition probabilities of breaking into foreign markets, which inherently reflect the size of foreign market entry costs.

Because foreign market entry costs for agricultural commodities are likely to be quite different based on exporter and importer development status, we split our sample into three groups – developed (DED), emerging (EMRG), and developing (DING) nations. For example, it is likely easier to identify distribution channels and learn about bureaucratic procedures in a developed country than it is in a developing nation due to, among other reasons, better legal institutions and lower corruption rates. This makes entry costs into developing foreign agricultural markets higher than the entry costs into developed markets. Additionally, as developed producers have easier access to financial institutions and credit they may be better able to afford to pay the entry costs into foreign markets compared to their counterparts from emerging and developing nations. For these reasons, in our estimation procedure, we separate both exporters and importers into the three groups based on their development status and estimate the effects of entry costs separately for the nine exporter-market combinations.

3 Data

We use bilateral total agricultural export (EXP_{ijt}) data from the United Nations. The balanced panel follows 86 trading partners for 27 years from 1971 to 1997. Table 1 presents the sample of countries by development status as classified by the International Monetary Fund (IMF). These trading partners represent a broad sample of developed (DED), emerging (EMRG) and developing (DING) economies.

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[3] One can additionally include two, three, or more lags of the exports term, but as we already discussed, previous evidence in Roberts and Tybout (1997) shows that start-up investments depreciate very quickly as firms that exported two years ago must pay nearly as much to reenter export markets as firms that never exported.

Additionally, we gather data on exporter and importer GDP (GDP_{it}^{EXP}, GDP_{jt}^{IMP}) from the World Bank's World Development Indicators (2002). Both trade and GDP data are in current U.S. dollars. Data on distance (great circle distance between principal cities, $DIST_{ij}$), language ($LANG_{ij}$), and colonial links (COL_{ij}) are from Centre D'Etudes Prospectives Et D'Informations Internationales (CEPII). Information on regional free-trade agreements (RFTA) comes from Teneryro (2007), and it was originally collected by Frankel (1997) and the World Trade Organization (WTO).

Table 2 presents the summary statistics. In terms of agricultural trade volume, developed nations trade mostly with other developed countries – the mean value of agricultural exports from developed nations to developed partners is about 3.42 (100 millions of U.S. \$), while the average value of exports form developed exporters to developing partners is only 0.12 (100 millions of U.S. \$). Similarly, emerging nations export mostly to developed partners, and much less to developing countries; and finally, developing exporters sell mostly to developed markets and very little to other developing trade partners. Hence, the data suggests that developing country markets are perhaps the hardest ones to enter. These differences, of course, can be driven by difference in aggregate demand for agricultural products across the three types of markets – developed, emerging, and developing nations. As incomes (GDP) in developed nations are much higher than incomes in developing countries, one would expect that demand in developed markets would be much stronger and potentially account for vast differences in the observed agricultural trade flows. In the next section, we estimate the differences in sunk entry costs into the three types of international agricultural markets (developed, emerging, and developing) by carefully modeling the determinants of bilateral agricultural trade using a dynamic version of gravity equation which includes controls for the foreign market demand.

4 Econometrics

4.1 The Econometric Model

Formally, let y_{ijt} be the nominal value of exports from country i to country j in time period t $(ij = 1,...,N,\ \ t = 1,...,T)$. N is the total number of pairs of trading partners and T is the total number of time periods. We consider a dynamic gravity model where y_{ijt} depends parametrically on the covariate vector

$$\mathbf{z}_{ijt} = \left[\log GDP_{it}^{EXP},\ \log GDP_{jt}^{IMP},\ \log DIST_{ij},\ LANG_{ij},\ COL_{ij},\ RFTA_{ijt}\right], \tag{6}$$

the lag of the dependent variable y_{ijt-1} and the unobserved pair specific heterogeneity c_{ij} in the form

$$y_{ijt} = \exp\left(\mathbf{z}_{ijt}\gamma + y_{ijt-1}\rho + c_{ij} + u_{ijt}\right), \tag{7}$$

where γ is a vector of coefficients for the explanatory variables and ρ is the lag coefficient, and u_{ijt} is a sequence of i.i.d. random variables distributed as Normal $(0,\ \sigma_u^2\ )$. Another interpretation of the model is that $c_{ij} + u_{ijt}$ is a composite error term and c_{ij} is the part of the error term that captures the serial correlation over time while u_{ijt} is the idiosyncratic error specific to time period t.[4]

Since the dependent variable y_{ijt} is the nominal value of exports, it is bounded below by zero, and a significant number of observations achieve this bound. To accommodate this well known feature in trade data, we follow Eaton and Tamura (1994) and estimate a modified dynamic gravity model in which the right hand side of (7) must achieve a minimum threshold value τ, before strictly positive values of y_{ijt} occur. This threshold parameter can be interpreted as the amount of trade that is lost in transit or the amount that "melts away," that is to say, trade will occur if desired trade exceeds the amount that will be lost, while trade will not occur if the desired amount of trade is less than the amount that will be lost.

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[4] Controlling for serial correlation is important. As pointed out by Heckman (1981a, b), an estimator that ignores this serial correlation will incorrectly attribute the persistence in the unobserved error term to to state dependence.

As a result, we have the following dynamic gravity model with unknown threshold

$$y_{ijt} = \max\left\{-\tau + \exp\left[\mathbf{z}_{ijt}\gamma + y_{ijt-1}\rho + c_{ij} + u_{ijt}\right], 0\right\}. \tag{8}$$

Rearranging and taking natural logarithms of both sides yields

$$\ln\left(y_{ijt} + \tau\right) = \max\left\{\mathbf{z}_{ijt}\gamma + y_{ijt-1}\rho + c_{ij} + u_{ijt}, \ln\tau\right\}. \tag{9}$$

With the normality assumption of u_{ijt} as well as other specifications above, for each pair of trade partners i and j, we have the following conditional density for the dependent variables over time:

$$\begin{aligned} & f(y_{ij1}, y_{ij2}, ..., y_{ijT}|y_{ij0}, \mathbf{z}_{ijt}, c_{ij}, \gamma, \rho) \\ &= \prod_{t=1}^{T}\left\{ (\begin{array}{c} \left[\Phi\left(\frac{\ln\tau - \mathbf{z}_{ijt}\gamma - y_{ijt-1}\rho - c_{ij}}{\sigma_u}\right)\right]^{1(y_{ijt}=0)} \\ \left[\frac{1}{y_{ijt}+\tau}\frac{1}{\sigma_u}\phi\left(\frac{\ln(y_{ijt}+\tau) - \mathbf{z}_{ijt}\gamma - y_{ijt-1}\rho - c_{ij}}{\sigma_u}\right)\right]^{1(y_{ijt}>0)} \end{array} \right\}_{(}. \end{aligned} \tag{10}$$

To complete the specification of the model, we need to make some assumptions regarding the relationship between the unobserved pair specific heterogeneity c_{ij} and the initial conditions y_{ij0}. As is well known, for dynamic panel data models with unobserved effects, an important issue is the treatment of the initial observations. For linear models with an additive unobserved effect, appropriate transformations such as differencing have been used to eliminate the unobserved effect, and GMM type estimators have been proposed to estimate the transformed model. For example, see Arellano and Honoré (2001) and Hsiao (2003) for surveys on this issue. For nonlinear models, however, the treatment becomes more complicated because the unobserved effect in general cannot be eliminated through some transformations with only a few exceptions.

As summarized in Hsiao (2003), there have been mainly three different ways of treating initial observations in parametric inference of dynamic nonlinear panel data models. The first approach is to assume the initial conditions for each cross-section unit (e.g. the trading partner pair ij in our context) as nonrandom. The second (and more reasonable) approach is to allow the initial condition to be random, and to specify a joint distribution of all outcomes on the response including that in the initial period conditional on the unobserved heterogeneity term and observed strictly exogenous covariates. The third approach is to approximate the conditional distribution of the initial condition, as suggested by Heckman (1981a). Wooldridge (2005) discusses the advantages and disadvantages of these three approaches. He also suggests a simple alternative approach that is to model the distribution of the unobserved effect conditional on the initial observations and exogenous variables. One of the advantages of Wooldridge's approach is that by specifying the (auxiliary) distribution of the unobserved heterogeneity conditional on the initial conditions to be normal, estimation of probit, standard Tobit and Poisson regression can be conducted using standard software.[5] Average transition probabilities can also be estimated in a straightforward manner.

In this paper, we adopt the approach proposed in Wooldridge (2005) and model the relationship between the unobserved heterogeneity and the initial conditions conditional on observed strictly exogenous variables as

$$c_{ij} = h(y_{ij0}, \mathbf{z}_{ij})\delta + \alpha_{ij}, \tag{11}$$

where α_{ij} is a sequence of i.i.d. random variables distributed as Normal (0, σ_a^2). y_{ij0} is the initial value of the dependent variable y_{ijt}, and $\mathbf{z}_{ij}$ is a set of explanatory variables that only vary over different pairs of trading partners but are time-invariant. It can be the row vector of all (nonredundant) explanatory variables in all time periods. That is, $\mathbf{z}_{ij} = (z_{ij1}, z_{ij2}, ...z_{ijT})$ and each z_{ijt} can be multidimensional as in Wooldridge (2005). Alternatively it can be $\mathbf{z}_{ij} = \overline{\mathbf{z}}_{ij}$, where $\overline{\mathbf{z}}_{ij}$ is the average of $\mathbf{z}_{ijt}$ over all the time periods as in Chib and Jeliazkov (2006).[6] In our application here, we follow Chib and Jeliazkov (2006) to use a parsimonious

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[5] Loudermilk (2006) and Li and Zheng (2006) apply the same idea as Wooldridge (2005) to dynamic panel data model with fractional depedent variables and dynamic Tobit panel data model, respectively.

[6] For the identification purpose, those time-constant variables cannot be in both $\mathbf{z}_{ijt}$ and $\overline{\mathbf{z}_{ij}}$.

specification

$$h(y_{ij0}, \mathbf{z}_{ij}) = \delta_0 + \delta_1 y_{ij0} + \delta_2 \overline{\ln GDP_i} + \delta_3 \overline{\ln GDP_j} \tag{12}$$

where $\overline{\ln GDP_i} = \frac{1}{T}\sum_{t=1}^{T} \ln GDP_{it}$ and $\overline{\ln GDP_j} = \frac{1}{T}\sum_{t=1}^{T} \ln GDP_{jt}$. With this additional assumption, the conditional density for the dependent variables with c_{ij} integrated out can be written as:

$$\begin{aligned} & f(y_{ij1}, y_{ij2}, ..., y_{ijT} | y_{ij0}, \mathbf{z}_{ij}, \gamma, \rho, \delta) \\ = & \prod_{t=1}^{T} \left\{ (\begin{array}{c} \left[\Phi \left(\frac{\ln \tau - \mathbf{z}_{ijt}\gamma - y_{ijt-1}\rho - h(\mathbf{y}_{ij0}, \mathbf{z}_{ij})\delta}{\sqrt{\sigma_u^2 + \sigma_a^2}} \right) \right]^{1(y_{ijt}=0)} \\ \left[\frac{1}{y_{ijt}+\tau} \frac{1}{\sqrt{\sigma_u^2+\sigma_a^2}} \phi \left(\frac{\ln(y_{ijt}+\tau) - \mathbf{z}_{ijt}\gamma - y_{ijt-1}\rho - h(\mathbf{y}_{ij0}, \mathbf{z}_{ij})\delta}{\sqrt{\sigma_u^2+\sigma_a^2}} \right) \right]^{1(y_{ijt}>0)} \end{array} \right\}_{(} . \end{aligned} \tag{13}$$

4.2 Estimation Strategy

We fit the model using the Gibbs sampler[7], and to this end we derive and report the posterior conditionals of the model. We introduce the latent variable y_{ijt}^* for the dependent variable, and rewrite the model in the following form

$$\begin{aligned} y_{ijt}^* &= \mathbf{z}_{ijt}\gamma + y_{ijt-1}\rho + h(y_{ij0}, \mathbf{z}_{ij})\delta + \alpha_{ij} + u_{ijt} \\ \ln(y_{ijt} + \tau) &= 1(y_{it}^* > \ln\tau) y_{it}^* \\ \alpha_{ij} + u_{ijt} | y_{i0}, \mathbf{z}_i &\sim\text{–i.i.d. Normal } (0,\ \sigma_u^2 + \sigma_a^2). \end{aligned} \tag{14}$$

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[7] Though in principle, the econometric model can be estimated using maximum likelihood method (MLE), the presence of $\sqrt{\sigma_u^2 + \sigma_a^2}$ in the denominator of several terms in the likelihood function (13) makes empirical implementation of MLE difficult as the maximization routine breaks down when trial values of $\sqrt{\sigma_u^2 + \sigma_a^2}$ are close to 0 during the estimation. The Bayesian method, on the other hand, does not suffer from this problem as estimation is reduced to drawing random variables from several well defined conditional posterior distributions.

As a result, likelihood (13) can be modified as follows to be conditioning on the latent variables y^*_{ijt} in addition to other conditioning variables included in (13)

$$\begin{aligned}
&f(y_{ij1}, y_{ij2}, ..., y_{ijT}|y^*_{ij1}, y^*_{ij2}, ..., y^*_{ijT}, y_{ij0}, \mathbf{z}_{ij}, c_i, \gamma, \rho) = \\
&\textstyle\prod_{t=1}^{T} \left\{1\left[\ln\left(y_{ijt} + \tau\right) = y^*_{it}\right] 1\left[y^*_{ijt} > \ln\tau\right] (+ 1\left[y_{ijt} = 0\right] 1\left[y^*_{ijt} \leq \ln\tau\right]\right\} (\qquad (15) \\
&* \frac{1}{\sqrt{2\pi(\sigma^2_u + \sigma^2_a)}} \exp\left\{ (\frac{1}{2(\sigma^2_u + \sigma^2_a)} \left[y^*_{ijt} \quad \mathbf{z}_{ijt}\gamma \quad y_{ijt-1}\rho \quad h(y_{ij0}, \mathbf{z}_{ij})\delta\right]^2 \right\}
\end{aligned}$$

Since we do not observe the latent variable y^*_{ijt} and integration over this variable will produce an analytically intractable likelihood, direct implementation of Bayesian MCMC would be difficult. Instead, we adopt the data augmentation approach suggested by Albert and Chib (1993), where the latent variables y^*_{ijt} is explicitly included in the MCMC iterations and are updated at each step. Another advantage of the data augmentation technique is that with the presence of y^*_{it}, updating the main parameters of interest, γ and ρ, becomes similar to the standard posterior updating for simple linear panel data models and therefore straightforward to implement. Denote $w_{ijt} = (\mathbf{z}_{ijt},\ y_{ijt-1},\ y_{ij0},\ \mathbf{z}_{ij})$, $\beta = (\gamma',\ \rho',\ \delta')'$, we have the following algorithm for the dynamic panel data gravity model with unknown threshold.

Algorithm 1 *MCMC for dynamic gravity with threshold panel data model*

1. Conditional on y_{ijt}, w_{ijt}, β, τ and $(\sigma^2_u + \sigma^2_a)$, y^*_{ijt} is updated from a normal distribution with mean $w_{ijt}\beta$ and variance $(\sigma^2_u + \sigma^2_a)$ with truncation at $\ln\tau$ from the right if the corresponding $y_{ijt} = 0$. If $y_{ijt} > 0$, $y^*_{ijt} = \ln(y_{ijt} + \tau)$.

2. Conditional on y^*_{ijt}, τ and w_{ijt}, update $(\sigma^2_u + \sigma^2_a)$ and β in one block. Using the improper flat prior for β and the independent gamma $(\frac{N_1}{2}, \frac{R_1}{2})$ prior for $1/(\sigma^2_u + \sigma^2_a)$, that is: $1/(\sigma^2_u + \sigma^2_a) \propto (1/(\sigma^2_u + \sigma^2_a))^{\frac{N_1}{2}-1} e^{-R_1\left(1/\left(\sigma^2_u+\sigma^2_a\right)\right)}$,

   a draw $\frac{1}{(\sigma^2_u+\sigma^2_a)}$ from $gamma(\frac{N_1+NT}{2}, \frac{R_1+\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y^*_{ijt}-w_{ijt}\widehat{\beta}\right)^2}{2})$ where $\widehat{\beta} = inv\left(\sum_{i=1}^{N}\sum_{t=1}^{T} w'_{ijt}w_{ijt}\right) \cdot \left(\sum_{i=1}^{N}\sum_{t=1}^{T} w'_{ijt}y^*_{ijt}\right)$ (and

   b update β from a normal distribution with mean $\widehat{\beta}$ and variance $inv\left(\frac{1}{(\sigma^2_u+\sigma^2_a)}\sum_{i=1}^{N}\sum_{t=1}^{T} w'_{ijt}w_{ijt}\right)$.

3. Conditional on y_{ijt}^{*}, w_{ijt}, β, and $(\sigma_u^2 + \sigma_a^2)$, update τ from its posterior distribution. Using the improper flat prior for τ, the posterior for τ can be written as

$$\pi(\tau | w_{ijt}, \beta,\ \sigma_u^2 + \sigma_a^2)) \prod_{t=1}^{T} \left\{ \begin{array}{c} \left[\Phi\left(\frac{\ln\tau - w_{ijt}\beta}{\sqrt{\sigma_u^2+\sigma_a^2}}\right)\right]^{1(y_{ijt}=0)} \\ \left[\frac{1}{y_{ijt}+\tau}\frac{1}{\sqrt{\sigma_u^2+\sigma_a^2}}\phi\left(\frac{\ln(y_{ijt}\underline{+}\tau)-w_{ijt}\widehat{\beta}}{\sqrt{\sigma_u^2+\sigma_a^2}}\right)\right]^{1(y_{ijt}>0)} \end{array} \right\}. \tag{16}$$

Note that the posterior distribution for τ does not have a form that can facilitate a direct random draw from it. To solve this problem, we propose to utilize the Metropolis-Hastings (MH) algorithm (Metropolis et al 1953; Hastings 1970) to draw from the density. More specifically, we propose a simple random walk proposal density as the following:

$$q(\tau^{new}|\tau^{old}) = \frac{f_t(\tau^{new}|\tau^{old}, h, \omega)}{1 \quad F_t(0|\tau^{old}, h, \omega)} \tag{17}$$

where $f_t(.|\tau^{old}, h, \omega)$ is a student t distribution with mean τ^{old}, variance h and degree of freedom ω. In practice, to draw from this proposal density, we draw τ^{new} from $f_t(.|\tau^{old}, h, \omega)$ and only accept draws that are greater than 0 to be consistent with the fact that $\tau > 0$ by definition. When a new value τ^{new} is drawn, the chain moves to the proposal value with probability

$$\begin{aligned} & \alpha\left[\tau^{old}, \tau^{new}\right] \\ = \ & \min\left\{\frac{\pi(\tau^{new}|w_{ijt}, \beta, (\sigma_u^2+\sigma_a^2))q(\tau^{old}|\tau^{new})}{\pi(\tau^{old}|w_{ijt}, \beta, (\sigma_u^2+\sigma_a^2))q(\tau^{new}|\tau^{old})}, 1\right\} \\ = \ & \min\left\{\frac{\pi(\tau^{new}|w_{ijt}, \beta, (\sigma_u^2+\sigma_a^2))\left[1 \quad F_t(0|\tau^{old}, h, \omega)\right]}{\pi(\tau^{old}|w_{ijt}, \beta, (\sigma_u^2+\sigma_a^2))\left[1 \quad F_t(0|\tau^{new}, h, \omega)\right]}, 1\right\} \end{aligned} \tag{18}$$

where the last equality comes from the facts that $f_t(\cdot|\cdot, h, \omega)$ is symmetric in τ^{new} and τ^{old}. If the candidate is not accepted then the chain does not change its value.

This completes our Bayesian estimation algorithm.

4.3 Average Transition Probabilities

As mentioned above, besides the lag coefficient, another key quantity of economic interest in our application is the transition probability to and from different exporting status. In particular, the absolute as well as relative magnitudes of the sunk export market entry costs can be revealed by the probability of exporting in the next period conditional on not exporting in this period. It is worth noting that a panel data set can provide a researcher with a unique opportunity to assess this kind of transition probabilities, as it contains sequential observations over time for the same pair of trading partners. Easy inference of the average transition probabilities (ATPs) is also one main advantage of the Bayesian method we propose in this paper. The inference of the ATPs becomes a by-product of the MCMC estimation procedure and hence does not add in any additional computation burden.

Denote the state of observing a positive amount of exports as state 1 and observing 0 exports as state 0. Then the probability for trading partners pair ij to transfer from state 0 to state 1 in period t is

$$\begin{aligned} p_{ijt}^{01} &= \Pr\left[\ln\left(y_{ijt}+\tau\right) > \ln\tau | y_{ijt-1}=0, \mathbf{z}_{ijt},\right] \\ &= \left[1 \quad \Phi\left(\frac{\ln\tau \quad \mathbf{z}_{ijt}\gamma \quad h(\mathbf{y}_{ij0}, \mathbf{z}_{ij})\delta}{\sqrt{\sigma_u^2+\sigma_a^2}} \right) \right]. \end{aligned} \tag{19}$$

In the Bayesian framework, the inference of the ATPs comes as a by-product during the estimation of the model parameters. More specifically, we can obtain summaries of the ATPs conditional on the observed data, but marginalized over all the unknown model parameters.[8] To fix the ideas, by definition, the posterior density of p_{ijt}^{01} conditional on the observed data, but marginalized over the unknown parameters, is

$$\pi(p_{ijt}^{01}|\text{data}) = \int \pi(p_{ijt}^{01}|\text{data, parameters}) d\pi(\text{parameters}|\text{data}). \tag{20}$$

A sample of p_{ijt}^{01} can be produced by the method of composition using the draws of parameters

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[8] Chib and Hamilton (2002) use this approach to obtain the average treatment effects.

from steps 2 and 3 in the algorithm described in Section 4.2. Given a posterior sample of p_{ijt}^{01} from $\pi(p_{ijt}^{01}|\text{data})$, which we denote by $\{p_{ijt}^{01(g)}\}$, $g = 1, ..., G$, the unit (ijth pair in t period) mean transition probability, can be estimated as

$$\overline{p_{ijt}^{01}} \approx G^{-1} \sum_{g=1}^{G} p_{ijt}^{01(g)} \text{ where } p_{ijt}^{01(g)} = \left[1 \quad \Phi \left(\frac{\ln \tau^{(g)} \quad \mathbf{z}_{ijt}\gamma^{(g)} \quad h(\mathbf{y}_{ij0}, \mathbf{z}_{ij})\delta^{(g)}}{\sqrt{\sigma_u^2 + \sigma_a^{2(g)}}} \right) \right]. \tag{21}$$

At a more aggregate level, the average transition probability for a randomly selected observation from the population may be defined as

$$p^{01} = \frac{\sum_{ij=1}^{N} \sum_{t=1}^{T} p_{ijt}^{01}}{NT} \tag{22}$$

whose posterior distribution (on which inference is based) is again available from the posterior sample on p_{ijt}^{01}, that is, $\{p_{ijt}^{01(g)}\}$.

5 Results and Discussion

We begin by presenting the estimates for our dynamic specification of the gravity equation using data on total agricultural trade.[9] As we discussed before, we consider trade between three types of exporters and markets – developed, emerging, and developing. We estimate the dynamic gravity equation separately for all nine combinations of exporters and markets. Table 3 presents the results for the main parameters of interest, γ and ρ.[10]

First, consider exports from developed exporters to the three types of markets. Most of the coefficients have the expected sign and their magnitudes are similar to those found in previous research. The effect of importer's GDP, $\log GDP_{jt}^{IMP}$, proxies for foreign market demand and it is expected to be positive and generally smaller than one, which is what we find. The impact of exporter's GDP, $\log GDP_{it}^{EXP}$, can be positive and smaller than one if

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[9] All the results are obtained from running a MCMC chain of 500 draws following burn-ins of 500 draws. The MCMC chain converges quickly.

[10] Results on the parameters in the auxiliary equation (δ) are omitted for brevity purpose. They are avaiable upon request.

the dependent variable is total trade (exports plus imports) or close to zero if the dependent variable is exports as in our specification. The impact of distance, which proxies for transport costs and potentially other trade costs dependent on geographical distance is expected to be negative and smaller than one in magnitude (see Disdier and Head, 2007). This is exactly what we find – while there is some variation in the magnitude of the effect on distance, all estimated coefficients on for developed exporters are negative and statistically significantly different from zero at the five percent level. The estimates imply that the elasticity of exports with respect to distance for developed exporters servicing developed foreign markets is -0.508 (0.010), while it is much higher in magnitude for developed exporters servicing developing markets, -0.922 (0.016).

The effect of common language, $LANG_{ij}$, is expected to be positive as it lowers informational barrier between trading partners, which, in turn, enhances trade. We find that the impact of $LANG_{ij}$ is indeed positive, large and statistically significant. The effect of a colonial relationship, COL_{ij}, is also generally estimated to be positive – past colonial ties are expected to raise current trade. We find that to be true for exports from developed exporters to both developed and developing markets, but not to emerging markets. The impact of regional trade agreements, $RFTA_{ijt}$, is expected to be positive, although such agreements tend to benefit trade in industrial merchandise more than trade in agricultural products. Because there are either too few or no observations with regional free trade agreements between developed and emerging as well as developed and developing countries, we cannot estimate the impact of $RFTA_{ijt}$ for such pairs of trading partners. The effect of such agreements for exports from developed countries to developed markets is estimated to be positive, as expected.

Finally, we assess the impact of the variable of interest – the export history, EXP_{ijt-1}. We find that current exports are both economically and statistically dependent on export history for developed exporters servicing all three types of markets – developed, emerging, and developing. However, note the difference in state dependence – the magnitude of the coefficient on EXP_{ijt-1} is 10 times larger for developed country exports to emerging markets than it is for those exports to developed markets. Also, the effect is 100 times larger for developed country exports to developing markets than it is for those exports to developed markets. In particular, the estimated coefficient on EXP_{ijt-1} for exports from developed countries to developing markets, implies that if last period's exports were10 percent higher, this periods exports would be 0.96 percent higher – where the elasticity of 0.096 is evaluated at the mean of the sample, 0.12 (see Table 2). On the other hand, the estimated coefficient on EXP_{ijt-1} for exports from developed countries to developed markets suggests that if last period's exports were 10 percent higher, the periods exports would be only 0.31 percent higher. Because the effect of export history, i.e. the size of the coefficient on EXP_{ijt-1}, reflects the magnitude of export sunk cost, our estimates imply that for developed exporters, it is hardest to break into developing markets, while start-up costs are lowest for entry into developed foreign markets.

We next estimate the dynamic gravity specification for emerging exporters. The coefficients on exporter's and importer's GDP, $\log GDP_{it}^{EXP}$ and $\log GDP_{jt}^{IMP}$, distance, $\log DIST_{ij}$, common language, $LANG_{ij}$, colonial ties, COL_{ij}, and regional free trade agreements, $RFTA_{ijt}$, are fairly similar to the estimates for developed exporters. However, the coefficients on are much larger than their respective counterparts for developed exporters. For example, the estimate of the effect of EXP_{ijt-1} on developed country exports to developed markets, 0.009 (0.002), is about 10 times smaller than the effect of EXP_{ijt-1} on emerging country exports to developed markets, 0.088 (0.005). As the size of the coefficient on EXP_{ijt-1}, reflects the magnitude of export market sunk cost, our estimates imply that it is much harder for emerging exporters to enter developed agricultural markets, than it is for developed exporter to enter developed agricultural markets. In fact, our estimates imply that it is harder for emerging countries to enter any market – developed, emerging and developing – as compared to developed exporters.

Lastly, we estimate the dynamic gravity equation for developing exporters. The coefficients on the traditional gravity equation variables ($\log GDP_{it}^{EXP}$, $\log GDP_{jt}^{IMP}$, $\log DIST_{ij}$, $LANG_{ij}$, COL_{ij}, $RFTA_{ijt}$) are for the most part consistent with intuition and similar to the estimates for developed and emerging exporters. On the other hand, the effects of EXP_{ijt-1} are estimated to be between 4 and 100 times (2 and 10 times) greater for developing exporters than for developed (emerging) exporters depending on the type of foreign market they serve. In particular, for developed foreign agricultural markets, the estimate of the impact of export history, EXP_{ijt-1}, on current exports is more than 100 times larger for developing exporters then for developed ones. This means that sunk costs to entry into developed agricultural markets are much higher for developing exporters than for developed ones.

Overall, our estimates lead to two important conclusions. First, for any type of exporter, it is harder to enter an emerging than a developed foreign agricultural market, and, in turn, it is harder to enter a developing than an emerging foreign agricultural market. Second, for any foreign agricultural market, entry probabilities are lower for an emerging than for a developed exporter, and, in turn, they are lower for a developing than for an emerging exporter. These findings are consistent with our priors that it is easier to identify distribution channels and learn about bureaucratic procedures in a developed country than it is in a developing nation, thus making entry costs into developing foreign agricultural markets higher than entry costs into developed markets. The evidence is also consistent with our expectations that developed producers may be better able to afford to pay the entry costs into foreign markets, compared to their counterparts from emerging and developing nations, as they have easier access to financial institutions and credit.

While the size of the estimated coefficients on EXP_{ijt-1} reflects the magnitude of the sunk cost to entry in foreign agricultural markets, a more concrete measure of these costs relevant for policy makers is perhaps the implied average entry probability, p^{01}_{ijt}. It is an estimate of the average transition probability from state 0 (no exports from country i to country j) to state 1 (positive exports from country i to country j) in period t. Based on our estimates of the dynamic gravity (Tobit) model in Table 3, we calculate the average entry probabilities for all 9 pairs of exporters and markets. The results are presented in Table 4.

As expected, the entry probabilities we calculate reveal the same story. It is more likely for a developed producer to enter a developed agricultural foreign market than for a developing producer – p_{ijt}^{01} for a developed exporter and developed market is 0.987, while it is only 0.734 for a developing exporter and developed market. This is economically large and statistically significant difference. When it comes to emerging and developing foreign agricultural markets, the difference in the entry probabilities between the developed and developing exporters is even greater – 0.925 vs. 0.331 for emerging markets, and 0.725 vs. 0.147 for developing markets. Conversely, for any of the three types of exporter, the entry probability into developed markets is much higher than the entry probability into developing markets – the difference is largest for developing exporters. All of these results confirm the evidence presented in Table 3.

Because the agricultural sector aggregates various commodities, whose international markets may have different entry costs, we use disaggregate data on the six most traded commodities to estimate our dynamic gravity equation. We then calculate the entry probabilities, which reflect the sunk (start-up) costs. The six commodities are Meat, Dairy, Fish, Cereals, Vegetables and Fruits, as well as Sugar. The results for the entry probability, p_{ijt}^{01}, by type of exporter and market are shown in Panels A to F of Table 5.

Note that the entry probabilities are not the same for the different commodities. In particular, the estimates imply that for any market, the entry costs for developed exporters are largest for Meat and smallest for Vegetables and Fruit. Similarly, for any given market, the entry costs for emerging and developing exporters are estimated to be largest for Dairy and smallest for Vegetables and Fruits. These results imply that the international markets for Vegetables and Fruits are the easiest to enter for any type of exporter and market, perhaps because they are fairly homogenous commodities and there is no need for exporters to modify them to better suit foreign consumers' tastes. On the other hand, Meat and Dairy feature some of the lowest entry probabilities, perhaps because consumers' tastes differ substantially across markets, making it more expensive for foreign producers to cater to local tastes.

6 Conclusion

Entry costs in international agricultural markets are an important source of exports persistence. Theory suggests that current exports depend on export history when sunk costs to entry are present. Motivated by this observation, we propose a Bayesian method to estimate a dynamic gravity model with unknown threshold of agricultural trade. We extend Eaton and Tamura's (1994) static gravity model with unknown threshold to a dynamic panel data gravity model with lagged censored dependent variable and unknown threshold.

We find that sunk costs, proxied by the probability of market entry, are economically and statistically important and they are different for developed, emerging and developing exporters and markets. For any exporter, it is most difficult to enter a developing market and least difficult to enter a developed market, perhaps because it is easier to identify distribution channels and learn about bureaucratic procedures in a developed country than it is in a developing nation. Additionally, for any market, entry probabilities are highest for developed exporters and lowest for developing producers, perhaps because developed producers may be better able to afford to pay the entry costs into foreign markets as they have easier access to financial institutions and credit. Finally, we also find that export market entry costs are lowest for Vegetables and Fruits and highest for Meat and Dairy, likely because consumers' tastes for Meat and Dairy differ substantially across markets, making it more expensive for foreign producers to cater to local tastes.

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Table 1. Sample countries.

Developed Economies (DED)	**Emerging Economies (EMRG)**	**Developing Economies (DING)**	
Australia	Argentina	Algeria	Madagascar
Austria	Brazil	Benin	Malawi
Belgium	Chile	Bolivia	Mali
Canada	China (Mainland)	Burkina-Faso	Malta
Denmark	Colombia	Burundi	Mauritania
Finland	Ecuador	Cameroon	Morocco
France	Hong Kong	Central African Rep.	Nepal
Germany	Hungary	Chad	Niger
Greece	Indonesia	Congo (Rep.)	Nigeria
Iceland	Korea (South)	Costa Rica	Pakistan
Ireland	Malaysia	Cote d'Ivoire	Paraguay
Israel	Mexico	Dominican Rep.	Saudi Arabia
Italy	Panama	Egypt	Senegal
Japan	Peru	El Salvador	Sri Lanka
Netherlands	Philippines	Gabon	Suriname
New Zealand	Singapore	Gambia	Syria
Norway	South Africa	Ghana	Togo
Portugal	Thailand	Guatemala	Zambia
Spain	Turkey	Guyana	Zimbabwe
Sweden	Uruguay	Haiti	
Switzerland	Venezuela	Honduras	
United Kingdom		India	
United States		Jamaica	

Table 2. Summary Statistics – Mean and St. Dev. (in parentheses).

Exporter-Market	EXP_{ijt}	GDP_{it}^{EXP}	GDP_{it}^{IMP}	$DIST_{ij}$	$LANG_{ij}$	COL_{ij}	$RFTA_{ijt}$	N
	(100 millions of US $)			(miles)				
DED - DED	3.42	4,960	4,960	5,456	0.14	0.04	0.26	13,662
	(10.95)	(10,800)	(10,800)	(5,750)	(0.35)	(0.20)	(0.44)	
DED - EMRG	0.54	(4,960	861	9,321	0.08	0.04	0.00	13,041
	(2.70)	(10,800)	(1,240)	(3,143)	(0.27)	(0.20)	(0.00)	
DED- DING	0.12	4,960	140	7,302	0.17	0.04	0.00	26,082
	(0.52)	(10,800)	(400)	(3,558)	(0.37)	(0.20)	(0.00)	
EMRG - DED	1.06	861	4,960	9,321	0.08	0.04	0.00	13,041
	(3.24)	(1,240)	(10,800)	(3,143)	(0.27)	(0.20)	(0.00)	
EMRG - EMRG	0.37	861	861	10,304	0.22	0.00	0.13	11, 340
	(1.57)	(1,240)	(1,240)	(6,244)	(0.42)	(0.00)	(0.33)	
EMRG - DING	0.04	861	140	9,355	0.13	0.00	0.11	23,814
	(0.23)	(1,240)	(400)	(4,295)	(0.33)	(0.00)	(0.31)	
DING - DED	0.16	140	4,960	7,302	0.17	0.04	0.00	26,082
	(0.59)	(400)	(10,800)	(3,558)	(0.37)	(0.20)	(0.00)	
DING - EMRG	0.02	140	861	9,355	0.13	0.00	0.01	23,814
	(0.15)	(400)	(1,240)	(4,295)	(0.33)	(0.00)	(0.11)	
DING - DING	0.01	140	140	6,487	0.29	0.00	0.00	46,494
	(0.06)	(400)	(400)	(3,951)	(0.45)	(0.00)	(0.00)	

Table 3. Dynamic Gravity Equation Bayesian Estimation Results – Posterior Mean and St. Dev. (in parentheses).

		Variable		Market	
			Developed	**Emerging**	**Developing**
Exporter	**Developed**	$logGDP_{it}^{EXP}$	-0.008 (0.049)	-0.002 (0.045)	-0.179^{***} (0.023)
		$logGDP_{it}^{IMP}$	0.681^{***} (0.049)	0.905^{***} (0.042)	0.608^{***} (0.029)
		$logDIST_{ij}$	-0.508^{***} (0.010)	-0.579^{***} (0.024)	-0.922^{***} (0.016)
		LANG_{ij}	0.398^{***} (0.026)	1.620^{***} (0.060)	0.471^{***} (0.027)
		COL_{ij}	0.677^{***} (0.045)	-0.484^{***} (0.079)	0.827^{***} (0.046)
		RFTA_{ijt}	0.473^{***} (0.023)	-	-
		$\boldsymbol{EXP_{ijt-1}}$	**0.009^{***}** **(0.002)**	**0.091^{***}** **(0.007)**	**0.801^{***}** **(0.021)**
	Emerging	$logGDP_{it}^{EXP}$	0.143^{***} (0.034)	0.189^{***} (0.043)	0.040^{*} (0.021)
		$logGDP_{it}^{IMP}$	0.430^{***} (0.037)	0.670^{***} (0.045)	0.200^{***} (0.029)
		$logDIST_{ij}$	-0.254^{***} (0.019)	-0.767^{***} (0.022)	-0.564^{***} (0.016)
		LANG_{ij}	0.090^{*} (0.046)	0.219^{***} (0.048)	0.044^{*} (0.029)
		COL_{ij}	0.670^{***} (0.061)	-	-
		RFTA_{ijt}	-	0.706^{***} (0.047)	1.000^{***} (0.029)
		$\boldsymbol{EXP_{ijt-1}}$	**0.088^{***}** **(0.005)**	**0.324^{***}** **(0.017)**	**2.011^{***}** **(0.038)**
	Developing	$logGDP_{it}^{EXP}$	0.068^{***} (0.029)	-0.151^{***} (0.028)	-0.339^{***} (0.024)
		$logGDP_{it}^{IMP}$	0.068^{***} (0.023)	0.448^{***} (0.021)	-0.119^{***} (0.024)
		$logDIST_{ij}$	-0.231^{***} (0.015)	-0.279^{***} (0.015)	-0.324^{***} (0.010)
		LANG_{ij}	-0.074^{***} (0.024)	0.416^{***} (0.026)	0.422^{***} (0.018)
		COL_{ij}	1.086^{***} (0.045)	-	-
		RFTA_{ijt}	-	0.129^{*} (0.078)	-
		$\boldsymbol{EXP_{ijt-1}}$	**1.171^{***}** **(0.027)**	**2.707^{***}** **(0.056)**	**5.044^{***}** **(0.093)**

Table 4. Entry Probabilities (p_{ijt}^{01}) – Posterior Mean and St. Dev. (in parentheses) for Exports of Total Agricultural Trade.

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.987^{***}	0.925^{***}	0.725^{***}
		(0.001)	(0.002)	(0.002)
	Emerging	0.945^{***}	0.804^{***}	0.380^{***}
		(0.002)	(0.003)	(0.003)
	Developing	0.734^{***}	0.331^{***}	0.147^{***}
		(0.003)	(0.003)	(0.002)

Table 5. Entry Probabilities (p_{ijt}^{01}) – Posterior Mean and St. Dev. (in parentheses) for Exports of Agricultural Commodities.

Panel A: Meat and Meat Preparations

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.682^{***}	0.350^{***}	0.226^{***}
		(0.003)	(0.004)	(0.002)
	Emerging	0.294^{***}	0.154^{***}	0.052^{***}
		(0.003)	(0.003)	(0.001)
	Developing	0.054^{***}	0.014^{***}	0.014^{***}
		(0.001)	(0.001)	(0.001)

Panel B: Dairy Products and Bird's Eggs

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.714^{***}	0.502^{***}	0.380^{***}
		(0.003)	(0.004)	(0.003)
	Emerging	0.112^{***}	0.119^{***}	0.033^{***}
		(0.002)	(0.003)	(0.001)
	Developing	0.011^{***}	0.008^{***}	0.008^{***}
		(0.001)	(0.001)	(0.001)

Panel C: Fish and Fish Preparations

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.823^{***}	0.389^{***}	0.236^{***}
		(0.003)	(0.004)	(0.003)
	Emerging	0.658^{***}	0.308^{***}	0.073^{***}
		(0.003)	(0.004)	(0.002)
	Developing	0.232^{***}	0.051^{***}	0.032^{***}
		(0.002)	(0.001)	(0.001)

Table 5 (cont'd.). Entry Probabilities (p_{ijt}^{01}) – Posterior Mean and St. Dev. (in parentheses) for Exports of Agricultural Commodities.

Panel D: Cereals and Cereal Preparations

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.794^{***}	0.490^{***}	0.387^{***}
		(0.002)	(0.003)	(0.002)
	Emerging	0.375^{***}	0.239^{***}	0.095^{***}
		(0.004)	(0.004)	(0.002)
	Developing	0.077^{***}	0.029^{***}	0.033^{***}
		(0.002)	(0.001)	(0.001)

Panel E: Vegetables and Fruits

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.863^{***}	0.506^{***}	0.327^{***}
		(0.002)	(0.004)	(0.002)
	Emerging	0.821^{***}	0.398^{***}	0.141^{***}
		(0.003)	(0.004)	(0.002)
	Developing	0.365^{***}	0.064^{***}	0.055^{***}
		(0.003)	(0.001)	(0.001)

Panel F: Sugar, Sugar Preparations and Honey

			Market	
		Developed	**Emerging**	**Developing**
Exporter	**Developed**	0.746^{***}	0.397^{***}	0.236^{***}
		(0.003)	(0.003)	(0.002)
	Emerging	0.393^{***}	0.211^{***}	0.079^{***}
		(0.004)	(0.004)	(0.002)
	Developing	0.114^{***}	0.016^{***}	0.023^{***}
		(0.002)	(0.001)	(0.001)