Determinants of World Demand for U.S. Corn Seeds: the Role of Trade Costs

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The expansion of the U.S. corn seed trade is not well understood. This article econometrically investigates world demand for U.S. corn seeds, focusing on trade costs impeding exports, including transportation, tariffs, and sanitary and phytosanitary (SPS) regulations. The analysis estimates a derived demand for seed by foreign corn producers using data from 48 countries for the years 1989 to 2004. An SPS count variable captures shifts in the cost of seeds faced by foreign users. A sample selection framework accounts for the large presence of zero trade flows. All trade costs have a significantly negative impact on U.S. corn seed exports.

Key words: corn, distance, phytosanitary, seeds, SPS, tariff, technical barriers, trade cost.

JEL codes: F13, F14, Q17, Q18.

The U.S. commercial seed market is the world's largest, with an estimated annual value exceeding US$6 billion per year in the late 1990s, followed by those of China and Japan. Over the past decade, the U.S. seed market has been growing in quantity and value, particularly for major field crops such as corn, soybeans, cotton, and wheat, which constitute two-thirds of the commercial seed market in the United States (Fernandez-Cornejo and Caswell 2006). Seed trade has been an integral part of this market expansion. The United States is a net and large exporter of corn seed for planting. The U.S. corn seed export value grew from approximately $68.5 million in 1989 to $174 million in 2004. Italy, Mexico, Canada, France, and Spain are the largest importers of U.S. corn seed. Together, these countries accounted for approximately 60% of total U.S. corn seed exports in 2004.[1]

However, the seed trade is arguably underdeveloped, with much potential to expand, especially in developing countries (McGee 1998). Only 10% of total U.S. commercial seed goes to developing countries such as India and China. These two countries represent large potential seed markets, along with Brazil and Argentina (Fernandez-Cornejo 2004).

The use of standards and technical regulations as instruments of commercial policy in world agrifood trade has been rising, as tariff and quota barriers continue to decline and as consumers demand safer agrifood products (Beghin 2008; Henson and Wilson 2005). Among nontariff measures, sanitary and phytosanitary (SPS) regulations and technical barriers to trade (TBTs) are of increasing importance as impediments to, and sometimes facilitators of, agrifood trade (Disdier, Fontagné, and Mimouni 2008; Moenius 2006).

Despite the substantial body of work analyzing the impact of standards and technical regulations on agricultural and food trade, little is known about seed trade determinants. Seed trade policies have not attracted much attention from economists, although seed scientists have raised concerns about SPS policies (Rohrbach, Minde, and Howard 2003; McGee 1998). The U.S. seed industry faces significant problems satisfying SPS regulations because of increasing concerns about seed safety, stricter SPS requirements in trade, competitiveness in export markets, and, occasionally, protectionism.

There is a large literature on the analysis of TBTs and SPS measures, including

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[1] On a regional basis, North America (36%), western Europe (32%), Asia (11%), other European countries (6%), and South America (4%) accounted for 89% of the total quantity of U.S. exports in 2004.

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works by Anderson, McRae, and Wilson (2001), Beghin and Bureau (2001), Deardorff and Stern (1998), and Maskus and Wilson (2001). Henson and Wilson (2005) provide a comprehensive discussion of these and other earlier contributions. Cipollina and Salvatici (2007) review more recent developments on this topic. Recent analyses are by Calvin, Krissoff, and Foster (2008), Peterson and Orden (2008), Yue, Beghin, and Jensen (2006), and Yue and Beghin (2009). Conspicuously absent in this SPS literature are explicit analyses of seed trade determinants and the impact of associated SPS regulations. This void is surprising because seeds are well-known vectors of invasive pests and species propagation. Accordingly, SPS measures have been extensively used in world seed trade in order to mitigate the introduction of exotic species, pests, and diseases and to limit risks to human and animal health. Examples include quarantines, inspections, tests, certificates, fumigation, and outright bans.

This article fills this gap and addresses the following questions: (*a*) which factors determine the seed trade from among a presumably relevant list—relative seed price, corn output, tariff, transportation cost, and SPS policies? and (*b*) what are their relative importance? These are pertinent research questions, which lead to a formal elucidation of seed trade and its policy determinants. To estimate the factors determining world demand for U.S. seed corn exports, we develop a parsimonious seed export demand model and use it for an econometric investigation of world demand for U.S. corn seeds. The empirical analysis relies on a newly constructed data set covering major corn- and silage-producing countries and their trade policies (tariffs and SPS measures) which are faced by U.S. seed exporters. The frequency measure of SPS policies is based on the EXCERPT (Export Certification Project Demonstration) regulation database collected for the USDA Animal and Plant Health Inspection Service by Purdue University.

Our investigation relies on a sectoral gravity equation type of model. An original feature of our setup is that the model is grounded in intermediate demand rather than final demand, as are most other gravity models. Many agricultural products are indeed intermediate inputs used in other industries, and thus our specification is likely to be of interest for other agricultural trade applications. The applied trade literature has neglected this simple but important point on the differentiation of intermediate and final demands (see Ghazalian et al. 2007 for a related intermediate demand approach). We find that trade costs are important determinants of seed export demand, while tariffs, SPS regulations, and distance negatively affect U.S. corn seed export demand.

A Gravity Equation for Imported Seed Demand

As in many gravity models, we use the simple constant elasticity of substitution (CES) structure to incorporate the intermediate demand for corn seed in corn production and eventually to calculate the tariff equivalent estimate of SPS regulations. The significant departure is that the CES applies to production rather than to final consumer preferences. Taking a dual approach to the specification of this technology, the cost function for corn production derived from a CES production function can be written as follows:

$$(1)\qquad C_j = Q_j\left(\sum_{i=1}^{n}\theta_i W_{ij}^{1-\sigma} + \sum_{k=1}^{m}\mu_{jk}R_{jk}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

where Q_j is corn production for country j; W_{ij} is the price paid by corn producers of country j for their seed corn sourced in country i; R_{jk} is the price of the kth nonseed input used in country j; σ is a parameter that determines the degree of substitutability of the inputs; and θ_i and μ_{jk} are technology productivity parameters associated with the various inputs used. Note that we assume that the productivity parameters of the seed input are the same in all countries, although seeds sourced in different countries can have different productivity. With that we try to capture, somewhat roughly, the fact that origin-differentiated seeds may differ in quality and may be imperfect substitutes. On the other hand, the μ_{jk} parameters associated with nonseed inputs are allowed to differ across countries, and thus we do allow for some heterogeneity in the technology for final corn production.

The conditional factor demands for corn seeds, by Shephard's lemma, are

$$(2)\qquad X_{ij} = \frac{\theta_i}{W_{ij}^{\sigma}}Q_j \times \left(\sum_{i=1}^{n}\theta_i W_{ij}^{1-\sigma} + \sum_{k=1}^{m}\mu_{jk}R_{jk}^{1-\sigma}\right)^{\frac{\sigma}{1-\sigma}}.$$

Seed input prices at destination j can be written as

$$(3) \qquad W_{ij} = W_i T_{ij}$$

where W_i is the export unit price (FOB) of seed corn sourced in country i and $T_{ij} \geq 1$ is the trade cost factor (also known as trade resistance) that reflects the impacts of tariffs, distance, and SPS regulations affecting the price of seed corn from country i and landed in country j. By using equation (3), the seed import demand in each country can be expressed as

$$(4) \qquad X_{ij} = \theta_i Q_j c_j^{\sigma} W_i^{-\sigma} T_{ij}^{-\sigma}$$

where c_j is the unit cost function for corn production defined as

$$(5) \quad c_j = \left(\sum_{i=1}^{n} \theta_i \left(W_i T_{ij} \right)^{1-\sigma} + \sum_{k=1}^{m} \mu_{jk} R_{jk}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Demand equations for nonseed inputs could similarly be derived from equation (1). But in our application we will not have data on them, and so we work with a specialized formulation that allows us to sidestep the modeling of their explicit impacts. Specifically, to proceed we will assume a competitive structure in final corn production, which justifies the assumption of constant return to scale implicit in our CES specification. In a competitive equilibrium, therefore, the unit production cost c_j will equal the expected output price, i.e., the expected corn price in country j. Furthermore, we do not have data on seed imports from all destinations, but we do have detailed data on export of U.S. corn seeds. So, in what follows, we focus on trade in corn seed coming from a single source (the United States).

A Model for U.S. Corn Seed Exports

Because we consider seed sourced in the Unites States only, in what follows we simplify the notation and drop the subscript i that denotes the source. To make the foregoing model operational, we also need to be specific on the formulation of the trade resistance factor. We write this factor as

$$(6) \qquad T_j = (1 + \tau_j)(1 + S_j)^{\beta}(1 + D_j)^{\gamma}$$

where T_j is the trade resistance factor, in country j, toward seed imports from the United States; τ_j is the (ad valorem) trade tax on seed corn levied by country j; S_j is a variable capturing the effects of SPS regulation in country j (which we will represent as the count of SPS measures that apply to U.S. corn seed exports to country j);[2] Dj is the distance from the United States to country j; and β and γ are coefficients that parameterize the effects of SPS variables and distance into tariff factor equivalent effects. More specifically, to measure the SPS effect, we use a frequency measure at the commodity market level, a count of SPS regulations affecting U.S. corn seeds. Our model embeds this measure in a cost factor and posits that the cost factor increases in the SPS count to capture its incidence.

With the foregoing parameterization, the import of U.S. corn seed in country j can be written as

$$(7) \qquad X_j = \theta Q_j c_j^{\sigma} W^{-\sigma} \times [(1 + \tau_j)(1 + S_j)^{\beta}(1 + D_j)^{\gamma}]^{-\sigma}$$

where, again, we have dropped the origin subscript (so that, for example, W represents the U.S. corn seed export price). This equation represents the basis of our estimating model in the empirical application.[3]

Empirical Formulation

The model is estimated with a sample of M observations of U.S. corn seed exports going to n countries. Our empirical model is the log transformation of equation (7), leading to the following specification:

$$(8) \qquad \ln\left(\frac{X_{jt}}{Q_{jt}}\right) = \alpha_0 + \sigma \ln\left(\frac{c_{jt}}{(1 + \tau_{jt})W_t}\right) - \alpha_1 \ln(1 + S_{jt}) - \alpha_2 \ln(1 + D_{jt}) + u_{jt}$$

where $t = 1, 2, \ldots, M$ and $j = 1, 2, \ldots, n$, the coefficients α_i are related to the structural

[2] The count variable is, admittedly, a crude indicator. A better proxy would aggregate the SPS measures weighted by their cost incidence. The lack of systematic information on the associated cost of each SPS measure rules out the preferred aggregation.

[3] It is readily shown that a share version of equation (7) would include a multilateral trade resistance term, thereby coming closest in spirit to recent gravity equation investigations (see e.g., Disdier, Fontagné, and Mimouni 2008). A disadvantage of such a formulation is that the model is nonlinear in the parameters, and for that reason we do not pursue it further as a vehicle for estimating the structural parameters of the model.

parameters as $\alpha_0 = \ln(\theta), \alpha_1 = \beta\sigma$, and $\alpha_2 = \gamma\sigma$, and u_{ij} is an error term that is assumed to be independently and identically distributed, so that observations over all destinations can be pooled.

Heteroskedasticity and the "Zeros" Problem

Two econometric issues that have been recognized to affect gravity-type estimations are those of heteroskedasticity and zero values for the left-hand-side (LHS) variable. Heteroskedasticity in the error term is suspected when the magnitudes of the residuals appear proportional to the regression function, the latter being a common property of empirical models in this area. In equation (8), on the other hand, following a common practice in applied econometrics, we allow for some proportionality between errors and trade values by, implicitly, postulating a multiplicative error structure for the model in equation (7). The error term itself, of course, is assumed to have a constant variance. An alternative approach, advocated by Silva and Tenreyro (2006) and gaining some popularity, relies on the so-called pseudo Poisson maximum likelihood (PPML) estimation method. This approach estimates the model in levels as in equation (7), with a multiplicative error term and the additional assumption that the conditional variance is proportional to the conditional mean. The claim is that PPML is robust to heteroskedastic errors.

A distinct problem is that of the LHS variable taking on zero values for a sizable portion of our data set (about 30% of the observations). This "zeros problem" presents an immediate challenge for the LHS transformation used in the log-linear model of equation (8). Martin and Pham (2008) and Burger, van Oort, and Linders (2009) provide a taxonomy and a brief review of the relevant literature and discuss a number of estimation strategies that have been used in this setting. Two common ways of dealing with this problem, in the context of the log-linear model in equation (8), are: (*a*) replace zero trade values by a small (arbitrary) number, so as to make the log transformation admissible; or (*b*) drop all observation with zero values (i.e., estimate the structural parameters with a truncated sample). The PPML estimation of (the stochastic version of) the model in equation (7), on the other hand, can readily admit zero observations for the LHS variable, and that is another reason why it is being advocated as a reasonable model estimation strategy.

All these methods are somewhat unsatisfactory in our context because zero values for the dependent variables here represent true absence of trade, rather than missing observations, and as such are themselves very much in need of explanation. Such a need is ignored by approaches that rely on the truncated sample of positive trade flows only, for example. Similarly, using the full data sample with the log-linear model in equation (8) (and the arbitrary replacement of zeros by a small number) or the PPML estimation of the model in levels (the stochastic version of equation (7)) does not address this issue either because, essentially, it treat all zeros equally. But in fact, some zeros might reflect cases that are just at or near the margin where countries are ready to trade. Clearly, such zeros would have a high probability to turn into actual trade and could be modeled as arising from the same process generating the observations with the positive trade volume. In contrast, other zero observations might be associated with high trade costs and thus possess a low probability to turn into positive trade. Perhaps not surprisingly, therefore, a large number of zero observations in the data can be problematic with the PPML approach, which can suffer from biased estimates, as shown by Martin and Pham (2008) and Burger, van Oort, and Linders (2009).[4]

A natural way to handle zero observations in our setting is the sample selection framework originated by Heckman (1979). As discussed later, this is our preferred approach, because it allows us to identify the impact of changes in exogenous variables on both the likelihood of trade (which we interpret as the "extensive margin") and the existing volume of trade (which we interpret as the "intensive margin"). We apply this estimation procedure to the log-linear model of equation (8). Let y_t denote the vector of the LHS variables at time t corresponding to the trade equation (8), and let z_t be the corresponding trade indicator variable that takes on value 1 if positive trade is observed, and value 0 if no trade is observed. These observable variables are related to two latent variables that satisfy the following linear processes:

$$(9) \qquad \begin{bmatrix} y_t^0 \\ z_t^0 \end{bmatrix} = \begin{bmatrix} H_t\pi \\ L_t\psi \end{bmatrix} + \begin{bmatrix} u_t \\ v_t \end{bmatrix}$$

[4] Zero-inflated Poisson regression could be used, but it would leave the sample selection issue unaddressed.

Table 1. Data Summary

Variable	Mean	Std. Dev.	Minimum	Maximum	Units
SPS count S	9.602	14.366	0	68	count
Distance D	8542.071	3268.792	0	15801	miles
Tariff τ	9.915	39.38	0	357.6	Ad val. (%)
U.S. Seed use X	14218.292	87492.541	0	653424.5	Metric tons
Expected unit cost c	175.145	158.317	23.795	1194.178	US$/mt
U.S. seed price fob W	3644.237	481.886	3082.062	4629.706	US$/mt
Corn production Q	13572.09	39632.325	57	319692.188	1000 mt

Correlation among Variables

	S	D	τ	X	c	W	Q
SPS count S	1						
Distance D	−0.001	1					
Tariff τ	0.023	0.240	1				
U.S. Seed use X	−0.102	−0.404	−0.040	1			
Expected unit cost c	−0.067	0.130	0.193	−0.079	1		
U.S. seed price fob W	−0.041	0.004	0.086	0.008	−0.061	1	
Corn production Q	0.081	−0.349	−0.010	0.898	−0.128	0.031	1

where H_t and L_t are vectors of conditioning variables, π and ψ are vectors on unknown parameters, and the error terms have bivariate normal distribution. Specifically,

$$(10)\quad \begin{bmatrix} u_t \\ v_t \end{bmatrix} \sim NID\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \omega^2 & \rho\omega \\ \rho\omega & 1 \end{bmatrix}\right).$$

Finally, the observables of the model are related to these latent variables as follows: $y_t = y_t^0$ if $z_t^0 > 0$ and $y_t = 0$ otherwise; and $z_t = 1$ if $z_t^0 > 0$, $z_t = 0$ otherwise. Heckman's (1979) procedure to get consistent estimates in this setting relies on a two-step approach, but given the normality assumption, a consistent maximum likelihood estimator is readily possible (Davidson and MacKinnon 2004).

Data Description

A summary of the data is presented in table 1. The data set is available in a supplementary appendix online and with AgEcon Search. The U.S. seed corn export data are based on reports of the USDA Foreign Agricultural Trade of the United States (FATUS), which reports both value and volume. Under FATUS, volume is derived from value divided by the unit value of the largest seed category. We found some irregularities in the volume data reported in FATUS. Hence, we transformed the seed export value (US$) into quantities (metric tons) using the U.S. seed corn price in respective years as the average export unit value. This step provides quantity data that are consistent with the value data and that are quality adjusted, as the export volume is expressed in the same volume unit for every country. The U.S. seed corn quantities and prices are from the Economic Research Service (ERS) of the USDA. Annual seed corn production in the United States is calculated by adding total exports of U.S. seeds to the estimated total domestic (U.S.) use of seeds.[5] Annual U.S. domestic use of seed is assumed to be equal to corn planted acres times the seed rate as assumed by USDA. Corn planted area for all purposes is taken from the National Agricultural Statistics Service (NASS), Agricultural Statistics Board, USDA. Average seeding rate per acre for corn is based on data from Cropping Practices surveys and the Agricultural Resource Management Survey (ARMS), ERS, USDA. The U.S. corn seed use data are by calendar year.

The seed export data are based on the calendar year. We concentrate on 1989 to 2004 because of the limited export data availability in FATUS. Our final country sample consists of forty-eight countries based on the following criteria. This sample was selected based on an average minimum corn production of 1 million metric tons (mmt) per year, including

[5] When estimating trade share by country, we compute shares based on total seed use for countries included in the sample, and hence shares do add up to one.

seed corn and forage, during the time period of the study. Although its corn production is smaller than 1 mmt, Australia was added to the sample because it has very restrictive corn seed regulations (a formal ban except for non-commercial corn seed imports) and hence adds across-country variation in the SPS count variable combined to across-country variation in other covariates, since Australia's applied tariff is zero. Total world corn production and each country's corn production are based on FAOSTAT statistics from the Food and Agriculture Organization (FAO) of the United Nations.

FAOSTAT provides production data on seed maize (Harmonized System [HS] code: 1005) as well as maize for forage and silage (HS code: 1214.90). Growers buy hybrid corn seed to produce silage just as they would to produce corn for other purposes. We found inconsistencies between large seed net imports and small corn outputs reported under HS 1005 in some countries in the FAOSTAT data. Notably, we found that Japan, the United Kingdom, and the Netherlands have sizable imports of corn seeds but no significant maize production in the FAOSTAT data. Most of these countries use corn for silage instead of maize. Given these facts, we account for the corn production for silage as being relevant for the overall demand for seed corn. To aggregate these two types meaningfully, we use eight bushels of grain maize per one ton of silage to get units in green maize physical equivalent. Corn production data are by calendar year. Our original sample consisted of fifty-four countries. We deleted Belarus, Moldova, Kazakhstan, and the Russian federation, for which we found irregularities (e.g., wide unexplainable swings) in corn production data that could not be reconciled using other data sources. We also deleted Malawi and Nigeria, for which data were incomplete.

As noted earlier, in our framework the expected producer price of corn is assumed to approximate the (unobserved) unit cost of corn seed production under the assumption of perfect competition in corn production and constant returns to scale (unit cost = marginal cost = expected price). Expected prices are, of course, not observable. Notionally, they embed available information at the time that expectations are formed, and empirical models for expected prices range from full rational expectation formulations to naïve expectation models. The simple model we use postulates an information set that includes the previous-period U.S. price (i.e., the most recent price pertaining to the most important market) and a time trend (to capture secular movements in the price of interest). Specifically, we approximate the expected price in any one country as the fitted values of a regression of observed corn prices of that country on the one-period-lagged U.S. corn price and a linear time trend. The current producer price is by calendar year and based on FAOSTAT.

Tariffs applied to U.S.-sourced corn seeds are based on the World Bank's World Integrated Trade Solution (WITS) database (see table 7 in the Data Appendix). Tariff data are currently limited to 1996–2004 in WITS. Hence, we found some pre-1996 data from the Trade Analysis and Information System (TRAINS) database and the Agricultural Market Access Database (AMAD). We use whatever data are available for 1989–1995 in TRAINS and AMAD and backtrack to 1989 assuming the same value for missing information. Tariff data are by calendar year and, although they are expressed in ad valorem form, include all tariffs. WITS and TRAINS are consistent for overlapping years, since WITS data originate from TRAINS raw data. There were very few overlapping data for tariffs across TRAINS and AMAD sources; hence, no inconsistencies were found between these two sources. Most countries exhibit flat or decreasing ad valorem tariffs, with the exception of Korea, Hungary, and Poland. In Korea and Hungary, there was a strong increase in tariffs in 1996, which then decreased in subsequent years. In Poland, the applied tariff increased first in 1996 and then again in 2001.

Direct air distance between the United States and the major commercial city of each country is based on Hengeveld's World Distance Tables, which are widely used in gravity equations and available from the Inter-University Consortium for Political and Social Research (ICPSR) database. For each country, one airport has been selected as the major air terminal from the International Air Transport Association Guide, on the basis of importance in international passenger and good traffic. For most countries, the name of the airport is identical to the name of the nearest large city, in order to use the known geographical latitudes and longitudes of these cities for calculating air distances.

The number of SPS regulations imposed by the importing country is based on data from EXCERPT, which updated the SPS regulations for each country in 2006. However, older regulations starting from 1996 are reported in the EXCERPT archives. We look at phytosanitary certificates, import permits, and field inspections, as well as some other demanding regulatory requirements, including seed testing, post-entry testing, and quarantine. Virtually all countries require a phytosanitary certificate, except Canada. Australia and China have a seed import ban, although China has imported a small amount of seeds in recent years. Some seed lines have to be imported by China to initiate local production. Hence, the Chinese trade ban has not been as tight in recent years, although seed imports remain very small relative to the size of the Chinese corn sector. We use a large number (50) for the SPS count (prohibitive SPS compliance cost) for China and Australia to mimic an SPS count equivalent to the prohibitive policies.

Over time, most countries have streamlined their SPS regulations. Argentina and Chile have low SPS counts. The most radical simplifications have occurred in some eastern European countries which are now members of the European Union (EU). Notably, in the last ten years, Hungary started with an SPS count of 68, streamlined it to 30 in 2003, and eventually adopted EU regulations (SPS count of 3) with EU accession in 2004. South Africa, India, and Indonesia also simplified their regulations by removing all SPS requirements. Egypt, Zimbabwe, and, surprisingly, Brazil have very high SPS counts (18 requirements). The Brazilian case is puzzling, as the country is a large corn producer that would benefit from accessing better seeds.

Econometric Results

As noted earlier, the sample selection framework of equations (9) and (10) represents our favorite estimation strategy, although, for comparison, we will also report the results of two single-equation estimation procedures: ordinary least squares (OLS) on the log-linear equation (8) (where zeros on the LHS are replaced by 0.1); and the PPML estimation of the stochastic version of the model in equation (7). The results of these two estimation procedures are reported in table 2. OLS on the log-linear model and the PPML model produce similar results as far as the sign and significance of the estimated effects, but the estimated magnitude of these effects is quite different. In particular, the PPML approach suggests a larger response to the SPS variable and a lower response to distance. Another feature of these results that is readily apparent is the difference between the estimates based on the full sample and those based on the truncated sample (positive trade only). This is so even for the PPML approach, which typically is presumed to be more robust to truncation. Hence, it appears that selection bias might be a relevant issue, further motivating the Heckman sample selection approach.

Table 3 reports results for sample selection specification in equations (9) and (10) estimated by maximum likelihood (ML), which produces asymptotically efficient estimators. Notice that both the selection and the trade equations depend on the trade cost components (tariff, distance, and SPS). In addition, a time trend appears in the selection model but not in the trade equation. Such a variable is meant to capture other secular effects on the evolution of trade patterns that are not explained by our limited set of exogenous variables and, in principle, could be advocated for equation (9). But the exclusionary restriction that we have adopted is meant to

Table 2. U.S. Corn Seed Exports: OLS on Log-linear Model, and PPML Model

	Estimated Structural Parameters			
	Full Sample		Truncated Sample	
Variable	Log-linear	PPML	Log-linear	PPML
Intercept (α_0)	11.1817* (1.3173)	4.5941* (.4548)	7.284* (0.7910)	3.7133* (0.4466)
Distance (γ)	0.4157* (0.0666)	0.0784* (0.0243)	0.2552* (0.0433)	0.0287 (0.0318)
SPS (β)	0.3421* (0.0914)	1.3293* (0.1489)	0.4732* (0.0809)	1.5898* (0.2109)
Elasticity of substitution (σ)	2.1365* (0.2672)	.9775* (0.1116)	1.5794* (0.1642)	0.7730* (0.1075)
R^2 (pseudo R^2 for PPML)	0.2016	0.1877	0.2976	0.1732
Observations	709	709	490	490

Note: In the log-linear model with full sample, X_{jt} is replaced by $X_{jt} + 0.1$ when $X_{jt} = 0$. Standard errors are in parentheses; an asterisk (*) denotes significant at the 1% level.

Table 3. Maximum Likelihood Estimation of Sample Selection Model Log-linear Gravity Equation Specification

	Selection Equation		Log of Trade Equation	
Variable	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept	16.4842*	1.7996	6.7485*	0.8297
Time	0.0596*	0.0134		
$\ln(1+D_j)$	−1.6129*	0.1915	−0.3442*	0.0657
$\ln(1+S_j)$	−0.1702*	0.0559	−0.7098*	0.1025
$\ln(c_j/((1+\tau_j)W))$	0.4747*	0.1236	1.4885*	0.1703
Recovered parameters				
Distance (γ)			0.2312	0.0465
SPS (β)			0.4769	0.0871
Elasticity of substitution (σ)			1.4885	0.1703
$\hat{\rho}$			−0.3645*	
$\hat{\omega}$			2.1508	
Observations	709		494	

Note: Maximized log-likelihood value = 1430.75; an asterisk (*) denotes significance at the 1% level.

aid identification (Davidson and MacKinnon 2004).[6] The selection equation has all parameters significant with the expected sign. The negative signs on the estimated parameters of the trade cost components in the selection model indicate that the likelihood to trade diminishes as the trade cost factors increase. Also, the positive sign on the estimated parameter of the time trend in the selection model indicates that the likelihood to trade has increased over time, consistent with trade integration.

The implied structural parameter estimates are reported in the lower part of table 3. These structural parameter estimates are significantly different from zero and similar in magnitude to the results reported in table 2 for the estimation of equation (8) with the truncated sample. The estimated correlation coefficient $\hat{\rho}$ is negative and statistically significant, indicating a sample selection bias in the data. A comparison of OLS parameter estimates for the log-linear model with the full sample in table 2 with the ML estimates in table 3 indicates the selectivity bias that affects the OLS method with full sample. In particular, consider the change in the estimates for distance and SPS from OLS to the ML estimates. The coefficient for distance decreases from 0.4157 in OLS to 0.2312 in ML. The coefficient for tariffs decreases from 2.1365 in OLS to 1.4885 in ML. On the other hand, the coefficient for SPS increases from 0.3421 in OLS to 0.4769 in ML. In summary, the impact of distance and tariffs is overestimated and the impact of SPS is underestimated when failing to correct for the selectivity bias in the data.

Although the sample selection approach is popular in empirical analysis, marginal effects are often misinterpreted when a regressor enters into both selection and trade equations. In this case, when $\hat{\rho} \neq 0$, it is incorrect to interpret the estimated parameters of the trade equation shown in table 3 as the marginal effect. Even if one were interested only in the conditional impact of a regressor (that is, conditional on trade taking place), in addition to the direct impact as per the estimated coefficients, one still needs to account for an indirect effect. This is apparent when one recalls that for observations for which trade takes place, the conditional mean of the trade equation (9) satisfies (see, e.g., Davidson and MacKinnon 2004):

$$(11)\qquad E[y_t|y_t>0] = H_t\pi + \rho\omega\frac{\varphi(L_t\psi)}{\Phi(L_t\psi)}$$

where $\varphi(\cdot)$and $\Phi(\cdot)$ denote the density and distribution functions, respectively, of the standardized normal and $\varphi(L_t\psi)/\Phi(L_t\psi) \equiv \lambda_t$ is known as the inverse Mills ratio. From equation (11), it follows that the marginal effect, on the conditional mean, of a regressor

[6] Strictly speaking, given the normality assumption, the nonlinearity of the inverse Mills ratio suffices for identification even when the elements of H_t and L_t are the same. But such an identification strategy is often criticized, and the exclusion of one variable (time trend in our case) is common for identification purposes. In response to a referee's inquiry, we looked at the impact of replacing the time trend with a set of time dummy variables in the selection equation, and that had virtually no effect on the estimated structural parameters.

Table 4. Conditional and Unconditional Marginal Effects of Trade Costs

Variable	Estimated Coefficient of Trade Equation[a]	Conditional Marginal Effect[b]	Unconditional Marginal Effect[b]
$\ln(1+D_j)$	−0.3442	−0.9921	−1.8091
$\ln(1+S_j)$	−0.7098	−0.7782	−0.8644
$\ln(c_j/((1+\tau_j)W))$	1.4885	1.6792	1.9194

[a] The first column is from table 2. [b]Because we use log specifications, these effects correspond to elasticities (see derivations in text).

R_k that appears both in H_t and L_t is:

$$\frac{\partial E[y_t|y_t>0]}{\partial R_{kt}} = \pi_k - \psi_k\rho\omega(\lambda_t^2 + \lambda_t L_t\psi). \tag{12}$$

Furthermore, when a regressor affects both the intensity of trade and the probability that trade takes place, the total unconditional impact is arguably the effect of interest. Following Hoffmann and Kassouf (2005), such an unconditional effect can be written as

$$\frac{\partial E[y_t]}{\partial R_{kt}} = \frac{\partial E[y_t|y_t>0]}{\partial R_{kt}} + \frac{\partial \ln\Phi(L_t\psi)}{\partial R_{kt}} \tag{13}$$

where $\Phi(L_t\psi) = 1 - \Phi(-L_t\psi)$ is the probability that trade takes place. Hence, to find the unconditional effect of a regressor that affects both the intensity of trade and the probability that trade takes place, the conditional effect in equation (12) needs to be augmented by $\partial \ln\Phi/\partial R_{kt} = \psi_k\lambda_t$.

The conditional and unconditional marginal effects, evaluated at the sample mean of the observations used to fit the model, are reported in columns 2 and 3 of table 4. As noted earlier, we relate these two marginal effects to the intensive and extensive margins to trade. Specifically, the conditional marginal effects represent the elasticities of trade given that trade takes place (intensive margin). The unconditional marginal effects represent the elasticities of trade for all countries, trading and not trading (both intensive and extensive margins).[7] The estimated unconditional marginal effects for the trade cost components are larger in absolute value than the conditional effects, because the former takes into account both extensive and intensive margins, whereas the latter measures only the intensive margin.

The tariff factor has the largest marginal effect, followed by distance and SPS factors. The striking result is the importance of the distance factor on both trade margins. The estimated parameters in the first column of table 3 provide a poor gauge of the total marginal effect of the respective explanatory variables on trade.

Distance has the strongest effect on the extensive margin (likelihood to trade) as measured by the difference between the unconditional and conditional marginal effects. This suggests that transportation cost (as proxied by distance) is the major trade cost inhibitor of the emergence of new trade, followed by tariffs and SPS measures, and that policies decreasing these costs associated with distance would presumably have a large impact. However, at the intensive margin, tariffs matter the most, followed by distance and SPS measures.

In summary, the results show that trade costs do matter considerably in corn seed trade. Tariff factors have the largest effect, followed by the cost factor reflecting geographical distance, and last, the factor for SPS regulations, provided that sample selection bias is properly addressed. Gauging the effects of trade costs based on the estimation of the intensive margin alone would be quite misleading. When properly computed using marginal effects derived from the sample selection model, the magnitude and ranking of the impacts of these trade costs on seed trade differ from the estimated regression coefficients on which they are based. The marginal effects are much larger in absolute value than the associated coefficients and reveal the relative importance of cost associated with distance.

We also note that our responses to distance are within the range of estimates reviewed by Disdier and Head (2008). Average tariffs on the U.S. seed trade have been moderate (10% in our sample) over the last two decades. Yet, the high response of corn seed exports to

[7] As noted by a reviewer, our implicit definition of the extensive margin is somewhat restrictive. More generally, new trade (the extensive margin) can arise because of the emergence of new destinations (Felbermayr and Kohler 2006), new exported varieties (Hummels and Klenow 2005), or the participation of new firms in export markets (Helpman, Melitz, and Rubinstein 2008). Because our model considers the same product (no new varieties), and our industry-wide modeling does not identify firm-level activity, we can narrowly interpret the change in the probability to trade as the change in the extensive margin, whereas the change in existing trade is the change in the intensive margin.

tariffs suggests that tariffs remain an important barrier that could be further reduced. Removing the remaining tariffs evaluated (in 2004) would increase existing (2004) seed trade by roughly 12%, specifically 11% through intensified trade and 1% through new trade. These estimates are obtained by applying the conditional marginal effect to the removal of positive ad valorem tariffs in countries with positive trade and by computing the extensive margin effect of removing the positive tariff in countries with no trade and applying it to the average observed trade level for 2004. The small effect on new trade occurs because many countries with positive tariffs have positive trade already, and several countries with no trade have zero tariffs.

SPS regulations also pose a significant barrier to U.S. seed exports, but unlike for tariffs, a complete unilateral removal may not be beneficial, as externalities could occur in the absence of SPS regulations. Nevertheless, in most case, a few SPS measures would suffice, such as an SPS certificate, eventual field inspection, or occasional treatments, focusing on the few relevant pests for each importing country. These few measures would be sufficient to eradicate most if not all vectors of externalities for corn seeds (McGee 1998). For the sake of estimating a trade effect from rationalizing SPS measures, we conjecture that five SPS measures would be sufficient to maintain the SPS integrity of the seeds to all destinations and compute the associated trade effects from removing SPS policies in excess of this reference count in 2004. This approach is somewhat arbitrary but provides an order of magnitude to a potential rationalization of SPS policies in export markets. As for tariffs, we apply the implied proportional reduction of SPS measures to the intensive margin for countries with positive trade and then apply the proportional reduction in SPS count to the extensive margin for countries with no trade, weighted by the average trade level prevailing in 2004. The total trade expansion effect of rationalizing SPS regulations is nearly 8.8%, of which 0.4% comes from the extensive margin (i.e., new trade).[8]

In sum, although the extensive margin is a critical component of the unconditional (total) trade margin, trade expansion from tariff liberalization and SPS policy rationalization would come principally through intensification of existing trade rather than from new export destinations.

[8] If only three SPS measures were necessary to maintain the SPS integrity of the seeds, then the total expansion of trade would be 11.4 %, of which 0.7% is through the extensive margin.

Concluding Remarks

The U.S. seed market is the largest in the world and is expanding. Seed trade has been an important part of this expansion. Despite these facts, seed trade and its determinants remain a somewhat neglected topic in agricultural trade research. We fill this gap with an analysis of trade costs associated with the U.S. corn seed trade. We develop a parsimonious seed export demand model with a sound conceptual foundation based on derived demand in production, accounting for major trade costs, including transportation and tariff factors, as well as the cost of SPS measures affecting seed trade flows. We use a count of SPS regulations affecting U.S. corn seeds embedded in a cost factor and posit that the cost factor increases in the SPS count.

We estimate the export demand equation based on a log-linear specification of seed export levels and using Heckman's sample selection model. The major empirical findings of the study are that all the trade costs have a statistically significant and negative impact on U.S. corn seed exports. The sample selection procedure addresses the large number of zero-trade observations in the data and is motivated by evidence of sample selection bias with alternative methods. The sample selection procedure also allows computation of extensive and intensive margins of trade when trade cost components are altered. Based on marginal effects computed from the sample selection model, the decreasing order of importance for trade costs is first tariffs, followed by distance, and then SPS regulations.

This study contributes to the existing literature in several ways. The research question addressed here, namely, the determinants of seed export demand, appears to have been ignored to date in the economic literature. Further, we derive a gravity-like approach to export demand based on derived demand in production, unlike in other applications of the gravity model to agricultural trade based on final demand. Lastly, the data set collected for the investigation is also novel in its SPS component and the development of the SPS count variable.

Our analysis has relevant policy and political economy implications. Trade policy barriers matter much in trade costs. Tariffs on agricultural goods remain important, although they have somewhat decreased with the Uruguay Round Agreement of the World Trade Organization (WTO) and with regional trade agreements. Tariffs on seed trade have been moderate (an average of 10% in our sample). Nevertheless, the high response of corn seed exports to tariffs suggests that tariffs remain an important barrier that could be further reduced. We estimate that the removal of remaining tariffs would induce a 12% increase in U.S. corn seed trade.

The importance of trade costs induced by SPS regulations raises the issue of sorting which of these regulations are legitimate, that is, science based, and which are not and could be eliminated or challenged using the WTO dispute settlement body. We consider a rationalization of "excess" SPS measures in countries ridden by many SPS policies. We find that such rationalization would increase trade by nearly 9%, mostly through intensification of trade. In the data presentation we also noted the important policy development in the enlarged European Union. The streamlining of SPS measures among EU-27 members has facilitated much trade expansion in the last decade.

When looking at these two policies together, the political economy of SPS measures in seed markets does not seem to fit the traditional argument of SPS and tariffs being policy substitutes in rent-seeking activities. Both have been significantly decreased, with a few exceptions for applied tariffs. SPS measures have not risen and substituted for falling tariffs through our 1989–2004 time span. The correlation between tariff and SPS is statistically weak and does not suggest any strategic interaction from rent-seeking pressures.

Finally, distance is irreducible, but cost associated with distance and transportation could be reduced, and could lead to new trade and intensification of existing trade.

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