Regional Trade Agreement, Global Trade Implications:

EU-Mercosur Agricultural Trade Liberalization

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Selected paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA July 26-28

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Abstract

We examine the impact of EU-Mercosur trade liberalization on bilateral trade patterns, both among exporting countries within these trade blocs and with their competitors. We focus in particular on the sensitivity of U.S. agricultural exports to expanded access for Mercosur in the European Union and for the European Union in Mercosur. We find that the U.S. market share is particularly sensitive to such an agreement to the extent that it lowers the trade costs faced by Brazilian and Argentine exporters in E.U. markets. U.S. market share is also vulnerable to increased access for Spain and Italy, but to a much lesser degree.

Key words: European Union, Mercosur, Mercosul, trade liberalization, United States, agriculture, agricultural trade, free trade agreements

In this paper we use a new approach to model the response of bilateral trade and production patterns to changes in trade costs in order to examine the impact of free trade in agricultural products between the E.U. and Mercosur. These two regional blocs are negotiating a comprehensive free trade agreement that would include agricultural products, which are Mercosur's largest exports to the E.U. (European Commission 2015). These two groups of countries currently trade quite large sums (see Table 1).

Increased access to each other's markets would create new opportunities for agricultural exporters on both continents, as agricultural trade between the two groups is quite a large portion of existing trade, as shown in Table 2. However, that opportunity may come at the expense of other trading partners. Building on Heerman et al. (2015), we examine the effects of expanded access for European Union and Mercosur agricultural exporters to each other's markets. Our approach allows us to examine how trade patterns among E.U. and Mercosur countries responds to liberalization, but also the effects on trading partners outside of the agreement. In particular, we focus on the agreement's implications for U.S. agricultural exports. This allows us to more precisely examine how shifts in bilateral flows are distributed across products.

As in Heerman et al. (2015), we model the global agricultural sector as a continuum of agricultural products differentiated by intrinsic properties only. Within each country, the productivity of the resources and technology available to farmers is heterogeneous across products. A country specializes in the set of agricultural products in which it is most productive, i.e., those that have the lowest unit costs of production. Countries with similar land and climate characteristics will systematically have high resource productivity for the same products and thus be likely to specialize in similar products.

Producers incur a cost to export which varies across products and markets due to differences in perishability, policy treatment and other factors. Thus the ordering of unit costs across agricultural products will vary across foreign and domestic markets. Trade liberalization lowers these costs and can expand the set of products in which a country has comparative advantage. This expansion may come at the expense of other exporters. In such cases, losses come disproportionately at the expense of competitor countries that specialize in similar products.

Our empirical methodology specifies a structural equation delivered by the model as a random coefficients logistic regression to estimate a set of parameters describing the distribution of trade costs and productivity across products for each exporter in each import market. These parameters are used to characterize comparative advantage, to measure bilateral trade costs and to define how bilateral trade patterns shift in response to changes in trade costs. While trade costs can be measured using a log-linear gravity model, such models imply strong restrictions on predicted shifts in trade patterns in response to changes in these costs. The methodology we use has the considerable additional benefit of allowing for product-specific treatment while requiring little data beyond what is necessary for a standard gravity model. We improve on the empirical approach in Heerman et al. (2015) using new data to better characterize the production requirements that influence countries' specialization within the agricultural sector.

Model

We model bilateral trade flows using the systematic heterogeneity model of Heerman et al. (2015). Similar to Eaton and Kortum (2002), in the systematic heterogeneity model, comparative advantage within the sector arises from heterogeneous productivity across products. Unlike the Eaton and Kortum (2002) approach, where product-specific productivity is the realization of an independently distributed random variable, in the systematic heterogeneity model product-specific productivity is a stochastic function of the coincidence of a product's land and climate requirements and exporter land and climate characteristics. The set of products in which a country specializes is thus influenced by its land and climate characteristics and countries with similar land and climate are endogenously more likely to compete head-to-head in the same products. This is revealed in bilateral trade elasticities that are increasing in the extent to which exporters are close competitors. The systematic heterogeneity model also allows bilateral trade costs to vary across products within the agricultural sector. This generates variation in the extent to which comparative advantage arising from productivity differences is revealed across agricultural products.

The model environment is comprised of I countries engaged in bilateral trade. Importers are indexed by n and exporters by i. The agricultural sector consists of a continuum of products indexed by $j \in [0,1]$. To produce quantity $q_i(j)$ of product j requires labor (N_i), land (L_i), and intermediate inputs Q_i combined according to the function:

$$(1) \qquad q_i(j) = z_i(j) \left(N_i^{\beta_i} \left(a_i(j) L_i\right)^{1-\beta_i} \right)^{\alpha_i} \mathbf{Q}_i^{1-\alpha_i}$$

where $z_i(j)$ represents product j-specific technological productivity and $a_i(j)$ represents product j-specific land productivity. Technological productivity is modeled as an independently distributed Frechet random variable with mean parameter T_i and dispersion parameter θ as in Eaton and Kortum (2002). Exporters with high values of T_i have a greater probability of a high realization of $z_i(j)$ for any given agricultural product.

Product-specific land productivity, $a_i(j)$, reflects the suitability of exporter i's environment for product j. We assume $a_i(j)$ follows a parametric density that is a deterministic function of exporter i's agro-ecological characteristics and product j's production requirements. For example, countries with volcanic soil and tropical climate will tend to have higher values of $a_i(j)$ for pineapple.

Markets are perfectly competitive. Therefore, the price offered by exporter i for product j in market n is equal to the unit cost of producing in country i and marketing in country n. Exporters face additional costs, $\tau_{ni}(j) > 1$ to sell product j in import market n. Trade costs are assumed to take the iceberg form, with $\tau_{nn}(j) = 1$ and $\tau_{ni}(j) \geq \tau_{nl}(j)\tau_{li}(j)$. We assume $\tau_{ni}(j)$ follows a parametric density across products that is a deterministic function of product-specific policies and other marketing requirements. Productivity and trade cost distributions are assumed independent of each other.

Trade occurs as buyers in each import market seek out the lowest price offer for each product. Heerman (2013) shows that exporter i's total share of importer market n agricultural expenditure is the unconditional probability it offers the lowest price for an agricultural product:

$$(2) \qquad \pi_{ni} = \int \pi_{ni}(j) dF_{\tilde{\boldsymbol{a}}_n}(\tilde{\boldsymbol{a}}) dF_{\boldsymbol{\tau}_n}(\boldsymbol{\tau}_n) \equiv \int \frac{T_i\left(\tilde{a}_i(j) c_i \tau_{ni}(j)\right)^{-\theta}}{\sum_{l=1}^{I} T_l\left(\tilde{a}_l(j) c_l \tau_{nl}(j)\right)^{-\theta}} dF_{\tilde{\boldsymbol{a}}_n}(\tilde{\boldsymbol{a}}) dF_{\boldsymbol{\tau}_n}(\boldsymbol{\tau}_n)$$

where $\tilde{a}_i(j) = a_i(j)^{-\alpha_i(1-\beta_i)}$, c_i is the cost of an input bundle, and $dF_{\tilde{\boldsymbol{a}}_n}(\tilde{\boldsymbol{a}}) dF_{\boldsymbol{\tau}_n}(\boldsymbol{\tau})$ is the joint density of $\tilde{\boldsymbol{a}} = [\tilde{\boldsymbol{a}}_1, \ldots, \tilde{\boldsymbol{a}}_I]$ and $\boldsymbol{\tau}_n = [\tau_{n1}, \ldots, \tau_{nI}]$ over all agricultural products consumed in import market n. Like a gravity model, equation 2 relates market share to exporter competitiveness and bilateral trade costs. It is a weighted sum of the product specific probability of having comparative advantage, $\pi_{ni}(j)$, where the weights reflect the importance of each product in market n consumption.

Bilateral Trade Elasticity in the Model

An important implication of the systematic heterogeneity model is that, unlike a standard log-linear gravity model, it generates a system of trade elasticities in which market share is more elastic with respect to changes in an exporter's closest competitors' trade costs. We refer to the elasticity of exporter i's market share with respect to competitor l's trade costs as a bilateral trade elasticity. This elasticity can be written:

$$\frac{\partial \pi_{ni}}{\partial \tau_{ni}} \frac{\tau_{nl}}{\pi_{ni}} = \begin{cases} \frac{\theta}{\pi_{ni}} \left(cov\left(\pi_{ni}(j), \pi_{nl}(j)\right) + \pi_{ni} \times \pi_{nl} \right) & if\ l \neq i \\ -\theta\left((1-\pi_{nl})\pi_{ni} - var(\pi_{ni}(j)) \right) & otherwise \end{cases} \tag{3}$$

The elasticity with respect to competitor country $l \neq i$'s trade costs is increasing in the covariance of product-specific comparative advantage, $cov\left(\pi_{ni}(j), \pi_{nl}(j)\right)$, which is driven by the covariance in $a_i(j)$ and $\tau_{ni}(j)$. Country i's market share is more likely to contract in response to a cut in competitor l's trade costs if both countries have high land productivity in the same products and low costs to deliver the same products to market n. Own trade elasticity is generally increasing in market share[1] and decreasing in the variance of the probability exporter i offers the lowest price over all agricultural products. Countries with high $var\left(\pi_{ni}(j)\right)$ tend to be globally competitive in a few agricultural products, but generally have low probability of comparative advantage in agricultural products.

In contrast, in a log-linear gravity model, $\pi_{ni}(j) = \pi_{ni}(k) = \pi_{ni}$, and therefore $cov(\pi_{ni}(j), \pi_{nl}(j)) = var(\pi_{ni}(j) = 0$. The elasticity of each exporter's market share with respect to a given competitor's trade costs is constant and directly proportional to the exporter's market share, regardless of whether they are likely head-to-head competitors. We refer to this restrictive pattern of trade elasticities as the independence of irrelevant exporters (IIE) property. In models with the IIE property, changes to a third country's trade costs are “irrelevant” to the ratio of any other two competitors’ market share in a given import market.[2] If the IIE property does not hold in the data, this assumption results in imprecise, if not misleading, predictions for the effects of changes in trade costs on bilateral trade and production patterns. This is especially important when the gravity model is the underlying model of bilateral trade in a general equilibrium model in which comparative statics exercises are conducted. Arkolakis, Costinot, and Rodríguez-Clare (2012) demonstrate that this is the case for many of the most common quantitative trade models, including many of those built on Eaton and Kortum (2002), Melitz (2003) and those based on the Armington assumption as in Anderson and van Wincoop (2003).

Importantly, the IIE property is unlikely to hold in a sector like agriculture where natural resources systematically affect the set of products in which a country has comparative advantage. For example, the IIE property implies that if Argentina obtained free access to the German market, buyers in Germany would substitute towards Argentine agricultural products and away from each of Germany’s other trading partners in a constant and direct proportion to Argentina’s initial agricultural market share. Argentina and the United States tend to specialize in similar agricultural products and thus compete head-to-head in European markets and elsewhere. In contrast, Venezuela’s land characteristics and tropical climate lead it to primarily export coffee and cocoa to European markets. Therefore, in contrast to the shifts imposed by the IIE property, we expect U.S. market share to experience a disproportionately large vulnerability to lower Argentine trade costs relative to Venezuela.

Specification and Data

We estimate parameters of the productivity and trade cost distributions as in Heerman et al. (2015) by specifying equation 2 as a random coefficients logit model. We begin as in Eaton and Kortum (2002) by defining $S_i = ln(T_i) - \theta ln(c_i)$. This is exporter i’s average agricultural sector technological productivity adjusted for unit production costs.

Land Productivity Distribution

We specify $a_i(j)$ as a parametric function of exporter agro-ecological characteristics and product agro-ecological requirements:

$$(4) \quad ln(a_i(j)) = \boldsymbol{X}_i\boldsymbol{\delta}(j) = \boldsymbol{X}_i\boldsymbol{\delta} + \boldsymbol{X}_i(\boldsymbol{E}(j)\boldsymbol{\Lambda})' + \boldsymbol{X}_i(\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)'$$

where $\mathbf{X}_i$ is a $1 \times k$ vector of variables describing country i's agro-ecological characteristics; $\boldsymbol{\delta}$ is a $k \times 1$ vector of coefficients; $\mathbf{E}(j)$ is a $1 \times m$ vector of product j-specific agro-ecological production requirements that can be observed and quantified; $\boldsymbol{\Lambda}$ is an $m \times k$ matrix of coefficients that describes how the relationship between elements of $\mathbf{X}_i$ and land productivity varies across products with $\mathbf{E}(j)$; and $\boldsymbol{\nu}_{\mathbf{E}}(j)$ is a $1 \times k$ vector that captures the effect of unobservable product j-specific requirements with scaling matrix $\boldsymbol{\Sigma}_E$.

We specify three types of characteristics in $\mathbf{X}_i$, climate, elevation and agricultural land availability:

$$\mathbf{X}_i = \begin{bmatrix} al_i & elv_i & trp_i & tmp_i & bor_i \end{bmatrix}$$

where al_i is the log of arable land per capita, which proxies for agricultural land abundance, elv_i is the share of rural land between 800 and 3000 meters above sea level, and the remaining elements are the shares of total land area in tropical, temperate, and boreal climate zones. These variables play two roles in the model. First, they relate characteristics of exporter i's agro-ecological characteristics to absolute advantage in agriculture through $\mathbf{X}_i\delta$. Second, they describe how agro-ecological characteristics systematically influence the set of products within the agricultural sector in which it has comparative advantage. As such, the coefficients describe the extent to which similarity along these dimensions drives countries to specialize in similar agricultural products and compete head-to-head in global markets.

The vector $j = \begin{bmatrix} \mathbf{E}(j) & \boldsymbol{\nu}_{\mathbf{E}}(j) \end{bmatrix}$ defines products in terms of their suitability for production under the conditions defined by $\mathbf{X}_i$. We define:

$$\mathbf{E}(j) = \begin{bmatrix} alw(j) & elv(j) & trp(j) & tmp(j) & bor(j) \end{bmatrix}$$

where $alw(j)$ describes product-j land requirements, $elv(j)$ captures its elevation requirements, and $trp(j)$, $tmp(j)$, and $bor(j)$ describe climate requirements.

While we do not directly observe land and climate requirements for each product, we can use observable economic information about their production around the world to construct the "observable" product requirements matrix $\mathbf{E}(j)$ for each of the $J = 134$ items for which the FAO publishes both production and trade data. This approach is valid under two assumptions: First, $\mathbf{E}(j)$ is distributed across products following the empirical distribution of requirements for agricultural products defined at the "item" level by the FAO. Second, exporting is positively correlated with high natural productivity.

We measure $elv(j)$ and $alw(j)$ as in Heerman et al. (2015) as the export-weighted average of exporters' share of land at high elevation (elv_i) and arable land per agricultural worker (alw_i), respectively.[3] Notice that we define the land intensity of product j using data on land per agricultural worker rather than agricultural land per capita, as we used in $\mathbf{X}_i$. While elements of $\mathbf{X}_i$ are intended to capture the structural factors that influence exporter i's potential comparative advantage, elements of $\mathbf{E}(j)$ are intended to capture the ideal conditions under which product j is produced. Therefore, products are represented by their observed production conditions, but countries are represented in terms of their potential production conditions.

A drawback of defining product requirements as export-weighted averages of country characteristics is that it is not very precise. Many important agricultural exporters have varied terrain and climate within their borders. For example, about 20 percent of global wheat exports originated in Canada in 2006. However, while a large share of total Canadian land area is in the boreal climate zone, its wheat production is concentrated in temperate climates. Therefore, a trade-weighted average of climate distributions would misrepresent wheat's boreal climate requirements.

We improve on the measurement of product-specific climate requirements used in Heerman et al. (2015), taking advantage of information on product-specific production across climate zones within countries provided by the GTAP land use database (Monfreda, Ramankutty, and Hertel 2009). As part of an effort to model the impact of climate change on the agricultural sector, Monfreda, Ramankutty, and Hertel (2009) estimate land rent for ten product categories in 18 agro-ecological zones (AEZs) within in each of several countries. An AEZ is a defined zone based on soil, landform and climactic characteristics. A country's estimated land rent in AEZ x for crop y is calculated by by apportioning the crop's total land rent across AEZ's in proportion to its share in the value of crop y production.

To calculate product climate requirements, we assign each of the crops in our data set to one of the ten GTAP aggregates. We then calculate the share of land rent in each zone and aggregate these shares into a distribution of land rent across tropical, temperate and boreal climate zones for each product, country pair. Finally, we define product j climate requirements as the export-weighted average of these land rent distributions. The GTAP land use database does not calculate a distribution of land rent across climate zones for animal products. Therefore, we use export-weighted averages of country climate distributions, as we did for land and elevation intensity, to calculate $\begin{bmatrix} trp(j) & tmp(j) & bor(j) \end{bmatrix}$ for these products.

Trade Cost Distribution

We specify product-j trade costs as:

$$ln\left(\tau_{ni}(j)\right) = \mathbf{t}_{ni}\boldsymbol{\beta}(j) = \mathbf{t}_{ni}\boldsymbol{\beta} + ex_i + \mathbf{t}_{ni}\left(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t\right)' + \xi_{ni} \tag{5}$$

where $\mathbf{t}_{ni}$ is a $1 \times m$ vector describing the relationship between exporter i and import market n, $\boldsymbol{\beta}$ is an $m \times 1$ vector of parameters; ex_i is an exporter-specific trade cost captured by a fixed effect; $\boldsymbol{\nu}_{\mathbf{t}_n}(j)$ is a $1 \times m$ vector that captures the effect of unobservable product j-specific trade costs with scaling matrix $\boldsymbol{\Sigma}_{\mathbf{t}}$, and ξ_{ni} captures unobservable or unquantifiable bilateral trade costs that are common across products and orthogonal to the regressors. We define:

$$\mathbf{t}_{ni} = \begin{bmatrix} b_{ni} & l_{ni} & rta_{ni} & \mathbf{d}_{ni} \end{bmatrix}$$

where b_{ni}, l_{ni} and rta_{ni} equal one if the two countries share a common border or language or are members of a common regional free trade agreement. The 1×6 vector $\mathbf{d}_{ni}$ assigns each country pair to one of six distance categories as defined in Eaton and Kortum (2002) (see Table 3).

Random Coefficients Logit Model Computation

Using our definitions of $a_i(j)$ and $\tau_{ni}(j)$ in equation 2, we obtain a random coefficients logit model of agricultural market share:

$$(6) \qquad \pi_{ni} = \int \frac{exp\{S_i + \theta\alpha_i(1-\beta_i)\mathbf{X}_i\boldsymbol{\delta}(j) - \theta\mathbf{t}_{ni}\boldsymbol{\beta}(j)\}}{\sum_{l=1}^{I} exp\{S_l + \theta\alpha_l(1-\beta_l)\mathbf{X}_l\boldsymbol{\delta}(j) - \theta\mathbf{t}_{nl}\boldsymbol{\beta}(j)\}} d\hat{F}_{E_n}(\mathbf{E})d\hat{F}_{\nu_n}(\boldsymbol{\nu})$$

where $d\hat{F}_{E_n}(\mathbf{E})d\hat{F}_{\nu_n}(\boldsymbol{\nu})$ is the empirical density of products imported by market n defined jointly by their land and climate characteristics, unobserved agro-ecological requirements and trade costs. We estimate equation 6 using a simulated method of moments approach similar to that in Berry, Levinsohn, and Pakes (1996), which is detailed in Nevo (2000) and Train (2009). To evaluate the integral, we use the "smooth simulator" suggested by Nevo (2000):

$$(7) \qquad \pi_{ni} = \frac{1}{ns}\sum_{j=1}^{ns} \frac{exp\left\{\tilde{S}_i + \theta\alpha_i(1-\beta_i)\boldsymbol{X}_i\boldsymbol{\delta}(j) - \theta\mathbf{t}_{ni}\boldsymbol{\beta}(j)\right\}}{\sum_{l=1}^{I} exp\left\{\tilde{S}_l + \theta\alpha_l(1-\beta_l)\boldsymbol{X}_l\boldsymbol{\delta}(j) - \theta\mathbf{t}_{nl}\boldsymbol{\beta}(j)\right\}}$$

where $\tilde{S}_i = S_i + \theta\alpha_i(1-\beta_i)\mathbf{X}_i\boldsymbol{\delta}$ is a country fixed effect. We use the minimum distance procedure suggested by Nevo (2000) to obtain $\hat{S}_i$ and $\boldsymbol{\delta}$ from $\hat{\tilde{S}}_i$. We finish by calibrating $\hat{\xi}_{ni}$ as the value that sets equation 6 equal to observed market share.

Data

The $ns = 100$ products used to evaluate equation 7 for each importer and its trading partners are drawn from $d\hat{F}_{E_n}(\mathbf{E})d\hat{F}_{\nu_n}(\boldsymbol{\nu})$. We construct this distribution in two steps as in Heerman et al. (2015). First, we use FAO item level import data to estimate $d\hat{F}_{E_n}(\mathbf{E})$, the empirical distribution of $\mathbf{E}(j)$ across products imported by each market by compiling a list of 1000 imported items defined by the vector $\mathbf{E}(j)$ for each market n. Unique values of $\mathbf{E}(j)$ are represented in $d\hat{F}_{E_n}(\mathbf{E})$ in proportion to their associated FAO item's share in total imports. That is, if 15% of importer n's total agricultural imports are of the FAO item "wheat", then $E(wheat)$ makes up 150 entries on $d\hat{F}_{E_n}(\mathbf{E})$. We draw $ns = 100$ values of $\mathbf{E}(j)$ using uniform draws from each country's distribution. The distribution is completed by associating each item on the list with $\boldsymbol{\nu}_n(j) = \begin{bmatrix} \boldsymbol{\nu}_{\mathbf{E}}(j) & \boldsymbol{\nu}_{\mathbf{t}_n}(j) \end{bmatrix}$ drawn from a standard multivariate normal distribution, effectively generating a "data set" of 1000 unique products imported by each market .

In our data set, bilateral market shares are calculated using 2006 production and trade data on the 134 agricultural items for which data on both bilateral trade and the gross value of production in U.S. dollars are available (FAO 2013). Data on arable land per capita and land per agricultural worker come from World Bank (2012). Climate information comes from the GTAP Land Use Database (Monfreda, Ramankutty, and Hertel 2009). Elevation data comes from CIESIN (2010). Elements of $\mathbf{t}_{ni}$ are obtained from the CEPII gravity data set (Head, Mayer, and Ries 2010).

Econometric Results

Land Productivity Distribution

Table 4 contains estimates for the land productivity distribution parameters $\boldsymbol{\delta}$, $\boldsymbol{\Lambda}$, and $\boldsymbol{\Sigma}_{\mathbf{E}}$. The total effect of each exporter characteristic in $\mathbf{X}_i$ on the probability of comparative advantage in a given product, $\pi_{ni}(j)$ is the sum of the mean effect in the first column and the product-specific effects in the owscolumns that follow.

Coefficients on all climate variables are normalized to sum to zero. As such, coefficients on exporter climate characteristics are interpreted with respect to the average climate; and the effects of product-specific climate requirements are interpreted with respect to the average production requirement.[4] The mean effect of having a higher than average amount of high elevation acreage is positive and large ($\delta_{elev} = 8.92$). This implies that having more high elevation land increases a country's agricultural market share on average. However, this benefitis decreasing for land intensive products, and products that are more intensively produced in temperate climates than the average product. In contrast, the benefit of high elevation land is greatly magnified for products that are more intensely tropical or boreal than the average product. This makes sense because boreal climates are associated with high elevations, therefore countries with higher than average acreage at high elevations are more likely to specialize in boreal crops, and key tropical export crops like coffee and tea are often grown at high altitudes. The statistically and econonomically insignificant value of the estimated coefficient on unobservable product characteristics ($\sigma_{al} = 0.00$), implies that the variation in the effect of elevation across products is sufficiently explained by the product requirements in $\mathbf{E}(j)$. The large, negative mean effect of tropical land share ($\delta_{trp} = -2.33$) implies that a larger than average amount of tropical land decreases agricultural market share on average. Positive, and larger in magnitude, coefficients on $trp(j)$ and $tmp(j)$ ($\lambda_{trp,trp} = 7.47$, $\lambda_{trp,tmp} = 3.12$) imply this effect is increasing for products that are more intensively tropical and temperate than average, and negative coefficients imply the disadvantage of a large share of tropical land is boreal products ($\lambda_{trp,bor} = -10.6$) and elevation-intensive products ($\lambda_{trp,elv} = -4.58$).

Estimates for $\tilde{S}_i$ are listed in Table 5. These values are normalized to sum to zero and are thus interpreted as average agricultural sector productivity relative to the average country *in the average product*. Recall that $\tilde{S}_i$ is increasing in average technological and land productivity, but decreasing in costs of production c_i. Therefore, a country with high average productivity may nevertheless have a small $\tilde{S}_i$ if it has, e.g., very high wages or land rental rates.

Trade Costs

Table 6 contains estimates for the trade cost distribution parameters $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma_t}$. Negative mean coefficient values imply higher trade costs, but lower expected market share. Elements of $\boldsymbol{\Sigma_t}$ capture the heterogeneity in the effect of each element of $\mathbf{t}_{ni}$ across products and can thus be interpreted like a standard error around the mean effect.

Positive mean effects imply that sharing a common language increases market share on average, while negative coefficients on increasing distance tends to decrease it. The negative mean effect of common RTA membership ($\delta_{rta} = -0.48$) and sharing a border ($\delta_b = -0.93$) may seem counterintuitive. However, the relatively larger magnitude of the estimated standard error ($\sigma_{rta} = 1.51$ and $\sigma_b = -2.78$) implies an RTA increases market share for some products and decreases it for others. This is illustrated in Figures 1 and 2, which show the variation in the estimated effect of a common border or RTA membership across all 6300 traded products in our data set. This variation is sensible in the case of agriculture since many RTA members, as well as countries that share borders, are likely to share comparative advantage in a similar set of products.

Values of $\hat{ex}_i$ are reported in Table 5. The values are normalized to sum to zero, so positive (negative) values imply that exporter i is a higher (lower)-than-average-cost exporter. Our results suggest that Canada and the United States are the lowest-cost exporters.

Predicted trade costs ranges

Unlike other gravity-like models of bilateral trade, in addition to variation in estimated bilateral trade costs across country pairs, the systematic heterogeneity model generates variation in bilateral trade costs across products *within* the agricultural sector. We can get an idea of the range of trade costs faced by an exporter in an import market by looking at the ratio of the maximum to the minimum predicted trade cost in a given import market. Table

7 reports the median of this ratio across markets for each exporter. The table reveals that Central and Eastern European countries, many of which are land-locked, tend to have the largest range of trade costs across products. For example, Hungarian agricultural exporters of the product facing the highest bilateral trade cost in the median market face an over 30-times larger barrier than the product facing lowest bilateral trade cost. With the very noticeable exception of Argentina, Mercosur exporters face a smaller range of trade costs across agricultural products in the median market.

Cross country substitution patterns and E.U.-Mercosur trade liberalization

Many E.U. and Mercosur countries produce and export the same grains and meat products that represent a large share of U.S. agricultural exports around the world. Brazil and Argentina are particularly important competitors in this respect. Among other products, the United States, Brazil and Argentina are all major global exporters of corn, soybeans and poultry. Exports from the United States, Brazil, and Argentina together comprised 70 percent of global corn exports, 91 percent of global soybean exports and 65 percent of global poultry exports in 2006 and these three commodities alone comprised roughly half of the total value of each of country's 2006 agricultural exports.

To measure the intensity of competition between the United States and Brazil, Argentina and its other competitors in the European Union and Mercosur, we calculate the bilateral trade elasticity of the United States with respect to each country using Equation 3. Table 8 reports the average ratio of this elasticity with respect to each competitor to the median U.S. bilateral elasticity across all 62 competitors in E.U. and Mercosur markets. For example, the model predicts that U.S. market share is on average 11.10 times more sensitive to Brazilian trade costs than it is to its median competitor in the E.U., and on average only 0.01 times as sensitive to Austrian trade costs. In part this is due to Brazil's absolute advantage in agriculture. It's average bilateral market share in Europe is roughly 1.3 percent, whereas Austria's is 0.4 percent. However, U.S. bilateral trade elasticity with respect to Brazil is on average almost 5-times its market share,[5] whereas it is an average of 0.12-times Austria's market share.

The table reveals particularly intense competition from Argentina, Brazil, Spain and Italy in both the European and Mercosur markets. The relative magnitudes of the Mercosur and E.U. averages suggest U.S. market share is generally more sensitive to Mercosur competitors than European competitors. Notice that U.S. market share is generally more elastic to competitors within their own trade bloc. Within blocs, exporters have the advantage of proximity and cultural familiarity, and thus tend to have lower trade costs, making them generally more competitive in these markets, everything else equal. This suggests, for example, that the U.S. and Brazil are likely to compete head-to-head in more products in Mercosur than Europe. There are a few competitors for which the converse holds.

These results suggest that U.S. market share is vulnerable to E.U.-Mercosur trade liberalization, particularly from increased Brazilian and Argentine access to the E.U. market and increased Spanish and Italian access to the Mercosur market. However, while bilateral elasticities reveal information about which countries are the closest U.S. competitors. Regional free-trade agreements involve more-or-less simultaneous cuts in trade costs among many countries. We explore the sensitivity of U.S., E.U. and Mercosur market share to E.U.-Mercosur trade liberalization using the total differential of π_{ni} with respect to trade costs of a subset of competitors:

(8)

$$d\pi_{ni,L} = \theta \left[\left(\sum_{l \in L} cov\left(\pi_{ni}(j), \pi_{nl}(j)\right) \frac{d\tau_{nl}}{\tau_{nl}} + \sum_{l \in L} \pi_{ni} \times \pi_{nl} \frac{d\tau_{nl}}{\tau_{nl}} \right) - \left((1-\pi_{ni})\pi_{ni} - var\left(\pi_{ni}(j)\right)\right) \frac{d\tau_{ni}}{\tau_{ni}} \right]$$

where $L \subseteq I$ are exporters l for which trade costs change, i.e., $d\tau_{nl} \neq 0$. We refer to equation 8 as exporter i's regional trade liberalization elasticity in market n. This elasticity is a measure of the change in bilateral market share from a change in trade costs of $l \in L$, holding all prices in the economy constant. We interpret it here as a measure of the sensitivity of exporter i's market share in import market n under regional liberalization.

Equation 8 has two components. The term in the first parentheses captures the effect of falling competitor trade costs. Exporter i's regional trade liberalization elasticity is decreasing to the extent its competitors: 1) have a high probability of comparative advantage in the same products as country i; and 2) have a large existing share of the country n market. The second term captures the effect of the decline in country i's own trade costs. Regional trade liberalization elasticity is generally increasing in own market share[6] and decreasing in $var(\pi_{ni}(j))$.[7]

Recall that in a log-linear gravity model of the agricultural sector, $cov(\pi_{ni}(j), \pi_{nl}(j)) = var(\pi_{ni}(j)) = 0$, and the magnitude of the regional trade elasticity is entirely driven by π_{ni}, and π_{nl}, measures of absolute advantage in agriculture. Therefore, any regional liberalization that lowers trade costs for highly competitive global agricultural exporters will significantly diminish the predicted elasticity of exporter i's market share. This absolute advantage effect is moderated in the systematic heterogeneity model to the extent that the high absolute advantage exporters in L specialize in exporting, e.g., tropical fruits to market n, while exporter i specializes in exporting temperate grains. Conversely, the effect of competitors' absolute advantage in agriculture is magnified if competitors in L specialize in the same products as exporter i.

We calculate a system of regional trade elasticities with respect to a one percent decline in Mercosur exporters' trade costs in the E.U., and in E.U. exporters' trade costs in Mercosur while U.S. and intra-trade bloc costs are unchanged.[8] This exercise is not intended to capture the likely outcome of E.U.-Mercosur negotiations. Rather, it is meant to be descriptive of how the structure of competition facing the United States and its competitors responds to E.U.-Mercosur trade liberalization.

Table 9 contains the ratio of each exporter's regional trade elasticity in Mercosur markets to the mean elasticity of E.U. exporters. Since E.U. trade costs are falling in this scenario, the elasticity is positive for E.U. countries, whereas it is negative for the United States and Mercosur exporters whose *relative* trade costs are consequently rising. For example, holding all prices in the economy constant, the model predicts that Italy's market share would increase 6.57-times more than the average E.U. exporter in the Argentine market, and U.S. market share would *decrease* 0.02-times as much as the average European increase.

Notice that Italy and Spain generally have the most elastic market shares in Mercosur. Recall from Table 8 that these countries are close competitors of the United States. Nevertheless, with the exception of the Brazilian and Venezuelan markets, the magnitude of the U.S. elasticity is a small fraction of the average European exporter's elasticity. Outside their domestic markets, the magnitudes of Mercosur exports elasticities are likewise uniformly less than the average European elasticity.

Table 10 likewise describes regional trade elasticity with respect to lower Mercosur trade costs in E.U. markets. Again, the table reports elasticities relative to the mean elasticity across the five Mercosur exporters. The negative U.S. market share elasticity again tends to be a very small share of the average positive Mercosur elasticity. U.S. sensitivity is relatively larger in the small markets of Belgium and Lithuania, but also in the more valuable German market. Brazil's market share is by far the most responsive in the European Union. Argentina's market share is close to the average in most import markets. The average relative elasticity of Paraguay, Uruguay and Venezuela is reported in the column labeled 'Other Average'. These countries' market shares are much less elastic than those of Brazil and Argentina. While there is variation in each exporter's regional elasticity across European markets, elasticities are generally similar throughout the E.U.

The presentation of regional elasticities relative to regional averages in Tables 9 and 10 suggests that the United States' market share loss is small relative to each trade bloc's gain in both Mercosur and the E.U. However, these tables do not reveal information about the relative impact of E.U.-Mercosur liberalization on U.S. market share in Europe to its impact in Mercosur. Table 11 contains the elasticity of U.S. market share to E.U.-Mercosur liberalization in each market, relative to the median U.S. regional trade liberalization elasticity. Values greater than one imply U.S. market share is more sensitive in the import market relative to the median import market. What is most notable is that U.S. market share is much more sensitive to expanded Mercosur access to the European Union than it is expanded E.U. access to Mercosur markets.

Conclusion

Overall, our model shows that the U.S. market share is vulnerable to E.U.-Mercosur trade liberalization, particularly from increased access to the E.U. by Brazil and Argentina. Brazilian and Argentine exporters compete head-to-head with the United States around the world in many products, particularly corn, soybeans, and tobacco. Allowing expanded and cheaper access to the E.U. market may cost U.S. agricultural exporters valuable European market share. These products represented roughly half of each country's total agricultural exports in 2006. Our results also suggest that U.S. market share in Mercosur markets vulnerable to increased access to E.U. exporters, particularly Spain and Italy. However, this challenge is to a much lesser degree than that presented by Brazil and Argentina in European markets, which are also more valuable to U.S. exporters.

The regional trade liberalization elasticities reported in this paper are calculated assuming a one percent cut in trade costs that is uniform across products. However, free trade agreements typically contain a myriad of product-specific exemptions and exceptions from further liberalization in the agricultural sector. Moreover, non-tariff measures are important barriers to agricultural trade and the probability of comparative advantage may be inflated by product-specific domestic support policies that have not been included in this model. Since these types of policies are applied generally, across trading partners they are less likely to be addressed in the context of regional free trade negotiations. An advantage of the systematic heterogeneity model is its ability to examine impacts of lower trade costs at a product-specific level while requiring only sector-level market share data. Future work will explore the impacts of liberalization at a product-specific level.

Notes

[1]π_{ni} is less than 0.5 for all country pairs

[2]This concept parallels that of the Independence of Irrelevant Alternative property in the differentiated products demand systems literature.

[3]The variable $alw(j)$ is the log of the associated export-weighted average.

[4]The average climate is 27% tropical, 69% temperate and 5% boreal. The average traded product is 26% tropical, 61% temperate and 13% boreal.

[5]A very large outlier in the bilateral elasticity's relationship to market share in the Estonian market is dropped from this average

[6]$\pi_{ni} < 0.5$ for every pair of countries in our data set.

[7]Countries with high $var(\pi_{ni}(j))$ tend to be highly competitive in select agricultural products, but generally do not have absolute advantage in the agricultural sector, e.g., African commodity exporters.

[8]We set $\theta = 4.12$ as in Simonovska and Waugh (2014)

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Figures

Figure 1. Distribution of Shared Border Effect

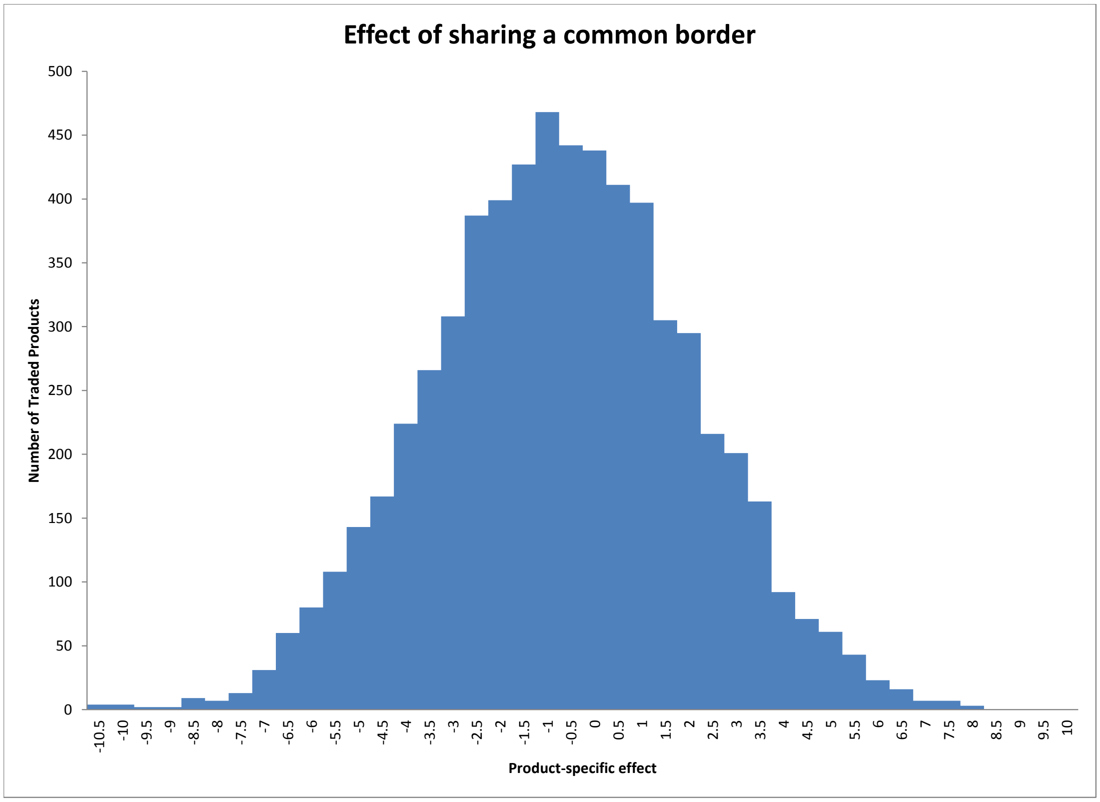
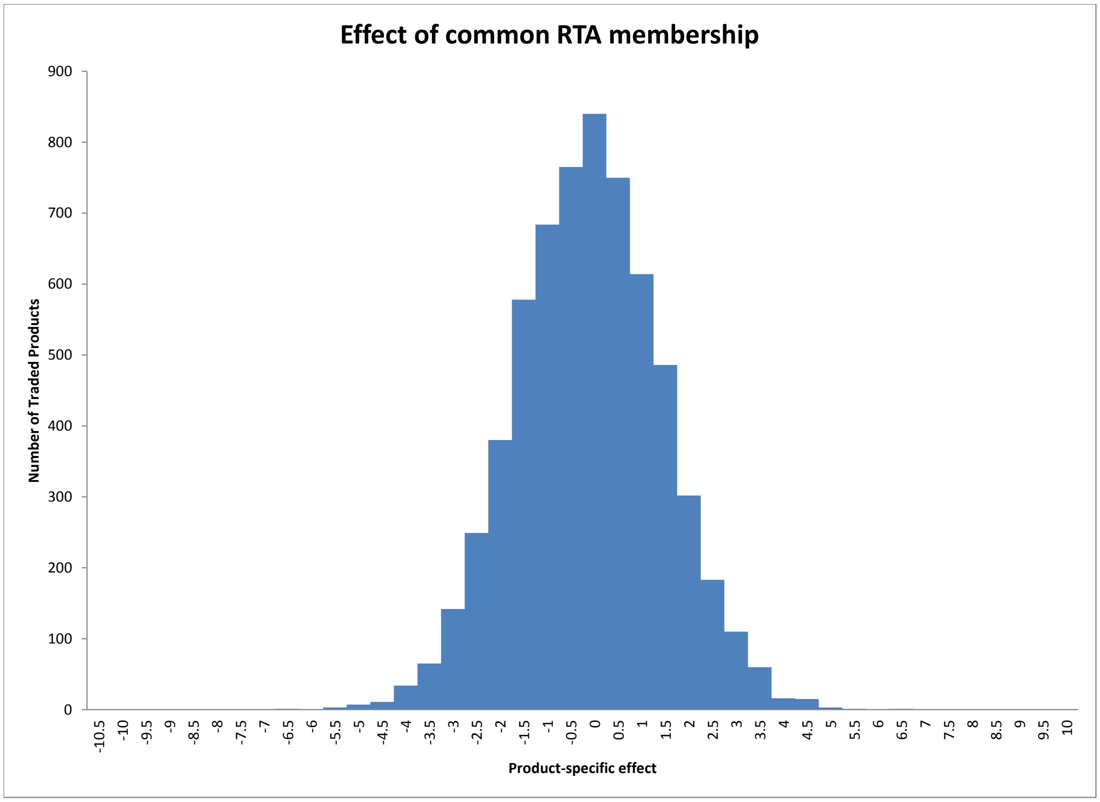


Figure 2. Distribution of Common RTA Effect



Tables

Table 1. E.U. Trade with Mercosur

Year	Imports	Share in Extra-EU	Exports	Share in Extra-EU	Total Trade
2003	28,296	3.0	17,354	2.0	45,751
2004	31,192	3.0	20,727	2.2	51,919
2005	35,332	3.0	23,535	2.2	58,867
2006	41,841	3.1	27,062	2.3	68,867
2007	48,146	3.3	32,127	2.6	80,273
2008	54,675	3.4	37,713	2.9	92,388
2009	39,465	3.2	30,978	2.8	70,443
2010	48,805	3.2	44,460	3.3	93,388
2011	56,490	3.3	50,770	3.3	107,260
2012	54,119	3.0	56,905	3.4	111,024
2013	47,112	2.8	56,956	3.3	104,068

Table 2. Trade Flows - European Union Trade with Mercosur, 2014

	Value (Million Euros)	Share (Percent)	Value (Million Euros)	Share (Percent)
	Imports		Exports	
Total	44,684	100	51,222	100
Agricultural Products	20,014	44.8	2.32	4.5

Table 3. Definition of Distance Variables

Variable	Population-weighted average distance between largest cities, miles
Distance 1	[0,375)
Distance 2	[375,750)
Distance 3	[750,1500)
Distance 4	[1500,3000)
Distance 5	[3000,6000)
Distance 6	[6000,maximum]

Table 4. Land Productivity Distribution Parameter Estimates

Exporter Characteristics ($\mathbf{X}_i$)	**Mean Effects ($\boldsymbol{\delta}$)**	**Unobserved Reqs ($\boldsymbol{\Sigma_E}$)**	**Agro-Ecological Requirements ($\boldsymbol{\Lambda}$)**				
			elv(j)	**alw(j)**	**trp(j)**	**tmp(j)**	**bor(j)**
ln Arable Land per Ag Worker	0.74***	-0.12***	-4.72***	0.16***	1.57***	0.56***	-2.14***
High Elevation	8.92***	0	0	-1.99***	13.82***	-12.93***	26.75***
Tropical Climate Share	-2.33***	0.6***	-4.58***	0.14	7.47***	3.12***	-10.6***
Temp. Climate Share	1.14***	-0.09	0	-0.43***	-3.53***	-0.01	3.55***
Boreal Climate Share	1.19***	-0.51***	4.57***	0.29**	-3.94***	-3.11***	7.05***

*** indicates significance at the 1% level, ** indicates significance at the 5% level
* indicates significance at the 10% level.
Note: Values in this table are inclusive of the term $\theta\alpha_i(1-\beta_i)$

Table 5. Average Agricultural Sector Productivity Estimates

Country	$\tilde{S}_i$	$\hat{ex}_i$
Argentina	3.76***	0.71***
Australia	-0.06	0.3*
Austria	-0.78*	0.87***
Belgium	-8.82***	2.48***
Bolivia	0.13	-1.9***
Brazil	1.21***	0.16
Bulgaria	0.12	0.26*
Canada	-4.94***	2.78***
Chile	-0.45	2.02***
China	6.83***	0.91***
Colombia	-9.22***	1.93***
Costa Rica	-12.32***	2.16***
Cote d'Ivoire	-0.85*	-1.28***
Czech Republic	-1.56***	-0.28*
Denmark	-0.97**	-0.03
Ecuador	-3.97***	0.63***
Estonia	1.11**	-2.59***
Ethiopia	5.13***	-1.38***
Finland	3.47***	-2.52***
France	-3.72***	1.93***
Germany	-3.69***	1.71***
Ghana	0.21	-2.06***
Greece	2.77***	0.25*
Honduras	0.08	-0.74***
Hungary	0.42	-0.67***
Iceland	0.85***	-2.45***
India	2.48***	-0.27*
Indonesia	-1***	0.72***
Ireland	1.15**	-1.53***
Israel	0.03	-0.04
Italy	-2.52***	2.17***
Japan	1.23**	0.13
Kazakhstan	1.68***	-2.02***
Kenya	3.3***	-1.51***
Lithuania	-1.28**	-1.56***
Malaysia	-1.74***	0.76***
Mexico	1.85***	0.77***
Morocco	3.08***	-0.78***
Netherlands	-1.6***	1.18***
New Zealand	8.26***	-0.62***
Norway	6.57***	-2.72***
Paraguay	0.28	-0.84***
Peru	-6.75***	1.64***
Poland	0.01	-0.44**
Portugal	-0.88*	-0.15
Russia	-0.78*	-0.12
Slovakia	4.68***	-2.27***
Slovenia	3.36***	-2.03***
South Africa	1.11***	2.77***
South Korea	5.17***	-1.42***
Spain	-4.68***	3.77***
Sri Lanka	-1.07**	-0.08
Sweden	0.73*	-0.8***
Switzerland	-0.63**	0.76***
Thailand	-1.01**	0.03
Tunisia	1.23**	-0.97***
Turkey	4.68***	1.43***
Ukraine	2.52***	-1.07***
UK	-3.49***	1.43***
Uruguay	2.58***	-0.52***
Venezuela	-3.09***	-1.89***
Vietnam	3.26***	-0.47***
USA	-3.41***	3.35***

Table 6. Trade Cost Distribution Parameters

Country Pair Characteristics	**Mean Effect ($\boldsymbol{\beta}$)**	**Unobserved Heterogeneity ($\boldsymbol{\Sigma_t}$)**
Common Border	-0.93***	2.78***
Common Language	1.52***	0.22
Common RTA	-0.34**	1.51***
Distance 1	-1.19***	2.91***
Distance 2	-2.79***	2.25***
Distance 3	-2.91***	0.35
Distance 4	-4.88***	0.97***
Distance 5	-6.9***	-0.13
Distance 6	-8.13***	0.36

*** indicates significance at the 1% level,
** indicates significance at the 5% level
* indicates significance at the 10% level.
Note: Values in this table are inclusive of the term θ.

Table 7. Predicted Trade Costs

Country	Ratio of medians
Argentina	37.34
Austria	26.31
Belgium	11.59
Brazil	3.02
Bulgaria	20.73
Czech Republic	20.21
Denmark	10.51
Estonia	15.47
Finland	10.16
France	8.28
Germany	16.55
Greece	6.43
Hungary	30.46
Ireland	5.32
Italy	14.02
Lithuania	14.83
Netherlands	10.17
Paraguay	1.97
Poland	18.47
Portugal	4.59
Slovakia	26.27
Slovenia	10.25
Spain	6.85
Sweden	9.55
UK	18.51
Uruguay	2.59
Venezuela	1.16

Table 8. U.S. Competitors

Ratio of U.S. bilateral trade elasticity to median bilateral elasticity across all countries, Average in bloc

	Relative Elasticity (*average in trade bloc*)	
Competitor	Mercosur	European Union
Argentina	9.71	7.35
Brazil	36.63	11.10
Paraguay	0.11	0.06
Uruguay	0.09	0.12
Venezuela	0.57	0.18
Mercosur Average	9.42	3.76
Italy	12.02	19.72
Spain	8.74	9.15
Germany	4.06	6.42
Denmark	3.39	3.77
Netherlands	2.10	4.15
Greece	1.06	1.29
UK	0.64	1.11
Bulgaria	0.82	0.81
Belgium	0.41	0.78
France	0.35	0.42
Portugal	0.19	0.32
Finland	0.23	0.31
Ireland	0.23	0.28
Sweden	0.07	0.10
Poland	0.05	0.06
Hungary	0.05	0.05
Czech Republic	0.02	0.02
Austria	0.02	0.02
Estonia	0.01	0.01
Slovenia	0.00	0.01
Slovakia	0.00	0.00
Lithuania	0.00	0.00
E.U. Average	1.57	2.22

Table 9. Regional Trade Liberalization Elasticity in Mercosur Markets

Ratio of exporter's regional trade elasticity to median E.U. regional trade elasticity

	Exporter								
Import Market	USA	Italy	Spain	Greece	Germany	UK	Brazil	Argentina	Paraguay
Argentina	-0.02	6.57	5.58	4.40	0.92	1.10	-0.16	-21.28	-0.20
Brazil	-0.73	1.95	6.10	0.35	1.15	0.15	-18.95	-0.63	-0.03
Paraguay	-0.05	0.13	15.69	4.16	0.78	0.01	-0.02	-0.21	-19.03
Uruguay	-0.01	0.00	12.22	0.00	0.00	4.69	-0.23	-0.17	-0.05
Venezuela	-0.83	0.00	14.45	0.00	0.00	0.02	-0.13	-0.14	0.00

Table 10. Regional Trade Liberalization Elasticity in E.U. Markets

Ratio of exporter's regional trade elasticity to median Mercosur regional trade elasticity

	Exporter							
Import Market	USA	Argentina	Brazil	Other Ave.	Spain	Italy	France	Germany
Austria	-0.03	0.28	4.60	0.04	-0.07	-0.05	-0.02	-0.23
Belgium	-0.19	1.50	3.27	0.08	-0.19	-0.07	-0.42	-0.10
Bulgaria	-0.04	0.84	4.15	0.00	-0.01	-0.02	-0.02	-0.01
Czech Republic	-0.02	0.07	4.92	0.00	-0.36	-0.02	-0.02	-0.03
Denmark	-0.07	0.47	4.41	0.04	-0.14	-0.03	-0.03	-0.07
Estonia	-0.04	5.00	0.00	0.00	-0.07	-0.02	0.00	-0.05
Finland	-0.04	0.17	4.83	0.00	-0.18	-0.01	-0.02	-0.06
France	-0.03	1.33	3.33	0.11	-0.33	-0.02	-3.36	-0.02
Germany	-0.12	0.62	4.00	0.13	-0.31	-0.04	-0.04	-2.81
Greece	-0.02	0.93	3.25	0.27	-0.01	-0.02	-0.12	-0.04
Hungary	-0.01	0.15	4.85	0.00	-0.02	-0.04	-0.01	-0.08
Ireland	-0.01	1.60	3.05	0.11	-0.12	-0.01	-0.13	-0.07
Italy	-0.04	0.97	3.52	0.17	-0.16	-3.27	-0.09	-0.09
Lithuania	-0.26	0.47	4.49	0.01	-0.06	-0.02	-0.01	-0.02
Netherlands	-0.03	0.99	2.37	0.55	-0.21	-0.01	-0.11	-0.04
Poland	-0.01	1.09	3.87	0.02	-0.17	-0.03	-0.02	-0.07
Portugal	-0.07	1.24	3.58	0.06	-0.53	-0.01	-0.17	-0.04
Slovakia	-0.02	1.67	3.33	0.00	-0.15	-0.03	-0.05	-0.05
Slovenia	0.00	1.26	3.39	0.12	-0.12	-0.17	-0.04	-0.05
Spain	-0.04	1.00	3.68	0.11	-3.96	-0.02	-0.13	-0.04
Sweden	-0.04	0.77	4.16	0.02	-0.22	-0.07	-0.03	-0.05
UK	-0.08	1.07	3.51	0.14	-0.40	-0.04	-0.07	-0.02

Table 11. Comparing the elasticity of U.S. market share in E.U. and Mercosur markets

Ratio of U.S. regional trade elasticity to the median across import markets

Import Market	Relative U.S. Elasticity
Belgium	10.81
Germany	2.78
Portugal	2.65
Lithuania	2.25
UK	1.31
Spain	1.23
Netherlands	1.01
Sweden	0.94
Italy	0.78
Bulgaria	0.66
Finland	0.60
Denmark	0.47
Brazil	0.44
Venezuela	0.39
France	0.20
Greece	0.14
Austria	0.08
Czech Republic	0.07
Poland	0.06
Ireland	0.05
Slovenia	0.03
Hungary	0.02
Slovakia	0.01
Paraguay	0.01
Estonia	0.00
Uruguay	0.00
Argentina	0.00