Asia-Pacific Integration with China vs. the United States:

Examining trade patterns under heterogeneous agricultural sectors

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Abstract

This article compares the effects on global agricultural trade patterns of Asia-Pacific regional economic integration led by the United States versus that by China. Our analysis employs a Eaton-Kortum type model in which agricultural producers have access to technology with heterogeneous productivity. Unlike the standard Eaton-Kortum model, product specific-productivity is linked to a country's land and climate characteristics and trade costs are product-specific. We derive a structural relationship between the probability a country has comparative advantage in a given export market for an individual agricultural product and the bilateral costs of trading that product controlling for the product-specific unit costs of production from a general equilibrium framework. We specify the relationship as a random coefficients logit model to estimate a country-specific distribution of trade costs and productivity across agricultural products. We use these estimated distributions to explore the set of bilateral relationships from which Asia-Pacific integration is likely to generate the largest shifts in agricultural trade patterns.

Key words: Asia-Pacific integration, agricultural trade, free trade agreements

China and the United States are two of the largest global trading powers. Together they represent almost 20% of world trade and 15% of total agricultural trade. Both countries are pursuing Asia-Pacific regional trade agreements with formal negotiations at different stages. The United States is leading discussions in the Trans-Pacific Partnership (TPP), which includes 11 other countries but excludes China. China is in discussions toward the

Regional Comprehensive Economic Partnership (RCEP) with 15 other Asia-Pacific countries, seven of which are also part of the TPP negotiations. The RCEP would exclude the United States. Transcending these active negotiations is the idea of a Free Trade Area of the Asia Pacific (FTAAP), a proposed trade bloc encompassing the United States, China, and 19 other Pacific-Rim countries, which has been periodically discussed in the context of Asia-Pacific Economic Cooperation (APEC).

In this study we examine how Asia-Pacific trade liberalization would shift patterns of agricultural production and trade using a novel model and empirical technique for predicting the response of bilateral market share to changes in trade costs. Since the TPP, RCEP and FTAAP are at very different stages of formal negotiations we abstract from the specific agreements, focusing instead on the outcomes for the United States and China. These two countries are by far the largest regional economies and are thus expected to dominate any trade blocs in which they participate, but their impacts on agricultural trade are likely to contrast sharply in both nature and magnitude. First, the United States is a technologically advanced agricultural producer and major global exporter, whereas China is a low cost producer and large net importer. Second, differences in the characteristics of Chinese and U.S. resources give each of them comparative advantage in distinct sets of agricultural products.

Our analysis employs a model in which agricultural producers have access to technology with heterogeneous productivity across products. In the model, as in Dornbusch, Fischer, and Samuelson (1977) and its multi-country extension in Eaton and Kortum (2002) (henceforth EK), trade costs impede the forces of comparative advantage from productivity differences. Falling trade costs reveal these differences, generating new gains from trade. Unlike EK and its antecedents, our approach links agricultural product-specific productivity to an exporter's land and climate characteristics and allows for heterogeneity in trade costs.

As in EK, the model delivers a structural relationship between the probability a country has comparative advantage in a given export market for an individual agricultural product and the bilateral costs of producing and exporting the product which resembles a standard gravity model.[1] However, tying product-specific productivity to exporter characteristics weakens the assumption that allows EK to transform this relationship into a log-linear equation. The log-linear model is convenient for the purposes of estimating trade costs and other determinants of trade patterns, but it is inadequate to describe how agricultural trade patterns shift in response to changes in trade costs. In the log-linear specification, the elasticity of trade with respect to a given exporter's trade costs is constant across all of its competitors.[2] This implies that the direction and magnitude of shifts in trade patterns is fully determined by each competitor's absolute advantage in agriculture without regard to whether they specialize in products that are similar to the country whose access has improved. This is a counter-intuitive assumption in the case of agriculture, where natural resource endowments have a strong and systematic influence on the set of goods in which a country specializes.

Instead, we specify the relationship between trade flows and country-specific costs of production and trade as a random coefficients logit model. The estimated parameters describe a distribution of productivity and trade costs across agricultural products for each exporter that is a deterministic function of its land and climate characteristics. Our approach generates larger magnitude trade elasticities among countries whose land and climate characteristics induce them to specialize in a similar set of agricultural products and who face similar costs to export those products. This empirical technique connects our product-level conceptual model to sector-level trade flows with minimal data requirements beyond what is required for a standard gravity model.

Model

The world is comprised of I countries engaged in bilateral trade. Importers are indexed by n and exporters by i. The agricultural sector is comprised of a continuum of products indexed by $j \in [0,1]$. Within each country, land productivity and technology are heterogeneous across products. Technology is the outcome of a country-specific research and development process as in EK. Land productivity is derived from the coincidence of a product's land and climate requirements and the nature of a country's land and climate endowment. To produce quantity $q_i(j)$ of product j requires labor (N_i), land (L_i) and intermediate inputs $(\mathbf{Q}_i)$ combined according to the nested Cobb-Douglas function:

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

where $z_i(j)$ is a technological productivity-augmenting random variable specific to product j in country i; $a_i(j)$ is country i, product j-specific land productivity; and $\mathbf{Q}_i$ is an aggregate of intermediate inputs from the agricultural, manufacturing and services sectors, combined in a Cobb-Douglas fashion as in Caliendo and Parro (2012) and Shikher (2012).

As in EK, technological productivity, $z_i(j)$ is independently distributed across products following a Frechet distribution with parametersT_i and θ:

$$(2) \quad F_{z_n}(z) = exp\left\{ -T_i z^{-\theta} \right\}$$

A high value of T_i means country i is more likely to have a high realization of $z_i(j)$. A smaller value of $\theta > 1$ implies a larger dispersion of technological productivity differences. We assume the dispersion of technological productivity is constant across countries.

The value $a_i(j)$ reflects the overall suitability of exporter i's land to produce 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. We assume $a_i(j)$ and $z_i(j)$ are independent.

Producers in exporting country i 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 $\tau_{ni}(j) \geq \tau_{nl}(j)\tau_{jl}(j)$. We assume $\tau_{ni}(j)$ follows a parametric density that is a deterministic function of product-specific policies and other marketing requirements. We assume trade costs are distributed independently of both $a_i(j)$ and $z_i(j)$.

Markets are perfectly competitive. Therefore, the price offered for product j, is equal to the unit cost of producing in country i and marketing in country n:

$$(3) \qquad p_{ni}(j) = \frac{\tilde{a}_i(j) c_i \tau_{ni}(j)}{z_i(j)}$$

where $\tilde{a}_i(j) \equiv a_i(j)^{-\alpha_i(1-\beta_i)}$ and c_i is the cost of an input bundle. Trade occurs as buyers seek out the lowest price offer for each product. The price actually paid for product j is therefore $p_n(j) = min_i\{p_{ni}(j)\}$. Given the assumption that technological productivity is independently Frechet distributed, the probability exporter i offers the lowest price for product j in market n is:

$$(4) \qquad Pr(p_{ni}(j) \leq p_{nl}(j) \forall l) = \pi_{ni}(j) = \frac{T_i \left(\tilde{a}_i(j) c_i \tau_{ni}(j)\right)^{-\theta}}{\sum_{l=1}^{I} T_l \left(\tilde{a}_l(j) c_l \tau_{nl}(j)\right)^{-\theta}}$$

Each exporter specializes in the set of products for which this probability is highest. Notice that equation 4 is increasing in $a_i(j)$. Thus we expect all exporters with similar densities of $a_i(j)$ to systematically specialize in a similar set of products. Notably, this does not imply complete specialization in a bilateral relationship at the sector-level or even in like products within a sector. Cross-country differences in realizations of $z_i(j)$ and even small differences in values of $a_i(j)$ can create comparative advantage and thus incentives for agricultural trade even among countries with very similar agro-ecological characteristics.

Heerman (2013) shows that exporter i's total share of market n agricultural expenditure is the unconditional probability it offers the lowest price for an agricultural product:

$$(5) \qquad \pi_{ni} = \int \frac{T_i \left(\tilde{a}_i(j) c_i \tau_{ni}(j)\right)^{-\theta}}{\sum_{l=1}^{I} T_l \left(\tilde{a}_l(j) c_l \tau_{nl}(j)\right)^{-\theta}} dF_{\tilde{\boldsymbol{a}}_n}\left(\tilde{\boldsymbol{a}}\right) dF_{\boldsymbol{\tau}_n}\left(\boldsymbol{\tau}_n\right)$$

where $dF_{\tilde{\boldsymbol{a}}_n}\left(\tilde{\boldsymbol{a}}\right) dF_{\boldsymbol{\tau}_n}\left(\boldsymbol{\tau}\right)$ 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 the gravity equation at the heart of the EK model, equation 5 relates market share to exporter competitiveness and bilateral trade costs, and can be specified to estimate a set of parameters that describe the joint distribution productivity and trade costs across products. In EK, independently distributed technology is the only source of productivity differences and trade costs are constant across products. This implies that the set of products in which an exporter has comparative advantage is randomly determined by realizations of $z_i(j)$ and is not influenced by the characteristics of its land endowment.

Our approach allows us to characterize agricultural sector-level trade patterns without abstracting from systematic differences in trade costs and sources of comparative advantage across products. This produces a more nuanced picture of how patterns of agricultural trade shift in response to liberalization. To see this, consider the elasticity of π_{ni} with respect to competitor country l's trade costs, which can be written:[3]

$$\frac{\partial \pi_{ni}}{\partial \tau_{ni}} \frac{\tau_{nl}}{\pi_{ni}} = \frac{\theta}{\pi_{ni}} \left(cov\left(\pi_{ni}(j), \pi_{nl}(j)\right) + \pi_{ni} \times \pi_{nl} \right) \;\; l \neq i \tag{6}$$

This elasticity varies across countries and competitors, whereas in a model where all heterogeneity is independently distributed across products, elasticity with respect to changes in country l's trade costs is constant across all competitors and directly proportional to π_{nl}. The elasticity in equation 6 is increasing in the covariance of product-specific comparative advantage, $cov\left(\pi_{ni}(j), \pi_{nl}(j)\right)$, which comes entirely from covariance in $a_i(j)$ and $\tau_{ni}(j)$. This implies that country i's market share is more likely to contract in response to a fall 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.

Equation 6 reveals the degree to which country i's market share is sensitive to changes in a single competitor's cost to access market n. To study the effects of Asia-Pacific integration we will examine the effect of simultaneous changes in multiple competitors' trade costs. We can obtain an estimate of the effect of multilateral liberalization on bilateral market share from the total differential of π_{ni} with respect to the average trade costs of a subset of competitors, $L \in I$:[4]

(7)

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

Equation 7 has two components: The term in the second parentheses captures the effect of the decline in country i's own trade costs. The first term captures the effect of its competitors' lower trade costs. From this term we can see that country i's market share gains from multilateral integration relative to bilateral trade cuts are decreasing in the extent to which the countries in subset L: 1) are likely to compete head to head with country i; and 2) have a large existing share of the country n market.

Specification

We estimate the parameters of the agricultural sector productivity and trade cost distribution by specifying equation 5 as a random coefficients logit model. To begin, as in EK we define $S_i = ln(T_i) - \theta ln(c_i)$ and capture it with a country fixed effect. Next, we specify $a_i(j)$ as a parametric function of exporter agro-ecological endowments and product agro-ecological requirements:

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

where $\mathbf{X}_i$ is a $1 \times k$ vector of variables describing country i's agro-ecological characteristics; δ 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; Λ is an $m \times k$ matrix of coefficients that describe how the relationship between elements of $\mathbf{X}_i$ and land productivity varies across products with these observable requirements; and $\boldsymbol{\nu}_E(j)$ is a $1 \times k$ vector that captures the effect of unobservable product j-specific requirements with scaling matrix $\boldsymbol{\Sigma}_E$.

We specify product-specific trade costs as:

$$(9) \quad ln\left(\tau_{ni}(j)\right) = \mathbf{t}_{ni}\boldsymbol{\beta}(j) = \mathbf{t}_{ni}\boldsymbol{\beta} + ex_i + \mathbf{t}_{ni}\left(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t\right)' + \xi_{ni}$$

where $\mathbf{t}_{ni}$ is a vector of variables that describe the relationship between exporter i and import market n. The term ex_i is an exporter-specific trade cost captured by a fixed effect. We assume that all product-specific trade costs are unobservable and capture them with $\boldsymbol{\nu}_{t_n}(j)$, a vector of standard normal random variables with scaling matrix $\boldsymbol{\Sigma}_t$. Finally, ξ_{ni} captures unobservable or unquantifiable bilateral trade costs that are common across products and orthogonal to the regressors.

Using our definitions of $a_i(j)$ and $\tau_{ni}(j)$ in equation 5, we obtain a random coefficients logit model of agricultural market share:

$$(10) \quad \pi_{ni} = \int \frac{exp\left\{S_i + \theta\alpha_i(1-\beta_i)\mathbf{X}_i\boldsymbol{\delta}(j) - \theta\mathbf{t}_{ni}\boldsymbol{\beta}(j)\right\}}{\sum_{l=1}^{I} exp\left\{S_l + \theta\alpha_l(1-\beta_l)\mathbf{X}_l\boldsymbol{\delta}(j) - \theta\mathbf{t}_{nl}\boldsymbol{\beta}(j)\right\}}$$

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 10 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):

$$(11) \quad \pi_{ni} = \frac{1}{ns}\sum_{j=1}^{ns} \frac{exp\left\{\tilde{S}_i + \theta\alpha_i(1-\beta_i)\boldsymbol{X}_i\boldsymbol{\delta}(j) - \theta\mathbf{t}_{ni}\boldsymbol{\beta}(j)\right\}}{\sum_{l=1}^{I} exp\left\{\tilde{S}_l + \theta\alpha_l(1-\beta_l)\boldsymbol{X}_l\boldsymbol{\delta}(j) - \theta\mathbf{t}_{nl}\boldsymbol{\beta}(j)\right\}}$$

where $\tilde{S}_i = S_i + \mathbf{X}_i\boldsymbol{\delta}$ and $ns = 100$. Finally, we use the minimum distance procedure suggested by Nevo (2000) to obtain S_i from $\tilde{S}_i$.[5]

Data

Bilateral market shares are calculated using 2006 production and trade data from the UN Food and Agriculture Organization (FAO) (FAO 2013). This data is available at the "item" level of aggregation. The FAO item-level classification does not correspond directly to a particular level in the HS or ISIC classification systems, but both trade and production data are classified under the same codes. We compile a set of 135 agricultural items for which data on both bilateral trade and the gross value of production in U.S. dollars are available for countries engaged in TPP and RCEP negotiations.

The variables that make up $\mathbf{X}_i$ and $\mathbf{E}(j)$ are chosen based on their relevance to specialization within the agricultural sector. Elements of the matrix $\mathbf{X}_i$ describe each exporter along the dimensions that systematically influence the pattern of specialization in agriculture. The matrix $\mathbf{E}(j)$ includes production requirements that match individual products to countries where we observe their production. In principle, with a fully specified vector $\mathbf{E}(j)$, the interaction between these matrices should reveal which products each country is most likely to produce. In practice, it tells us which countries are likely to produce the same products.

We define $\mathbf{X}_i = \begin{bmatrix} lpaw_i & elv_i & trp_i & tmp_i & bor_i \end{bmatrix}$, where $lpaw_i$is log arable land per agricultural worker, 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. Data on arable land per agricultural worker comes from World Bank (2012). Elevation data comes from CIESIN (2010). Climate information comes from the GTAP Land Use Database (Monfreda, Ramankutty, and Hertel 2008).

We assume $\mathbf{E}(j)$ is distributed across products following the empirical distribution of requirements for agricultural products defined at the "item" level by the FAO. We calculate the observable requirements for each of these items as an export-weighted average of the elements of $\mathbf{X}_i$: $\mathbf{E}(j) = \begin{bmatrix} lpaw(j) & elv(j) & trp(j) & tmp(j) & bor(j) \end{bmatrix}$. Products and their estimated requirements are listed in the Appendix.

The requirements capture the intensity of product j cultivation at high altitudes, $elv(j)$; the land intensity of production, $lpaw(j)$; and the intensity of cultivation in each climate zone. Similarly, we define $\mathbf{t}_{ni} = \begin{bmatrix} brd_{ni} & lng_{ni} & \mathbf{d}_{ni} \end{bmatrix}$, where bdr_{ni} and lng_{ni} equal one if the two countries share a common border or language and the 1×6 vector d_{ni} assigns the country pair to one of six distance categories, as in EK.[6]

The ns=100 products used to evaluate equation 11 for each importer and its trading partners are drawn from the empirical distribution of the products it imports. To construct this distribution, we first use FAO item level import data to estimate $\hat{F}_(\mathbf{E}_n)(\mathbf{E})$ the empirical distribution of $\mathbf{E}(j)$ across products imported by each market. We compile a list of 100 items imported by each market and define them by their corresponding value of $\mathbf{E}(j)$. Unique values of $\mathbf{E}(j)$ are included in proportion to the share of the item they represent 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 15 entries the list that represents $\hat{F}_(\mathbf{E}_n)(\mathbf{E})$. Next we draw ns = 100 values of $\mathbf{E}(j)$ at random from each country's distribution. The distribution $\hat{F}_(\mathbf{E}_n)(\mathbf{E})\hat{F}_(\boldsymbol{\nu}_n)(\boldsymbol{\nu})$ is completed by associating each product with $\boldsymbol{\nu}_n(j) = [\boldsymbol{\nu}_{\mathbf{E}}(j)\boldsymbol{\nu}_(\mathbf{t}_n)(j)]$ drawn from a standard multivariate normal distribution, effectively generating a "data set" of $ns \times I$=5800 products imported by each market.

Parameter Estimates

Table 2 contains estimates for $\boldsymbol{\delta}$, $\boldsymbol{\Lambda}$, and $\boldsymbol{\Sigma}_{\mathbf{E}}$. Coefficients on all climate variables are normalized to sum to zero. As such, the effects of 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. The average climate is 28% tropical, 57% temperate and 15% boreal. The average traded product is 32% tropical, 57% temperate and 11% boreal.

The total effect of each exporter characteristic is the sum of the mean effect in column 1 and the product-specific effects in the columns that follow. Figures 1 and 2 contain frequency plots of the total effects of $temp_i$ and $trop_i$ across all 5,800 traded products. These figures show that larger than average tropical and temperate climate endowments increase the probability of offering the lowest price in some products and decrease it for others.

As an example of how to interpret the estimates in Table 2, consider the effect of the share of land in a tropical climate. The mean effect, $\hat{\delta}_{trop} = 1.42$ implies that market share is increasing in the extent to which a country has a larger than average share of land in a tropical climate zone. The negative and statistically significant value of $\hat{\lambda}_{lpaw} = -0.56$ indicates that this advantage is decreasing for land-intensive products. In contrast, $\hat{\delta}_{temp} = -0.18$ implies that market share is decreasing in the extent to which a country has a larger-than-average share of land in a temperate climate zone. This disadvantage is diminished significantly, and even overtaken, for land-intensive products $\hat{\lambda}_{lpaw} = 0.2$.

Table 3 contains estimates for $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma_t}$. Negative coefficient values imply higher trade costs, but lower market share. The values in $\boldsymbol{\Sigma_t}$ can be interpreted like a standard error around the mean effect. Thus the larger magnitude values of $\hat{\sigma}_{brd} = 3.41$ and $\hat{\sigma}_{lng} = -2.64$ relative to the corresponding mean effects imply that sharing a border or language increases trade costs for some products and decreases them for others (Figure 3). This is sensible in agriculture, where countries that are geographically near or culturally similar are likely to specialize in similar products. As such, the benefit of proximity for an exporter is diminished by the fact that it is more likely to be competing head-to-head with domestic producers that do not face the additional burden of trade costs. These values may also be picking up the effects of policy barriers that raise trade costs on import-competing products.

In contrast, trade costs consistently increase with the distance between the importing and exporting country. The mean effect of each distance variable is negative and the magnitude of the mean effect increases almost monotonically as the distance grows from the nearest category, Distance 1 to the most distant category, Distance 6. The effect of unobserved heterogeneity is smaller in magnitude than the mean effects, implying that the total effect of distance remains negative for substantially all products.

Coefficient estimates for $\tilde{S}_i$ and ex_i are listed in Table 4. These values are normalized to sum to zero. Values of ex_i greater than zero imply that the country has lower than average export costs. Values of $\tilde{S}_i$ are interpreted as a measure of overall competitiveness in the average product relative to the average country. Recall that $S_i = T_i - \theta ln(c_i)$, which is increasing in average productivity, T_i, but decreasing in costs of production, c_i. Therefore, a country with high productivity in the average product may nonetheless have a negative value of $\hat{S}_i$ if it has, e.g., very high wages. Moreover, the normalization within product space makes these values difficult to interpret since a country with very high productivity in general, may have relatively lower productivity in the average product.

Implications for Asia-Pacific Integration led by China vs. the United States

In this section we compare shifts in patterns of production and trade under Asia-Pacific integration led by the United States vs. China. First we examine the distribution of the United States and China's productivity across agricultural products. We use these distributions to explore the extent to which the two countries are "natural competitors". That is, the extent to which they would compete head-to-head in the same products based on their agricultural resources alone. Next we use the parameter estimates in Tables 2 and 4 with equation 7 to examine how the model predicts U.S. and Chinese market shares shift in response to liberalization in the Asia-Pacific region. Note that these are partial equilibrium estimates and thus do not incorporate additional effects from changes in relative input prices.

China and the United States are not natural competitors in agriculture

To assess whether the United States and China will tend to be close competitors in export markets we first compare each Asia-Pacific country in terms of its land and climate characteristics in Table 5. Both the United States and China have predominantly temperate climates with moderate shares of rural land at high altitudes. The key difference between the two countries is in the amount of arable land per agricultural worker. Arable land per agricultural worker is more than 180 times greater in the United States than it is in China.

In fact, the size of land holdings is a critical challenge to China's agricultural sector and an asset to the United States. China's agricultural economy is dominated by 200 million small family farms that operate on less than 0.5 hectares based on 2006 data (Gao, Huang, and Rozelle 2012). As a result of limited land resources and incomplete reform of land tenure practices, aggregation of production in China is costly and the resulting atomistic land structure leads to higher cost and land inefficiencies (Lohmar et al. 2009). In contrast, the average U.S. farm size is 176 hectares and production is heavily concentrated in large farms (NASS 2012).

We can examine the level of natural competitiveness more explicitly by comparing the U.S. and Chinese productivity distributions across products. Product-specific natural competitiveness is defined here as the percent deviation of each country's total productivity in product j, $\hat{S}_i + \mathbf{X}_i\hat{\boldsymbol{\delta}}(j)$ from the average total productivity for that product. The distribution is normalized in this manner because productivity is systematically higher for some products than others, and competitiveness depends on relative productivity. We calculate this value for each of the $j = [1, 132]$ items in the FAO data and plot them in Figures 4 and 5.

First, notice in Figure 4 that the United States has higher than average productivity for almost all products, whereas China's productivity is less than the average. To highlight the role of differences in U.S. and Chinese land endowments we sort product-specific competitiveness in terms of decreasing land intensity in Figure 1. Notice that the products in which China's productivity is higher than the U.S. are among the most land-intensive. More generally, the distribution of U.S. competitiveness is virtually a reflection of China's distribution. This suggests that in the absence of trade costs, the United States and China would specialize in entirely different sets of products.

Observed U.S. and Chinese agricultural trade patterns are consistent with our estimated distribution of competitiveness. The United States tends to export land-intensive commodities such as grains, oilseeds and livestock, while China exports labor intensive horticultural products. China does obtain a significant share of its consumption of the land-intensive grains rice, wheat, and corn domestically, but producers of these commodities benefit from to government support policies designed to maintain self-sufficiency, a factor that is not directly addressed by our model. In third-country markets, the United States and China compete in very few products. Both countries export fresh fruit and vegetables such as apples, carrots and turnips, but generally supply these products to different markets.

The closest natural competitors to China and the United States will be those countries whose $\mathbf{X}_i$ matrices are most similar along the dimensions most important for predicting product-specific land productivity. We define "similarity" between two countries as the weighted Euclidean distance between their characteristics, where the weights on each element are the mean effect coefficients in Table 2. Countries in Table 5 listed after China are given in decreasing similarity to the United States. Not surprisingly, Canada, a land abundant country without land in a tropical climate zone is the most similar to the United States. Chile is the most similar country to China. Like China, Chile is a net exporter of fresh fruits (such as apples) and net importer of many land intensive products. Figure 5 adds the distribution of competitiveness for Canada and Chile to those of the United States and China. Products are sorted in order of decreasing U.S. competitiveness. Both China and the United States' distribution follow very closely with their matched competitor.

Figures 4 and 5 suggest that in the absence of trade costs U.S. and Chinese producers would almost never compete head-to-head in the same products. However, transportation costs, tariffs, and other policy and marketing costs may be as important to competitiveness in a given import market as technological and natural productivity differences. Regardless of whether they arise from government policy or a countries geographical location relative to its trading partners, these costs obscure the gains from trade on the basis of productivity differences.

Given the economic and statistical significance of the border, language and distance variables in Table 3, we expect stronger covariance in product-specific probability of comparative advantage within regions than across, and larger existing market shares among neighboring countries, everything else equal. These forces will tend to increase an exporter's elasticity with respect to its own neighbors' trade costs as well as the trade costs of competitors that are geographically close to the import market. Since the countries involved in Asia-Pacific integration are located in geographically and culturally distinct regions straddling the Pacific Ocean, both effects play an important role in determining trade patterns.

Table 6 contains the U.S. market share elasticity with respect to each of its competitors in each import market calculated from equation 6. The magnitude of these elasticities reflect the intensity of competition and the openness of the import market. The largest effect implies that a 1% increase in Australia's costs to access the New Zealand market increase U.S. market share by 0.277%. Overall results confirm that the U.S. tends to be in closest competition with Canada and Australia, the most similar countries in terms of land and climate characteristics. China is among the U.S.'s closest competitors in only a few Asian markets, reflecting its large share of these import markets. However, the magnitude of the elasticity with respect to Chinese trade costs is generally quite small.

Asia-Pacific Integration

To explore the effects of Asia-Pacific integration on patterns of trade, we use parameter estimates from Tables 2, 3 and 4 with equation 7 to examine shifts in market share. We model Asia-Pacific integration as a straight 50% cut in average bilateral trade costs for each exporter in the United States, China and 12 other import markets on both sides of the Pacific. The list of countries included are in Tables 7 and 8. The scenario we have chosen for this exercise is purposely abstract[7] and makes no attempt to replicate Asia-Pacific trade agreements under discussion. Our intention is to get an idea of how agricultural trade patterns respond to hypothetical reductions in trade costs, rather than to mimic the impact of a specific agreement.

Tables 7, 8 and 9 contain estimates of the market share effects of three liberalization scenarios: 1) Asia-Pacific integration led by the United States; 2) Asia-Pacific integration led by China; and 3) Asia-Pacific integration that includes both the United States and China. Under all three scenarios, Asia-Pacific integration increases market share for every participating exporter in every participating market. The 50% reduction in trade costs generates a quantitatively large expansion in many markets, but the magnitude varies substantially across country pairs.

Comparing U.S.- to China-led integration, we first note that U.S. market share expansion is much larger than all other exporters under both scenarios in which the United States participates. This suggests that lower barriers to agricultural trade offer substantial opportunities for U.S. producers to expand their access abroad. The simple average increase in the percent of the market held by the United States across countries is 5.02% under U.S.-led integration, far exceeding China's under the corresponding scenario (1.30%).

Second, export market share for other Asia-Pacific countries tends to be larger under China-led integration than under U.S. led integration. Recall from equation 7 that increases in market share are decreasing in competitors' existing shares. An agreement that leaves out one of the world's largest exporter - The United States - will thus naturally offer larger increases to all other participants.

The bulk of most countries' market share expansion is concentrated within geographical sub-regions of the Asia-Pacific. This is particularly true in the case of China. China's market share gains are only economically significant in neighboring Asian countries (Japan, Malaysia) and tend to be smallest in Oceania and the Americas. Similarly, Southeast Asian countries see the largest increases in market share within Southeast Asia, likewise in the Americas. U.S. gains are also strongest in its fellow NAFTA markets. However, the magnitude of this gain is certainly exaggerated by the design of our experiment. A 50% cut in bilateral trade costs is extreme, given that NAFTA was all but fully implemented in 2006.

The above results underline the importance of trade costs in determining global agricultural trade patterns. Recall from equation 5 that market share is decreasing in trade costs. The parameter estimates in Table 3, suggest that neighboring countries will have a larger share of each other's markets than distant countries, particularly for products in which cultural similarity offers additional advantage. While every country has real expansions in market share for their producers outside their neighborhood, the increases tend to be quite small.

While we find that trade costs are key determinants of Asia-Pacific agricultural trade patterns, liberalization does allow the largest exporters to exploit productivity differences arising from variation in land and climate characteristics. For Canada, Australia and China the biggest shifts in flows under the Asia-Pacific integration scenarios are concentrated in neighboring sub-regions with dissimilar land and climate characteristics. Australia's largest market share expansion takes place in its nearby, but climatically dissimilar neighboring region of Southeast Asia. Like Australia, Canada's market share increases most in countries with a dissimilar agricultural endowment. Unlike Australia, Canada's market share increases most outside of Southeast Asia. In fact, the countries in which Canada's market share expands are virtually the complement of Australia's. In contrast, the United States and Indonesia are able to expand market share in a broad range of countries far from their borders. This suggests that these countries are sufficiently competitive in a broad range of products to overcome significant trade barriers and realize climate-based comparative advantage.

A final takeaway from Tables 7-9, despite the partial equilibrium setting, is that Asia-Pacific integration appears to be more trade creating than trade diverting. Bilateral market share gains from participating in Asia-Pacific integration are much larger than the losses from exclusion in every import market. Table 7 shows that U.S. export market shares are little affected by China-led Asia-Pacific Integration. Table 8 shows that Chinese market shares are little changed under a U.S.-led Asia-Pacific Agreement. This reflects the fundamental differences in participating countries' comparative advantage as well as the large geographical distances. Table 9 includes selected countries outside of the Asia-Pacific region. Again, exclusion from the trade bloc has largely insubstantial effects on market shares. Brazil and Argentina are notable exceptions: Under full Asia-Pacific integration, Argentina loses a large share of the Chilean, Peruvian and Malaysian markets and Brazil experiences smaller, but still notable losses in Canada and Japan.

Conclusion

In this paper we present a model of agricultural trade that links the set of products in which an exporter specializes to the agro-ecological features of its land endowment. While its structure resembles a standard gravity model, our approach is tailored to understanding shifts in trade flows rather than determinants of trade patterns. We use the model to estimate parameters that describe a distribution of productivity across products for each country. The results illustrate the role agro-ecological characteristics play in determining the set of products in which a country specializes.

The estimated distributions of productivity across agricultural products imply that in the absence of trade costs, the United States and China would specialize in a very different set of agricultural products. In contrast, countries more agro-ecologically similar to the United States, such as Canada would be close competitors. Estimated elasticities that incorporate the role of trade costs confirm that Canada is, indeed a close U.S. competitor in most export markets. However, these costs place China among the United States' closest competitors in a handful of Asian countries. Nevertheless, the magnitude of this elasticity implies that U.S. market share is still relatively insensitive to changes in Chinese trade costs.

Our hypothetical simulations of Asia-Pacific integration illustrate the complex forces of agro-ecology, productivity differences and trade costs that jointly determine patterns of agricultural trade. We find that integration would shift market share toward the largest and most competitive agricultural exporters, most notably the United States, but also Australia, Canada, China, Indonesia, and Thailand. For most of these countries the increases in market share are largely among the markets in their own "neighborhood", reflecting the continued importance of transportation and other trade costs in determining agricultural trade patterns. The exceptions are the United States and Indonesia, whose relative productivity allows them to overcome trade barriers and exploit comparative advantage from their land and climate characteristics. The finding that Asia Pacific Integration is more trade creating rather than trade diverting supports the notion that natural comparative advantage generate significant gains from agricultural trade.

The design of our experiment is abstract and is not intended to replicate any free trade agreements currently under discussion. Nevertheless, we have demonstrated that a more complex structure of competition among exporters can be revealed using very little data beyond what is required for a standard gravity model of the agricultural sector. This allows for more nuanced predictions of how trade patterns shift in response to Asia-Pacific integration. In future work, we will use our results to parameterize the general equilibrium model of Heerman (2013), which embeds the model of bilateral trade flows that is the focus of this paper. This model will allow us to draw broader conclusions about likely shifts in trade patterns as well as welfare effects of Asia-Pacific integration.

Notes

[1]The gravity equation is the most widely used empirical model of trade. Its theoretical foundation to explain trade flows arises from Ricardian, Heckscher-Ohlin and monopolistic competition frameworks (Deardorff 1998; Anderson 2010).

[2]Importantly, Arkolakis, Costinot, and Rodríguez-Clare (2012) demonstrate that this feature is not unique to EK, but occurs in a broad class of commonly used quantitative trade models that deliver structural gravity models.

[3]Equation 6 assumes that all input prices are held constant for the purposes of clarity. It is therefore a partial equilibrium elasticity.

[4]Again, this is a partial equilibrium expression.

[5]See Train (2009) Chapter 13 for a discussion of approaches to estimating a random coefficients logit model.

[6]See Table 1 for definitions

[7]A 50% cut in trade costs is very large, particularly since there are existing free trade agreements among many of the countries we consider. Moreover, we make no effort in this exercise to shelter any individual products from cuts. In reality, free trade agreements do not uniformly lower trade costs for all agricultural products. Finally, since we apply reductions in purely proportional terms, bilateral trade costs maintain uneven levels across countries. A 50% cut in trade costs between two countries with high trade costs implies a larger magnitude cut than a 50% cut in trade costs between two countries where trade costs are very low.

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Figures

Figure 1. Tropical Land Share Effect

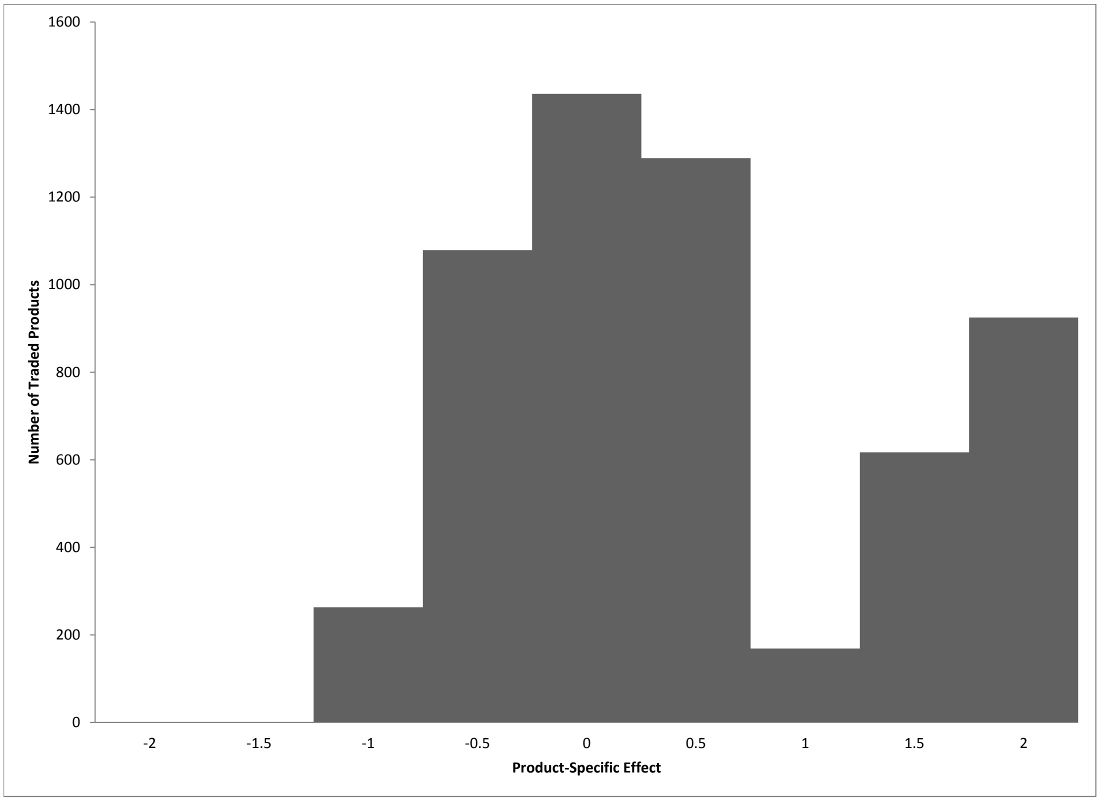


Figure 2. Temperate Land Share Effect

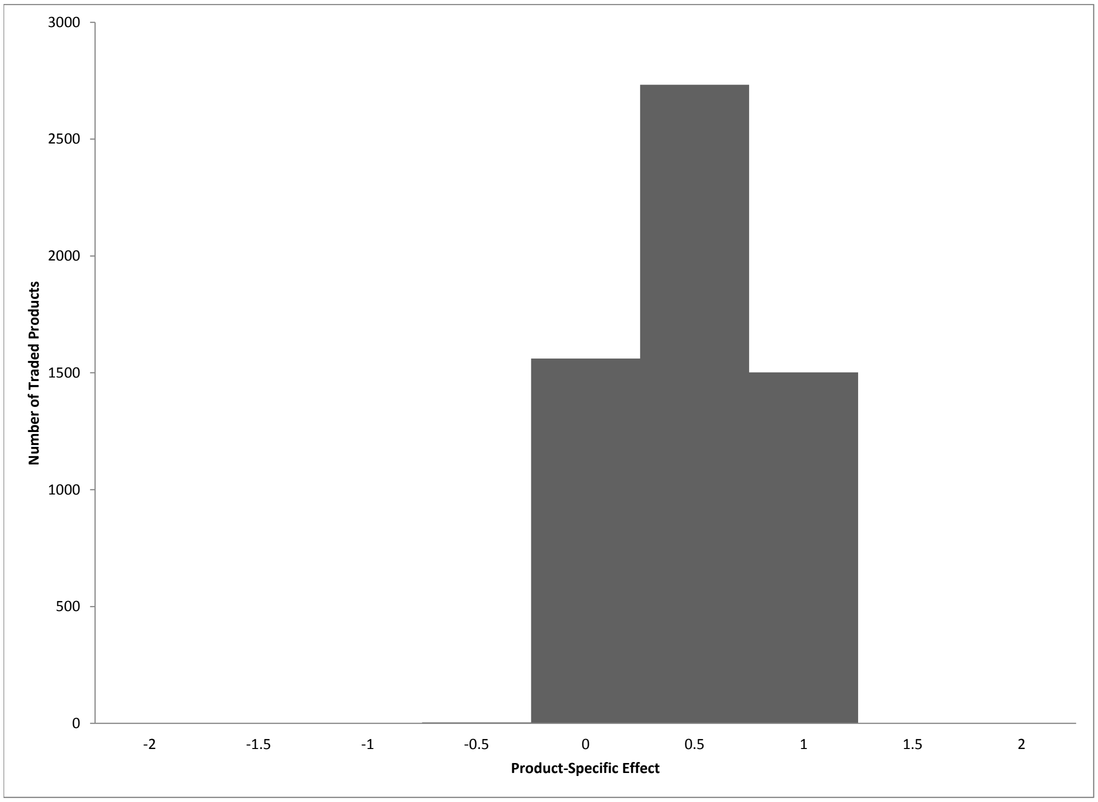


Figure 3. Effect of a Shared Border

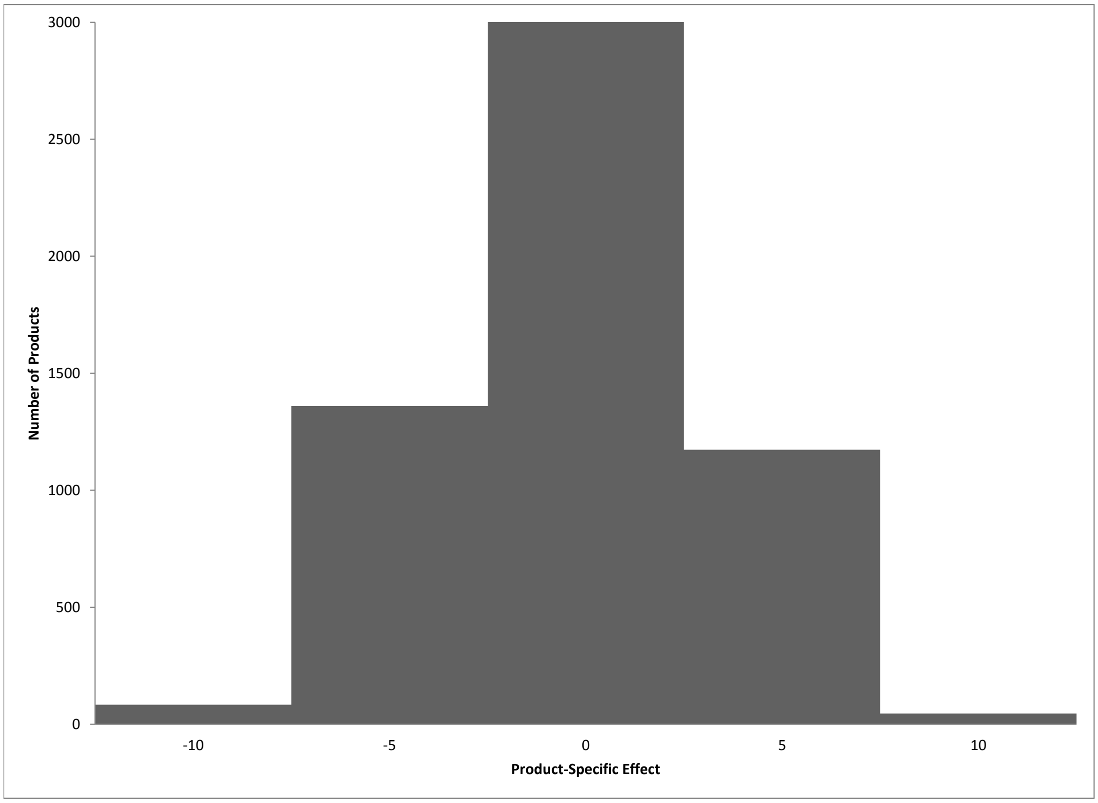


Figure 4. Distribution of Competitiveness across Ag Products

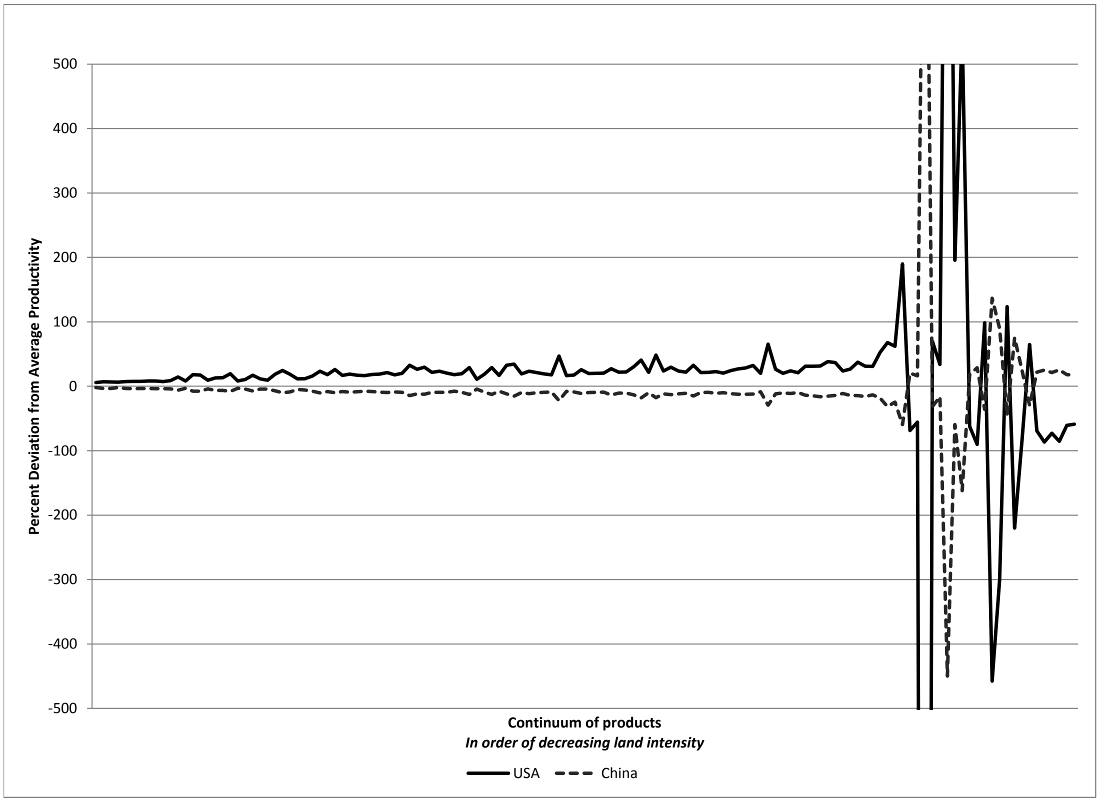
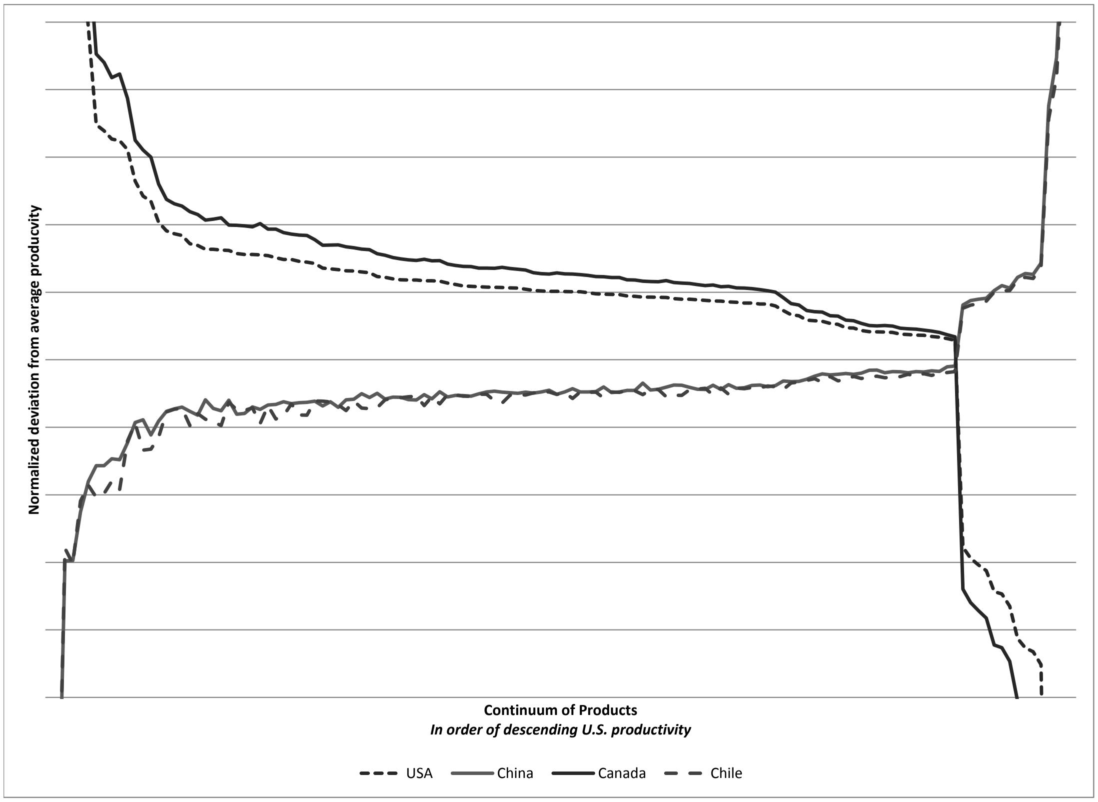


Figure 5. Distribution of Competitiveness: Close Competitors



Tables

Table 1. 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 2. Land Productivity Distribution Parameter Estimates

Exporter Characteristics	Mean Effect ($\boldsymbol{\delta}$)	Unobserved Reqs ($\boldsymbol{\Sigma_E}$)	Agro-Ecological Requirements ($\boldsymbol{\Lambda}$)				
			elv(j)	lpaw(j)	trp(j)	tmp(j)	bor(j)
Tropical Climate Share	1.42***	0.0	0.67*	-0.56***	0.2	0.01	-0.21
Temp. Climate Share	-0.18***	-0.07	-0.02	0.2**	-0.12	-0.04	0.16
Boreal Climate Share	-1.25***	0.07	-0.65	0.36***	-0.08	0.03	0.05
ln Arable Land per Ag Worker	-0.18***	0.0	0.0	-0.01	-0.15	0.3*	-0.15
High elevation	1.29***	-0.08	-0.05	-0.53**	-1.83***	-1.83***	3.66

*** indicates significance at the 1% level, ** indicates significance at the 5% level
* indicates significance at the 1% level.

Table 3. Trade Cost Distribution Parameters

Country Pair Characteristics	Mean Effect ($\boldsymbol{\beta}$)	Unobserved Heterogeneity ($\boldsymbol{\Sigma_t}$)
Common Border	-2.76***	3.41***
Common Language	-0.44*	-2.64***
Distance 1	-1.9***	0.68*
Distance 2	-6.57***	2.26***
Distance 3	-6.54***	0.33
Distance 4	-7.84***	0.09
Distance 5	-10.28***	1.07***
Distance 6	-11.07***	-0.07

*** indicates significance at the 1% level,
* indicates significance at the 5% level
* indicates significance at the 1% level.

Table 4. Country Fixed Effects Estimates

Country	$\hat{\hat{S}}_i$	$\hat{ex}_i$	Country	$\hat{\hat{S}}_i$	$\hat{ex}_i$
Argentina	1.699***	0.788***	Australia	1.006***	0.545***
Austria	-2.759***	0.117	Brazil	1.646***	1.218***
Bulgaria	-0.447	-0.105	Canada	-4.976***	2.503***
Chile	1.034**	0.918***	China	1.595***	0.99***
Colombia	1.672***	0.23***	Costa Rica	2.14***	-0.631***
Cote d'Ivoire	1.633***	-0.344**	Czech Republic	-1.675***	-0.425**
Denmark	-1.562***	0.22	Ecuador	1.79***	-0.056
Estonia	1.508***	-2.601***	Ethiopia	1.532***	-0.525***
Finland	0.177	-1.404***	France	-2.178***	1.418***
Germany	-4.908***	2.029***	Ghana	2.345***	-1.048***
Greece	0.508	-0.003	Honduras	1.796***	-0.796***
Hungary	0.929**	-0.596***	Iceland	-0.116	-2.393***
India	1.678***	0.692***	Indonesia	1.328**	1.254***
Ireland	0.854*	-1.388***	Israel	0.866**	-0.207*
Italy	-3.247***	1.765***	Japan	-1.305**	0.05
Kazakhstan	1.169**	-1.897***	Kenya	1.885***	-0.456**
South Korea	0.702**	-0.634***	Lithuania	1.339***	-2.067***
Malaysia	-0.509	1.422***	Mexico	1.189**	0.423**
Morocco	1.103**	-0.921***	Netherlands	-3.484***	1.62***
New Zealand	1.915***	0.06	Norway	1.171***	-2.288***
Peru	1.778***	-0.103	Poland	-1.181***	-0.048
Portugal	-1.496***	-0.515***	Russian Federation	-2.152***	0.116
Slovakia	1.551***	-2.133***	Slovenia	0.317	-2.197***
South Africa	1.275***	0.293*	Spain	-4.365***	2.134***
Sri Lanka	1.64***	0.284*	Sweden	-2.327***	-0.059
Switzerland	-4.879***	0.644***	Thailand	1.639***	0.585***
Tunisia	1.613***	-1.221***	Turkey	1.488***	0.515***
United Kingdom	-5.179***	1.79***	Ukraine	1.016**	-0.522***
Vietnam	1.564***	0.417**	USA	-3.347***	2.543***

*** indicates significance at the 1% level, ** indicates significance at the 5% level
* indicates significance at the 1% level.

Table 5. Exporter Characteristics, Selected Asia-Pacific Countries

Country	Tropical	Temperate	Boreal	High Elevation	Land/Ag Worker
USA	0.00	0.80	0.20	0.21	68.38
China	0.02	0.67	0.31	0.30	0.37
Canada	0.00	0.14	0.86	0.13	97.56
Australia	0.27	0.73	0.00	0.02	128.60
Mexico	0.38	0.62	0.00	0.26	3.70
New Zealand	0.02	0.78	0.20	0.21	2.52
Japan	0.00	0.99	0.01	0.16	1.58
Chile	0.04	0.45	0.52	0.21	1.55
Peru	0.63	0.20	0.17	0.10	0.90
Malaysia	1.00	0.00	0.00	0.10	1.12
Thailand	0.99	0.01	0.00	0.09	0.97
Indonesia	1.00	0.00	0.00	0.11	0.48
Vietnam	0.88	0.12	0.00	0.16	0.25

Table 6. US Competitors in the Asia-Pacific Region

Estimated elasticity of U.S. market share with respect to Competitor trade cost in Import Markets

	Import Markets											
Exporters	Canada	Mexico	Chile	Peru	Australia	New Zealand	Japan	China	Indonesia	Malaysia	Thailand	Vietnam
Australia	0.018	0.001	0.000	0.000	0.000	0.277	0.0450	0.013	0.072	0.137	0.052	0.038
Canada	0.000	0.024	0.083	0.078	0.294	0.107	0.066	0.003	0.021	0.053	0.008	0.019
Chile	0.029	0.031	0.000	0.051	0.000	0.007	0.003	0.001	0.001	0.001	0.000	0.000
China	0.012	0.001	0.003	0.000	0.009	0.004	0.056	0.000	0.038	0.131	0.030	0.020
Indonesia	0.020	0.002	0.017	0.002	0.013	0.001	0.047	0.011	0.000	0.133	0.008	0.039
Japan	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.000
Malaysia	0.006	0.001	0.001	0.000	0.015	0.000	0.017	0.017	0.001	0.000	0.001	0.042
Mexico	0.043	0.000	0.017	0.066	0.001	0.001	0.009	0.000	0.001	0.000	0.001	0.003
New Zealand	0.023	0.001	0.000	0.000	0.242	0.000	0.015	0.001	0.001	0.011	0.001	0.000
Peru	0.008	0.001	0.008	0.000	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000
Thailand	0.008	0.000	0.003	0.001	0.005	0.002	0.063	0.011	0.012	0.131	0.000	0.042
Vietnam	**0.003**	0.000	0.007	0.000	0.007	0.004	0.004	0.002	0.002	0.036	0.002	0.000

Interpretation Note: The value in bold text implies that a 1% increase in Vietnam's cost of exporting to Canada results in a 0.003% increase in the United States' share of the Canadian agricultural products market.

Table 7. Asia-Pacific Integration led by the United States

Estimated changes in exporter percent of importer's agricultural products market

Exporters	Import Markets: Australia	Canada	Chile	Indonesia	Japan	Malaysia	Mexico	New Zealand	Peru	Thailand	Vietnam	USA	Exporter Ave. Gain
Australia	-5.52%	0.59%	0.00%	3.49%	1.93%	5.23%	0.21%	1.11%	0.00%	2.51%	1.76%	0.44%	1.57%
Canada	1.13%	-21.53%	2.43%	0.99%	2.81%	1.99%	3.59%	0.41%	4.79%	0.38%	0.88%	1.62%	1.91%
Chile	0.03%	2.47%	-8.45%	0.04%	0.15%	0.05%	0.85%	0.53%	0.92%	0.01%	0.01%	1.57%	0.60%
China	-0.03%	-0.26%	-0.01%	-0.09%	-0.37%	-1.96%	-0.01%	0.00%	0.00%	-0.06%	-0.05%	-0.02%	-0.24%
Indonesia	0.78%	2.22%	1.30%	-8.98%	2.04%	6.19%	0.33%	0.10%	0.20%	0.39%	1.86%	2.07%	1.59%
Japan	0.02%	0.06%	0.00%	0.05%	-22.99%	0.03%	0.00%	0.00%	0.00%	0.05%	0.02%	0.02%	0.02%
Malaysia	0.89%	0.67%	0.08%	0.05%	0.72%	-19.27%	0.11%	0.02%	0.05%	0.06%	1.97%	0.50%	0.47%
Mexico	0.09%	4.69%	0.07%	0.03%	0.41%	0.01%	-12.28%	0.07%	0.45%	0.06%	0.15%	2.20%	0.75%
New Zealand	0.92%	0.73%	0.01%	0.03%	0.66%	0.42%	0.14%	-3.80%	0.00%	0.06%	0.02%	0.24%	0.29%
Peru	0.05%	0.69%	0.35%	0.01%	0.04%	0.00%	0.03%	0.05%	-7.36%	0.01%	0.01%	0.49%	0.16%
Thailand	0.27%	0.88%	0.20%	0.57%	2.70%	4.85%	0.05%	0.14%	0.07%	-7.53%	1.91%	0.57%	1.11%
Vietnam	0.40%	0.32%	0.57%	0.11%	0.17%	1.35%	0.01%	0.31%	0.05%	0.07%	-9.47%	0.36%	0.34%
USA	**1.44%**	12.02%	5.09%	3.84%	12.68%	4.08%	7.30%	1.18%	2.30%	4.19%	1.06%	-9.11%	5.02%

Interpretation Note: The value in bold text implies that a 50% cut in trade costs among all exporters and import markets in the table results in the U.S. gaining 1.44% of the Australian agricultural products market

Table 8. Asia-Pacific Integration led by China

Estimated changes in exporter percent of importer's agricultural products market

	Import Markets												
Exporters	Australia	Canada	Chile	China	Indonesia	Japan	Malaysia	Mexico	New Zealand	Peru	Thailand	Vietnam	Exporter Ave. Gain
Australia	-4.75%	0.76%	0.00%	0.65%	3.53%	2.06%	5.18%	0.22%	1.20%	0.00%	2.55%	1.76%	1.63%
Canada	1.26%	-12.75%	2.59%	0.16%	1.00%	3.01%	1.97%	3.76%	0.45%	4.86%	0.38%	0.88%	1.85%
Chile	0.03%	2.74%	-4.77%	0.02%	0.04%	0.16%	0.05%	1.07%	0.53%	0.96%	0.01%	0.01%	0.51%
China	0.53%	1.44%	0.25%	-2.87%	1.81%	2.55%	4.92%	0.17%	0.24%	0.00%	1.47%	0.94%	1.30%
Indonesia	0.77%	2.39%	1.33%	0.56%	-6.98%	2.18%	4.96%	0.34%	0.10%	0.20%	0.40%	1.86%	1.37%
Japan	0.02%	0.06%	0.00%	0.00%	0.05%	-13.26%	0.03%	0.00%	0.00%	0.00%	0.05%	0.02%	0.02%
Malaysia	0.89%	0.73%	0.08%	0.85%	0.05%	0.76%	-20.00%	0.12%	0.02%	0.05%	0.06%	1.97%	0.51%
Mexico	0.09%	5.07%	0.10%	0.01%	0.03%	0.43%	0.01%	-5.36%	0.07%	0.51%	0.06%	0.15%	0.59%
New Zealand	1.03%	0.95%	0.01%	0.06%	0.03%	0.71%	0.41%	0.15%	-2.90%	0.00%	0.06%	0.02%	0.31%
Peru	0.05%	0.76%	0.37%	0.00%	0.01%	0.05%	0.00%	0.03%	0.05%	-6.07%	0.01%	0.01%	0.12%
Thailand	0.27%	0.95%	0.20%	0.53%	0.58%	2.89%	4.94%	0.05%	0.14%	0.08%	-4.88%	1.91%	1.14%
Vietnam	0.40%	0.35%	0.58%	0.11%	0.11%	0.18%	1.34%	0.01%	0.31%	0.05%	0.07%	-9.35%	0.32%
USA	**-0.27%**	-1.70%	-0.27%	-0.03%	-0.15%	-1.16%	-0.74%	-0.44%	-0.14%	-0.17%	-0.11%	-0.06%	-0.44%

Interpretation Note: The value in bold text implies that a 50% cut in trade costs among all exporters and import markets in the table results in the U.S. losing 0.27% of the Australian agricultural products market.

Table 9. Full Asia-Pacific Integration

Estimated changes in exporter percent of importer's agricultural products market

Exporters	Import Markets: Australia	Canada	Chile	China	Indonesia	Japan	Malaysia	Mexico	New Zealand	Peru	Thailand	Vietnam	USA
Argentina	*0.00%*	*-0.11%*	*-0.95%*	*-0.02%*	*-0.03%*	*-0.02%*	*-1.33%*	*-0.06%*	*0.00%*	*-1.37%*	*-0.04%*	*-0.02%*	*-0.07%*
Australia	-6.03%	0.58%	0.00%	0.64%	3.46%	1.90%	5.02%	0.21%	1.11%	0.00%	2.49%	1.75%	0.44%
Brazil	*-0.02%*	*-0.35%*	*-0.04%*	*-0.03%*	*-0.02%*	*-0.49%*	*-0.08%*	*-0.02%*	*0.00%*	*-0.01%*	*-0.11%*	*-0.02%*	*-0.05%*
Canada	1.12%	-22.73%	2.43%	0.15%	0.98%	2.77%	1.91%	3.59%	0.41%	4.79%	0.38%	0.87%	1.62%
Chile	0.03%	2.45%	-8.69%	0.02%	0.04%	0.15%	0.05%	0.85%	0.53%	0.92%	0.01%	0.01%	1.57%
China	0.52%	1.32%	0.25%	-4.98%	1.78%	2.35%	4.76%	0.16%	0.24%	0.00%	1.43%	0.94%	0.44%
Colombia	*0.00%*	*-0.51%*	*-0.07%*	*0.00%*	*0.00%*	*-0.10%*	*0.00%*	*-0.01%*	*-0.01%*	*-0.06%*	*0.00%*	*0.00%*	*-0.17%*
Cote d'Ivoire	*0.00%*	*-0.29%*	*0.00%*	*0.00%*	*-0.01%*	*0.00%*	*-0.57%*	*0.00%*	*0.00%*	*0.00%*	*-0.01%*	*-0.01%*	*-0.02%*
Ecuador	*0.00%*	*-0.15%*	*-0.48%*	*0.00%*	*0.00%*	*-0.03%*	*0.00%*	*-0.02%*	*-0.03%*	*-0.01%*	*0.00%*	*0.00%*	*-0.10%*
India	*-0.24%*	*-0.20%*	*0.00%*	*-0.01%*	*-0.02%*	*-0.03%*	*-0.67%*	*-0.01%*	*-0.02%*	*0.00%*	*-0.02%*	*-0.07%*	*-0.04%*
Indonesia	0.77%	2.19%	1.30%	0.55%	-10.74%	2.01%	4.80%	0.33%	0.10%	0.20%	0.39%	1.85%	2.06%
Italy	*-0.03%*	*-0.33%*	*-0.01%*	*0.00%*	*0.00%*	*-0.05%*	*-0.01%*	*-0.01%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*-0.04%*
Japan	0.02%	0.06%	0.00%	0.00%	0.05%	-25.26%	0.03%	0.00%	0.00%	0.00%	0.05%	0.02%	0.02%
Malaysia	0.88%	0.67%	0.08%	0.84%	0.05%	0.71%	-23.41%	0.11%	0.02%	0.05%	0.06%	1.96%	0.49%
Mexico	0.09%	4.64%	0.07%	0.01%	0.03%	0.40%	0.01%	-12.45%	0.07%	0.45%	0.06%	0.15%	2.19%
New Zealand	0.92%	0.73%	0.01%	0.05%	0.03%	0.65%	0.40%	0.14%	-4.04%	0.00%	0.06%	0.02%	0.24%
Peru	0.05%	0.68%	0.35%	0.00%	0.01%	0.04%	0.00%	0.03%	0.05%	-7.36%	0.01%	0.01%	0.49%
South Korea	*0.00%*	*-0.02%*	*0.00%*	*0.00%*	*0.00%*	*-0.04%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*-0.01%*
Spain	*-0.04%*	*-0.12%*	*-0.03%*	*0.00%*	*0.00%*	*-0.03%*	*0.00%*	*-0.07%*	*0.00%*	*-0.01%*	*-0.01%*	*0.00%*	*-0.09%*
Thailand	0.27%	0.87%	0.20%	0.52%	0.56%	2.66%	4.78%	0.05%	0.14%	0.07%	-8.93%	1.90%	0.57%
USA	**1.44%**	11.90%	5.08%	2.13%	3.80%	12.48%	3.92%	7.29%	1.18%	2.30%	4.16%	1.05%	-9.54%
Vietnam	0.39%	0.32%	0.57%	0.10%	0.11%	0.17%	1.30%	0.01%	0.31%	0.05%	0.07%	-10.39%	0.36%

The value in bold text implies that a 50% cut in trade costs among all exporters and import markets in the table results in the U.S. gaining 1.44% of the Australian agricultural products market