Increased economic integration in the Asia-Pacific region: What might be the potential impact on agricultural trade?

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Abstract

In this paper, a structural gravity model is presented which features intra-sector heterogeneity in agricultural productivity systematically linked to land and climate characteristics. The "systematic heterogeneity" (SH) gravity model predicts that countries with similar land and climate characteristics will tend to specialize in the same agricultural products. Agricultural trade flow elasticities then depend on comparative advantage, with larger-magnitude trade flow responses predicted among countries more likely to specialize in similar agricultural products and thus compete head-to-head in foreign markets. Based on estimating a random-coefficients logit model for a sample of 63 countries and 123 agricultural items, countries trading in the Asia-Pacific region with comparative advantage in similar products are identified. Drawing on this, two scenarios are evaluated using the model: tariff cuts agreed under the CPTPP on products in the data set among CPTPP member countries; the US obtaining equivalent access to CPTPP markets and following Australia by offering zero tariffs on all agricultural products in the model.

Keywords: Agricultural trade, gravity, trade costs

1. Introduction

The Trans-Pacific Partnership (TPP) signed in 2015 was expected to have a significant effect on agricultural trade in the Asia-Pacific region. By 2025, TPP agricultural trade was forecast to increase by $8.5 billion, the US increasing its agricultural exports to other countries in the agreement by $2.8 billion, a 33 percent increase in its market share (Burfisher et al., 2014). This increase in US agricultural trade would have been driven largely by the fact that the agricultural sector would have gained preferential market access to several countries with whom the US currently has no regional trade agreement (RTA), most notably Japan.

Although the United States has withdrawn from the TPP, the remaining 11 member countries agreed on a new treaty in November 2017 at the Asia Pacific Economic Cooperation (APEC) summit in Vietnam, the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP). Substantively, CPTPP retains most of the provisions of TPP, including significant reductions in agricultural tariffs between the member countries. In addition to establishment of CPTPP, several of its members are also participating in negotiations to form the Regional Comprehensive Partnership (RCEP). RCEP is a proposed RTA between the 10 member countries of the Association of Southeast Asian Nations (ASEAN), and the 6 countries with whom ASEAN has existing RTAs, which include China and India. RCEP, which would be the world's largest trading bloc, accounting for 39 percent of global GDP, is scheduled to be completed in November 2018.

It is clear that increased economic integration within each, as well as the crossover between the RTAs, has the potential to significantly affect agricultural trade flows in the region, as well has have an impact on the extent of preferential access for US agricultural exports. For example, Heerman, Arita, and Gopinath (2015) find that if the US is excluded from trade liberalization in the Asia-Pacific, the expected loss in the US share of agricultural exports in the region is increasing in the extent to which close competitors such as Canada and Australia gain new market access.

In this paper, the potential economic impact on agricultural trade of increased economic integration in the Asia-Pacific region is evaluated using a systematic heterogeneity (SH) general equilibrium (GE) gravity model developed by Heerman (2016), and previously applied by Heerman and Zahniser (2018) to potential rollback of the North American Free Trade Agreement (NAFTA). Specifically, the model features intra-sector heterogeneity in agricultural productivity linked to land and climate characteristics. The model predicts that countries with similar land and climate characteristics will systematically tend to specialize in the same agricultural products. Agricultural trade flow elasticities then depend on comparative advantage, with larger-magnitude trade flow responses predicted among countries more likely to specialize in similar agricultural products and thus compete head-to-head in foreign markets.

The disadvantage of introducing non-random sources of comparative advantage and trade costs is that the gravity-like structural relationship used to parameterize the model cannot be specified in the log-linear form commonly used in gravity modeling (Head and Mayer, 2014). Instead, we specify the equation relating bilateral trade flows to trade costs and country characteristics as a random coefficients logit model (Berry, Levinsohn and Pakes, 1995). This allows a country's sensitivity to changes in a competitor's trade cost to vary across competitors without breaking the agricultural sector into several sub-sectors (Heerman 2016; Heerman, et al., 2015; Heerman and Sheldon, 2017).

Based on estimating a random-coefficients logit model for a sample of 63 countries and 134 agricultural items, and using interactions between exporter land and climate characteristics and product land and climate production requirements, we identify countries trading in the Asia-Pacific region likely to have comparative advantage in similar products. These countries' trade flows are then more elastic to changes in each other's trade costs. From this, it is possible to evaluate the extent to which the US is likely to be denied preferential market access to countries that are members of CPTPP and/or RCEP. For example, we are able to evaluate the extent to which the United States' close competitors gain a larger market share under the CPTPP relative to the TPP than do countries like Malaysia.

The remainder of this paper is structured as follows: in sections 2 and 3 respectively, the background to the Trans-Pacific integration under the CPTPP and its relationship to agricultural trade is described, and the underpinnings to the SH model are outlined; this is followed by a description, specification and solution of the SH model in sections 4, 5 and 6, and then a discussion of an evaluation of TPP in section 7; finally, the paper is summarized and some conclusions are drawn in section 8.

2. Background on Trans-Pacific integration and agriculture

CPTPP and agricultural trade

Over the period 2010-12, agricultural imports by CPTPP members and the United States totaled $279 billion, of which 51 percent were sourced from other CPTPP partners and the United States, while 43 percent of their agricultural exports went to these countries. Canada and Mexico are both highly dependent on other countries in this group for both agricultural exports and imports, mostly due to their trade with the US. In the case of the US over the same period, 42 and 47 percent of its agricultural exports and imports respectively went to/were sourced from CPTPP members (Burfisher et al., 2014).

Agricultural products traded between these Trans-Pacific trading partners are currently subject to higher applied tariffs on average, than manufactured products – 5.2 vs. 1.8 percent - although bilateral protection varies considerably by country (Disdier, Emlinger and Fouré, 2015). For example, average applied agricultural tariffs are 3.6 percent at the US border compared to 23 percent at the Japanese border. Agricultural tariffs also vary based on whether trading partners are members of an existing RTA, and also by product. For example, Mexico's average applied agricultural tariff against CPTPP members and the United States is 15.6 percent, ranging from 30.7 percent against Australia to 3.2 and 1 percent on agricultural imports from Canada and the US, its NAFTA partners. In the case of specific agricultural products, different countries currently have high levels of protection for different products. For example, Canada protects its markets for dairy products, poultry and eggs, its average applied tariff on US dairy products being 110 percent, even though Canada and the US are both members of NAFTA. Japan protects its markets for beef rice, wheat, barley, sugar, dairy products, and selected fruit and vegetables, Japanese applied import duties on cereals exceeding 200 percent, largely due to the level of protection afforded to its rice sector. In the case of the US, sugar, selected dairy products and tobacco are protected with the applied tariff on tobacco products currently applied at 350 percent (Freund, Moran and Oliver, 2016).

Burfisher et al. (2014) estimate the impact of removing all agricultural tariffs and tariff-rate quotas (TRQs) by 2025 using a computable general equilibrium (CGE) model.[1] The estimates indicate that TPP would have resulted in a 6.6 percent increase in agricultural trade by 2025. This increase would account for an additional $8.5 billion in the agricultural marketplace. TPP was also expected to increase US market access to several countries where it currently has no RTA, notably Japan, where 50 percent of US agricultural exports would have faced zero tariffs once TPP was implemented. In the case of other agricultural products, preferential access would have been given under new tariff-rate quotas, where specified levels of imports would be subject to low tariffs, including dairy products imported by Canada, and rice, wheat and barley imported by Japan. With Japan being its fifth largest agricultural export market, reduction in their agricultural tariffs has been a long-held objective of US trade policy, and one not addressed as yet in the WTO. With increased market access, the study anticipated that TPP would result in a 33 percent overall increase in US agricultural exports and a 10 percent increase in imports by 2025.

Of course, while TPP was expected to result in considerable liberalization of agricultural trade, the nature of the agreement was such that there would have been a phase-in period across countries and products. Once the agreement took effect, almost 32 percent of tariff lines in Japan, 31 percent in Vietnam, 92 percent in Malaysia, all but one tariff line in Australia, and 99 percent in New Zealand were to be eliminated, with additional liberalization being phased in over 15 to 20 years (Hendrix and Kotschwar, 2016). However, significant barriers to market access would have remained in some areas, notably the dairy

[1] Both the modeling approach and scenario analysis carried out in Burfisher et al. (2014) are substantially different from the model and scenarios considered in this paper. The results are not intended to be directly compared.

sector, where the Canada, Japan and the US backed off dairy sector reform in order to maintain domestic support programs.

3. Model background

Until recently, the conventional view in international economics was that the gravity equation lacked microeconomic foundations (Head and Mayer, 2014). However, it is now considered general enough to be applied beyond a sub-set of countries or sectors (Eaton and Kortum, 2002; Anderson and Wincoop, 2003; Arkolakis, Costinot, and Rodríguez-Clare, 2012), and that importer and exporter fixed effects can be used to account for the multilateral trade resistance terms derived from different theoretical models (Feenstra, 2004). In addition, evaluating a standard gravity equation on the basis of exports (imports) to (by) country *n*, at the firm/industry/sector-level as opposed to the economy-wide level using bilateral trade, has a clear analytical justification, drawing on a range of trade theories, e.g., Melitz (2003); Anderson and Wincoop (2004); Chaney (2008); Anderson and Yotov (2010a; 2010b; 2012); Costinot, Donaldson, and Komunjer (2012); and Costinot and Rodríguez-Clare (2014). As a result, robust estimation of firm/industry/sector-level gravity equations using export (import) data is now common in the agricultural economics literature, some recent applications including: Reimer and Li (2010) (crop trade); Jayasinghe, Beghin, and Moschini (2010) (US corn seed exports); Cardamone (2011) (fruit exports); Chevassus-Lozza and Latouche (2012) (French firms' agri-food exports); Xu (2015) (agricultural trade); and Dal Bianco et al. (2016) (wine exports).

An important characteristic of the range of structural gravity models is that the quantitative implications that can be drawn from them are very dependent upon a key parameter: the elasticity of trade with respect to trade frictions such as tariffs (Simonovska and Waugh, 2014). Arkolakis et al. (2012) argue that the elasticity of trade, denoted as ε, is one of two sufficient statistics necessary for calculating the welfare effects of trade, the other being the share of expenditure within a specific country on domestically produced goods denoted as λ. They show that the change in a country's real income, $\hat{W} = W' / W$, resulting from say a reduction in trade costs can be calculated as $\hat{W} = \hat{\lambda}^{1/\varepsilon}$, where $\hat{\lambda} = \lambda' / \lambda$ is the change in the share of domestic expenditure on imports. Importantly, changes in welfare are independent of the class of trade model, i.e., the source of the gains from trade depends on the type of trade model being estimated, but the aggregate gains from trade do not. Arkolakis et al. (2012) show that the welfare formula can be derived from three different structures: an Armington model (see Anderson and Wincoop, 2003), a Ricardian model (see Eaton and Kortum, 2002), and a heterogeneous firms model (see Melitz, 2003), where the margin of adjustment occurs respectively through consumption, reallocation of labor across sectors, and reallocation across firms within sectors.

For this equivalence result to hold, Arkolakis et al. (2012) impose a key restriction on the partial elasticities: the import demand system is CES. Given the elasticities capture the percentage change in relative imports by country *n* from country *i* given a change in trade costs τ_{ni}, the CES assumption implies that: there is a symmetric impact on relative demand X_{ni}/X_{nn} for imports by *n* for all exporters $i \neq n$; and, any change in a third country's trade costs $\tau_{ni}{}'$ has the same proportional impact on X_{ni} and X_{nn}. In other words, changes in relative demand depend only on changes in trade costs τ_{ni}. Given this result, Arkolakis et al. (2012) show that these effects can be recovered from a simple logarithmic gravity equation, the estimated parameter for changes in trade costs being treated as an estimate of the trade elasticity ε, and the change in real income of country n due to the trade shock being estimated as, $\hat{W}_n = \hat{\lambda}_n^{1/\varepsilon}$, irrespective of the margin of adjustment.[2]

Turning to trade in agricultural products, we argue that the CES assumption is overly restrictive, i.e., the elasticity of each exporter *i*'s trade flows with respect to a given competitor's, i', trade flows is constant and directly proportional to the exporter's market share in *n*, irrespective of whether or not *i* competes with i'. As noted earlier, Heerman et al. (2015), refer to this restriction as the IIE property, i.e., changes in a third country's trade costs τ_{ni}' are "irrelevant" to the ratio of any two competitors' market share in a given import market *n*. The results of Arkolakis et al. (2012) indicate that IIE is implicitly imposed in trade models such as Eaton and Kortum (2002), Melitz (2003) and Anderson and Wincoop (2003). Heerman et al. (2015) argue that the IIE property is very unlikely to hold in the case of agricultural trade due to characteristics of natural endowments (land, soil, and climate) and production requirements being non-random drivers of comparative advantage within the agricultural sector. Consequently, econometric results assuming IIE will likely be imprecise, and any predictions about the effect of changes in trade costs on bilateral agricultural trade and production patterns, along with any estimated welfare effects, may be quite misleading.

Consider the Japanese tariff reductions offered to CPTPP member countries such as Australia, Canada and Malaysia. If the IIE property holds, the reduction in agricultural tariffs would imply that Japanese buyers substitute to Australian, Canadian and Malaysian products

[2] Adao, Costinot, and Donaldson (2017) also note that general equilibrium trade modelling based on the gravity equation is considerably more parsimonious than using CGE models as developed by the Global Trade Analysis Project (GTAP) which has 13,000 structural parameters (Hertel, 2013).

and away from its all other trading partners, including the United States, in a constant and direct proportion to their initial market shares. However, this makes little sense if we consider that Australia, Canada and the United States have similar land endowments and climate characteristics, and therefore systematically specialize in a similar set of agricultural products, which contrasts with Malaysia which has little available land and has a tropical climate. Consequently, one would expect that exclusion from TPP will result in the United States losing a proportionately larger market share in Japan relative to Australia and Canada than it will lose relative to Malaysia.

In the context of this paper, the focus is on an extension of Eaton and Kortum (2002). The latter assumes that comparative advantage within manufacturing is a function of a random productivity variable that is independently distributed across products in the sector. Specifically, no two countries are more likely to compete against each other exporting the same products than any other country, i.e., the IIE property is assumed to hold. Extensions of Eaton and Kortum (2002) to multisector analysis by, inter alia, Burstein and Vogel (2010), Chor (2010), Costinot et al. (2012), Shikher (2011, 2012), Caliendo and Parro (2015), Tombe (2015), and Kerr (2017) implicitly recognize the limitation of this assumption, allowing average productivity, and in some cases the dispersion of productivity to vary across sectors, generating non-random patterns of trade specialization across sectors and sub-sectors.

However, these models still maintain the assumption of random heterogeneity within each sector or sub-sector, the IIE property holding at that level. In addition, there are practical limitations to a multi sub-sector approach within agriculture (Heerman, 2016; Heerman and Sheldon, 2017). First, the researcher has to be able to define sub-sectors of like products such that specialization of a country within that sub-sector can be assumed to be randomly determined *ex ante*. For example, Reimer and Li (2010) focused on trade in crop agriculture, a well-defined sub-sector, but this still ignores the fact that agricultural product-specific farm and trade policies may be enough to distort any underlying forces of comparative advantage for crops that are substitutes in production. Second, disaggregation to sub-sectors requires considerably more bilateral trade and production data, and in the case of agriculture, where many products are thinly traded, there is the critical empirical issue of dealing with zero trade flows.

The key departure in this paper is the introduction of systematic heterogeneity into the agricultural sector. Specifically, the likelihood a country has a comparative advantage in a set of products depends not only on a randomly drawn technological productivity-augmenting parameter, but also a set of country and product-specific characteristics including land and climate. For example, agricultural R&D in the US might generate a disease-resistant variety of bananas, but the land and climate requirements for growing bananas means the United States is unlikely to be a competitive exporter, and would therefore not be affected by any changes in the banana-importing regime of the EU.

Alternatively, the US has a technological advantage in producing genetically-modified corn for which it also has the appropriate land and climate requirements, and it could face increased competition in the Mexican export market from close competitors like Brazil if market access for US agriculture were to become more-costly as a result of the NAFTA renegotiations.

Allowing for systematic heterogeneity also means that trade costs may vary across products and countries within sectors. This matters in agriculture where trade costs can differ significantly due to the intrinsic characteristics of products and/or the types of trade and other policies applied to those products. For example, compared to Brazil, the US has very low trade costs of exporting corn and soybeans to Mexico, partly due to geographical proximity, but also because it has a very efficient storage and transportation system that minimizes the cost of spillage etc. So any increase in trade barriers to Mexican imports from the US would be partially mitigated by the higher costs of importing more corn and soybeans from Brazil. Likewise, the costs of the US exporting processed pork products to Mexico will have higher handling costs than corn due to the risks of perishability and the need for refrigerated transportation. Importantly, the relative difference between these advantages are not likely to be constant.

Trade policies also vary significantly across countries, with average MFN applied tariff rates in agriculture ranging from 1.2 percent in Australia, through 33.5 percent in India, to 66.7 percent in Egypt (Bagwell, Bown and Staiger, 2016). These average differences in tariffs can be captured in standard gravity models, but hide significant differences across products. Applied agricultural tariffs exhibit a good deal of heterogeneity across both products and countries. For example, Jales et al. (2005) report that developed countries typically have a number of very high agricultural tariffs and a large number of low tariffs, implying low mean tariffs with a high degree of tariff dispersion. By contrast, developing countries tend to have higher mean agricultural tariffs, and less tariff dispersion. In the case of TRQs, 1,400 have been introduced since 1995, with over-and in-quota tariffs averaging 123 and 63 percent respectively (Jales et al., 2005).

4. The systematic heterogeneity model

The SH model builds on the probabilistic Ricardian model of Eaton and Kortum (2002), which captures how the distribution of comparative advantage across products around the world drives production and trade patterns. In the model, the set of products in which a country has comparative advantage is determined by the distribution of productivity within sectors. As in Eaton and Kortum (2002), comparative advantage is product-specific and is generated by differences in productivity. Unlike Eaton and Kortum (2002) and other analyses based on their pioneering work, the specific set of products in which a country has comparative advantage within the agricultural sector is systematically influenced by land and climate characteristics rather than entirely by chance. We further allow trade costs to vary across products within the agricultural sector. This allows the influence of comparative advantage on trade to be weaker (stronger) for products for which intrinsic characteristics or policy barriers make them systematically more expensive (inexpensive) to trade.

The Model

The world is comprised of I countries engaged in bilateral trade. Importers are indexed by n and exporters by i. There are two tradable sectors, agriculture and manufacturing, k=A, M, and one non-tradable sector. Tradable sectors are each comprised of a continuum of products indexed by $j \in [0, 1]$. From the buyer's perspective, individual products are distinguished only by their intrinsic characteristics, not by the source country. Countries are endowed with consumers who inelastically supply labor N_i and land L_i. Labor is allocated freely across all three sectors. Land is specific to agriculture. All production is constant returns to scale, and markets are perfectly competitive.

Productivity

Heterogeneous productivity within a sector is generated in part by differences in production technology. Following Eaton and Kortum (2002) and the many extensions of their model, we model technological productivity, $z_i^k\,(j)$, as independently distributed across products following a Fréchet distribution with parameters T_i^k and θ:

$$F_{Z_n}^k(z) = \exp\{-T_i^k z^{-\theta}\} \qquad k = A, M \tag{1}$$

A high value of T_i^k means that country i is more likely to have a high draw of $z_i^k\,(j)$, implying greater average productivity. A smaller value of $\theta > 1$ implies a larger dispersion of technological productivity. The value of $z_i^k(j)$ is an outcome of an R&D process that, by our independence assumption, can realize higher than average values on any product, regardless of product or country characteristics. The process is equally likely to deliver a high value of $z_{Canada}^A(wheat)$ as it is $z_{Canada}^A(tomatoes)$, regardless of the natural advantage Canada's great plains offer for wheat production versus the disadvantage its cold winters and short summers imply for tomato production. In fact, despite this disadvantage, Canadian producers' use of greenhouse technology has contributed to its ability to be a competitive exporter of some varieties of tomato to the United States.

In the agricultural sector, the distribution of productivity across products has a second component, which is systematically influenced by the characteristics of its land and climate. Product-specific land productivity is represented by the random variable $a_i(j)$, which reflects the suitability of exporter i's natural environment for producing product j. We assume that $a_i(j)$ follows a continuous, parametric density that is a deterministic function of exporter i's agro-ecological characteristics and product j's agro-ecological production requirements. For example, Mexico is likely to have higher values of $a_{Mexico}(tomatoes)$ and would thus be more likely to have comparative advantage in growing tomatoes, all else equal. As such, Mexico is more likely to compete head-to-head with other countries whose climates also make them systematically more likely to have comparative advantage in growing tomato varieties.

Production and Trade

The technology to produce quantity $q_i^k\ (j)$ of tradable product j combines labor, land, and intermediate inputs according to the nested Cobb-Douglas function:

$$qk_i(j) = z_i^k(j)\left(N_i^{\beta^k}(a_i(j)L_i)^{1-\beta^k}\right)^{\alpha^k}\boldsymbol{Q_i^k}^{1-\alpha^k} \qquad k = A; M \quad \beta^M = 1 \qquad (2)$$

where $\boldsymbol{Q}_i^k$ is an aggregate of intermediate inputs from all three sectors combined in a Cobb-Douglas fashion as in Caliendo and Parro (2012):

$$\boldsymbol{Q}_i^k = Q_i^{A^{\xi_A^k}} Q_i^{M^{\xi_M^k}} Q_i^{S^{\xi_S^k}} \qquad \textstyle\sum_{l=A,M,S}\xi_l^k = 1 \qquad (3)$$

Q_i^A and Q_i^M are individual products from the agricultural and manufacturing sectors combined according to a Dixit-Stiglitz technology with elasticity of substitution $\sigma > 0$ (Equation 4). Equation links the three sectors. A high value of, e.g. ξ_S^A, implies inputs from the services sector are important in the production of agricultural products.

$$Q_i^k = \left(\int_0^1 q_i^k(j)^{\frac{\sigma-1}{\sigma}}\,dj\right)^{\frac{\sigma}{\sigma-1}} \qquad k = A, M \qquad (4)$$

The services sector produces a homogeneous good using only labor with productivity z_i^S. Producers in exporter i face additional costs $\tau_{ni}^k(j) \geq 1$ to sell a product in import market n. These trade costs are assumed to take the iceberg form, with $\tau_{nn}^k(j) = 1$ and $\tau_{ni}^k(j) \geq \tau_{nj}^k(j)\tau_{ji}^k(j)$.

Differences in trade costs across products influence the extent to which comparative advantage creates trade. As in Eaton and Kortum (2002), we assume trade costs are constant for all manufactured products, i.e., $\tau_{ni}^{M}(j) = \tau_{ni}^{M}\ \forall j$. Trade costs are product-specific for agricultural products. We assume agricultural trade costs follow a continuous, parametric density that is a deterministic function of product-specific policies and marketing requirements. We assume $\tau_{ni}^{A}(j)$ is independent of both $a_i(j)$ and $z_i^A(j)$.

Trade occurs as buyers in market n seek to purchase each product from the source country that offers the lowest price. With perfect competition the prices offered for product j, by exporter i in market n are:

$$p_{ni}^{A}(j) = \frac{\tilde{a}_i(j) c_i^A \tau_{ni}^A(j)}{z_i^A(j)} \quad and \quad p_{ni}^{M}(j) = \frac{c_i^M \tau_{ni}^M}{z_i^M(j)} \tag{5}$$

where $\tilde{a}_i(j) = a_i(j)^{-\alpha^A(1-\beta^A)}$ and $c_i^k$is the cost of a sector k input bundle. For cost-minimizing producers:

$$c_i^k = \kappa^k w_i^{\alpha^k \beta^k}\, r_i^{\alpha^k(1-\beta^k)} {p_i^{A}}^{(1-\alpha^k)\xi_A^k} {p_i^{M}}^{(1-\alpha^k)\xi_M^k} \tag{6}$$

where κ^k is a constant, w_i^k is the wage, r_i^k is the land rental rate, and p_i^k is a price index for intermediate goods produced by sector k.

The set of products in which a country has comparative advantage are those for which it is most likely to have the lowest price offer. Similar to Eaton and Kortum (2002), the set of manufacturing products in which a country has comparative advantage is determined solely by random realizations of $z_i^M(j)$. Specialization patterns in the agricultural sector are also non-randomly influenced by the distribution of $a_i(j)$ and $\tau_{ni}^A(j)$. A model that does not account for product-specific land productivity based on systemic factors would neither account for Mexico's systematic advantage due to the suitability of its land and climate for tomato production, nor would it account for the systematically larger trade cost advantage of Mexico and Canada in tomatoes compared to, e.g., rice, which is less perishable and therefore easier to store and transport.

Equilibrium

Equilibrium consists of factor prices w_i and r_i, price indices for tradable goods p_i^A and p_i^M, bilateral trade shares π_{ni}^A and π_{ni}^M, and labor allocation rules such that producers and consumers are optimizing, factor and product markets clear, and trade is balanced.

Given the aggregation technology buyers use to assemble individual goods from each sector, Caliendo and Parro (2012) and Shikher (2012) show that our assumptions on the trade costs and technology of the manufacturing sector imply that a unit price index for the manufacturing sector is:

$$p_n^M = \gamma {\Omega_n^M}^{-\frac{1}{\theta}} \tag{7}$$

where $\Omega_n^M = \sum_{l=1}^{I} T_l^M (c_l^M \tau_{nl}^M)^{-\theta}$, $\gamma = \Gamma\left[\frac{\theta+1-\sigma}{\theta}\right]^{\frac{1}{1-\sigma}}$, and $\Gamma(\cdot)$is the gamma function. Heerman (2016) shows that an agricultural price index is:

$$p_n^A = \gamma \left(\int \Omega_n^A(j)^{\frac{\sigma-1}{\theta}} dF_{a_n}(\tilde{\boldsymbol{a}}) dF_{\tau_n}^A(\boldsymbol{\tau^A}) \right)^{\frac{1}{1-\sigma}} \tag{8}$$

where $\Omega_n^A(j) = \sum_{l=1}^{I} T_l^A \left(\tilde{a}_l(j) c_l^A \tau_{nl}^A(j)\right)^{-\theta}$ and $dF_{a_n}(\tilde{\boldsymbol{a}}) dF_{\tau_n}^A(\boldsymbol{\tau})$ is the joint density of $\tilde{\boldsymbol{a}} = [\tilde{\boldsymbol{a}}_{\boldsymbol{1}}, \dots, \tilde{\boldsymbol{a}}_{\boldsymbol{I}}]$ and $\boldsymbol{\tau^A} = [\boldsymbol{\tau_{n1}^A}, \dots, \boldsymbol{\tau_{I(I-1)}^A}]$ over agricultural products consumed in import market n.

Invoking the law of large numbers, Eaton and Kortum (2002) show that the share of expenditure spent on imports from country i is equal to the probability it offers the lowest price:

$$\Pr\left(p_{ni}^M(j) = p_n^M(j)\right) \equiv \pi_{ni}^M = \frac{T_i^M \left(c_i^M \tau_{ni}^M\right)^{-\theta}}{\sum_{l=1}^{I} T_l^M \left(c_l^M \tau_{nl}^M\right)^{-\theta}} \tag{9}$$

An exporter's share of market n's expenditure on a specific agricultural products is likewise equivalent to the probability that it offers the lowest price for that product. Since land productivity and trade costs are distributed independently of each other, this can be expressed as follows:

$$\Pr\left(p_{ni}^A(j) = p_n^A(j)\right) \equiv \pi_{ni}^A = \int \frac{T_i^A \left(\tilde{a}_i c_i^A \tau_{ni}^A\right)^{-\theta}}{\sum_{l=1}^{I} T_l^A \left(\tilde{a}_l c_l^A \tau_{nl}^A\right)^{-\theta}} dF_{a_n}(\tilde{\boldsymbol{a}}) dF_{\tau_n}^A(\boldsymbol{\tau}^{\boldsymbol{A}}) \tag{10}$$

This expression is derived in Heerman (2016). Notice that the numerator in Equations 9 and 10 is country i's contribution to the sectoral price index. Thus, if π_{ni}^k is large, production and trade costs in exporter i have a large influence on sector k prices in country n.

The consumer's problem is to choose quantities of individual products $q_i^k(j)$ from all three sectors to maximize utility:

$$u_i(Q) \; = \; {Q_i^A}^{\lambda^A} {Q_i^M}^{\lambda^M} {Q_i^S}^{\lambda^S} \tag{11}$$

subject to the budget constraint: $X_i = w_i N_i + r_i L_i$. Here Q_i^k is the sector k's aggregate defined by Equation 4. This utility function implies that consumers spend a constant share λ^k of their total income on products from sector k.

Individual products are purchased by consumers for final consumption and by producers as intermediate inputs. Total demand for sector k's goods is thus:

$$X_i^k = \lambda^k X_i + (1 - \alpha^k)(\xi_k^M Y_k^M + \xi_k^A Y_k^A\ ) \tag{12}$$

where Y_i^k is country i's gross sector k production and $(1 - \alpha^k)(\xi_k^M Y_k^M + \xi_k^A Y_k^A\ )$ is demand for sector k intermediate inputs.

To solve the model for equilibrium, we follow Levchenko and Zhang (2014). Trade balance and market clearing conditions imply:

$$Y_i^k = \lambda_i^k Xi \ + \ (1-\alpha^k)\left(\xi_k^M \sum_{n=1}^{I} \pi_{ni}^M X_n^M + \xi_k^A \sum_{n=1}^{I} \pi_{ni}^A X_n^A\right) \quad k \ = \ A; M \qquad (13)$$

First order conditions of the producer's problem deliver optimal labor force allocations:

$$Y_i^k = \frac{w_i N_i^k}{\alpha^A \beta^A} \qquad (14)$$

and labor market clearing implies: $N_i = \sum_{k=A,M,S} N_i^k$. Finally, land rent is obtained from the agricultural producer's problem:

$$\frac{r_i L_i}{\alpha^A(1-\beta^A)} = \frac{w_i N_i^A}{\alpha^A \beta^A} \qquad (15)$$

and the non-tradeable sector price index is $p_i^S = w_i$.

Trade Elasticity

Heerman et al. (2015) show that in the SH gravity model, elasticity of market share with respect to a change in bilateral trade costs between exporter i and the importing country n can be written as, and for simplicity dropping the k superscript:

$$\frac{\partial \pi_{ni}}{\partial \tau_{nl}} \frac{\tau_{nl}}{\pi_{ni}} = \begin{cases} -\theta\left((1-\pi_{ni}) - \dfrac{1}{\pi_{ni}} var\big(\pi_{ni}(j)\big)\right) & l = i \\ \dfrac{\theta}{\pi_{ni}}\left(cov\big(\pi_{ni}(j), \pi_{nl}(j)\big) + \pi_{ni} \times \pi_{nl}\right) & l \neq i \end{cases} \qquad \text{(E1)}$$

Elasticities depend on cross-product differences in $\pi_{ni}(j)$, with $var\big(\pi_{ni}(j)\big)$ and $cov\big(\pi_{ni}(j), \pi_{nl}(j)\big)$ functions of the distributions of $a_i(j)$ and $\tau_{ni}(j)$. The direct effect of lower bilateral trade costs is decreasing in $var\big(\pi_{ni}(j)\big)$. This implies that market share is less elastic for exporters that specialize in products for which competition is less intense, or for which trade costs remain high. The indirect effect of a change in a competitor's bilateral trade costs is increasing in $cov\big(\pi_{ni}(j), \pi_{nl}(j)\big)$. The indirect elasticity will therefore be larger among competitors with similar distributions of $a_i(j)$, and further augmented when $\tau_{ni}(j)$ is also similar.

In a standard gravity model $\pi_{ni}(j) = \pi_{ni}$: the probability of comparative advantage in an individual product does not depend on product or exporter characteristics. Every exporter is thus equally likely to offer the lowest price in every agricultural product and $var\big(\pi_{ni}(j)\big) = cov\big(\pi_{ni}(j), \pi_{nl}(j)\big) = 0$. Therefore, trade elasticities are a constant proportion of market share:

$$\frac{\partial \pi_{ni}}{\partial \tau_{nl}} \frac{\tau_{nl}}{\pi_{ni}} = \begin{cases} -\theta(1 - \pi_{nl}) & l = i \\ \theta \pi_{nl} & l \neq i \end{cases} \tag{E2}$$

These latter elasticities, which characterize the manufacturing sector in our model, are a representation of the IIE property, which is imposed in every structural gravity model derived from a trade model that assumes a CES import demand system.[3]

5. Specification and data

We estimate parameters of the productivity and trade cost distributions for agriculture as in Heerman et al. (2015) by specifying Equation 10 as a random coefficients logit model. For the manufacturing sector, we follow Eaton and Kortum (2002) and others and specify a log-linear model from Equation 9. We begin as in Eaton and Kortum by defining $S_i^k = \ln\big(T_i^k\big) - \theta \ln\big(c_i^k\big)$. This is exporter i's average sector k technological productivity adjusted for unit production costs.

[3] In an exchange economy setting with factor demands, Adao et al. (2017) also relax the IIE assumption, generating equivalent elasticities that nest the case of CES factor demand.

Land Productivity Distribution

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

$$ln(a_i(j)) = \boldsymbol{X}_i\boldsymbol{\delta}(j) = \boldsymbol{X}_i\boldsymbol{\delta} + \boldsymbol{X}_i(\boldsymbol{E}(j)\boldsymbol{\Lambda})' + \boldsymbol{X}_i(\nu_E(j)\boldsymbol{\Sigma}_E)' \qquad (16)$$

where $\boldsymbol{X}_i$ 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; $\boldsymbol{E}(j)$ is a $1 \times m$ vector of product j-specific agroecological 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 $\boldsymbol{X}_i$ and land productivity varies across products with $\boldsymbol{E}(j)$; and $\boldsymbol{\nu}_E(j)$ is a $1 \times k$ vector that captures the effect of unobservable product j-specific requirements with matrix $\boldsymbol{\Sigma}_{\boldsymbol{E}}$.

We specify three types of exporter characteristics—agricultural land, elevation, and climate:

$$\boldsymbol{X}_i = [al_i \quad elv_i \quad trp_i \quad tmp_i \quad bor_i]$$

where al_i is the log of arable land per capita, 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. The vector $j = [\boldsymbol{E}(j) \quad \boldsymbol{\nu}_{\boldsymbol{E}}(j)]$ defines products in terms of their suitability for production under the conditions defined by $\boldsymbol{X}_i$. We define:

$$\boldsymbol{E}(j) = [alw(j) \quad elv(j) \quad trp(j) \quad tmp(j) \quad bor(j)]$$

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. These variables relate exporter i's agro-ecological characteristics to absolute advantage in agriculture through $\boldsymbol{X}_i\boldsymbol{\delta}$ and describe how they systematically influence the set of products within the agricultural sector in which it has comparative advantage through $\boldsymbol{X}_i\ (\boldsymbol{E}(\,j)\boldsymbol{\Lambda})'$.

Trade Cost Distribution

We specify product- j trade costs as:

$$ln(\tau_{ni}^{k}(\,j)) \;=\; \boldsymbol{t}_{ni}\boldsymbol{\beta^k}(\,j) \;=\; \boldsymbol{t}_{ni}\boldsymbol{\beta^k} \;+ ex_i^k + \boldsymbol{t}_{ni}\,(\boldsymbol{\nu}_{t_n}^{k}(\,j)\boldsymbol{\Sigma}_t^k)' + \xi_{ni}^k \qquad (17)$$

where $\boldsymbol{t}_{ni}$ is a $1 \times m$ vector describing the relationship between exporter i and import market n, $\boldsymbol{\beta^k}$ is an $m \times 1$ vector of parameters; ex_i^k is an exporter-specific trade cost captured by a fixed effect; $\boldsymbol{\nu}_{t_n}^{k}(\,j)$ is a $1 \times m$ vector that captures the effect of unobservable product j-specific trade costs with scaling matrix $\boldsymbol{\Sigma_t^k}$, and ξ_{ni}^k captures unobservable or unquantifiable bilateral trade costs that are common across products and orthogonal to the regressors.[4] We define:

$$\boldsymbol{t}_{ni} \;= [b_{ni} \quad l_{ni} \quad rta_{ni} \quad \boldsymbol{d}_{ni}]$$

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 $\boldsymbol{d}_{ni}$ assigns each country pair to one of six distance categories as defined in Eaton and Kortum (2002, see Table 1).

Estimating Productivity and Trade Cost Distribution Parameters

Using our definitions of $a_i(\,j)$ and $\tau_{ni}^{A}(\,j)$ in Equation 10, we obtain a random coefficients logit model of agricultural market share:

[4] Given our assumption that manufacturing trade costs are constant across products, Equation 17 becomes: $ln(\tau_{ni}^{M}) = \;\boldsymbol{t}_{ni}\boldsymbol{\beta^M} \;+ ex_i^M + \xi_{ni}^M$.

$$\pi_{ni} = \int \frac{\exp\{S_i + \theta\alpha_i(1-\beta_i)\boldsymbol{X}_i\boldsymbol{\delta}(j) - \theta\boldsymbol{t}_{ni}\boldsymbol{\beta}(j)\}}{\sum_{l=1}^{I}\{S_i + \theta\alpha_l(1-\beta_l)\boldsymbol{X}_l\boldsymbol{\delta}(j) - \theta\boldsymbol{t}_{nl}\boldsymbol{\beta}(j)\}} d\hat{F}_{E_n}(\boldsymbol{E})d\hat{F}\boldsymbol{v}_n(\boldsymbol{v}) \tag{18}$$

where $d\hat{F}_{E_n}(\boldsymbol{E})d\hat{F}\boldsymbol{v}_n(\boldsymbol{v})$ 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 18 using a simulated method of moments approach similar to that in Berry, Levinsohn, and Pakes (1995), which is detailed in Nevo (2000) and Train (2009). To evaluate the integral, we use the "smooth simulator" suggested by Nevo (2000):

$$\hat{\pi}_{ni} = \frac{1}{ns}\sum_{\mathrm{j=1}}^{\mathrm{ns}} \frac{\exp\{\tilde{S}_i + \theta\alpha_i(1-\beta_i)\boldsymbol{X}_i\boldsymbol{\delta}(j) - \theta\boldsymbol{t}_{ni}\boldsymbol{\beta}(j)\}}{\sum_{l=1}^{I}\{\tilde{S}_i + \theta\alpha_l(1-\beta_l)\boldsymbol{X}_l\boldsymbol{\delta}(j) - \theta\boldsymbol{t}_{nl}\boldsymbol{\beta}(j)\}} \tag{19}$$

where $\tilde{S}_i = S_i + \theta\alpha_i (1-\beta_i)\boldsymbol{X_i}\boldsymbol{\delta}$ is a country fixed effect. We use the minimum distance procedure suggested by Nevo (2000) to obtain $\hat{S}_i$ and $\boldsymbol{\delta}$ from $\hat{\tilde{S}}_i$.

To estimate productivity and trade cost parameters in the manufacturing sector, we follow Eaton and Kortum (2002), Waugh (2010) and others, using S_i^M and the definition of manufacturing trade costs in Equation 9, and then use linear methods to estimate:

$$\ln\left(\frac{\hat{\pi}_{ni}^M}{\hat{\pi}_{nn}^M}\right) = S_i^M - S_n^M - \theta\boldsymbol{t}_{ni}\boldsymbol{\beta}^{\boldsymbol{M}} \tag{20}$$

Data

Parameters of the distributions of productivity and trade costs are estimated using production and trade data from 2006, the most recent year for which we have a complete data set for both sectors. The age of the data used to parameterize the model is a disadvantage to the extent that the data do not capture structural changes in supply and demand stemming from income and productivity growth, as well as changes in trade and other policies that affect bilateral market access. However, sources of natural resource-based comparative advantage can be assumed to be unchanged, and differences in relative average technological productivity can be assumed to be small. In future work, we will update the model to more recent years by simulating changes in policy and average productivity.

Sector-level bilateral market shares are calculated by dividing bilateral import value by sector-level expenditure, calculated as $X_i^k = Y_i^k + EX_i^k - IM_i^k$. Domestic market share is calculated as $\pi_{nn}^k = 1 - \sum_{i \neq n} \pi_{ni}^k$. For the agricultural sector, our data consist of the 134 agricultural items for which data on both bilateral trade and the gross value of production in US dollars are available (FAO, 2013). These are mostly primary agricultural products. Data on bilateral market shares for the manufacturing sector are calculated using 2006 production and trade data from CEPII.[5] Elements of $\boldsymbol{t}_{ni}$ are obtained from the CEPII gravity data set (Head, Mayer, and Ries, 2009).

We do not observe land and climate requirements for each product, but we do observe conditions of their production around the world. We use observable characteristics of exporting countries to construct a matrix of "observable" product requirements, $\boldsymbol{E}(j)$, 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, $\boldsymbol{E}(j)$ 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 resource 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

[5] Manufacturing production value is interpolated from previous years for some countries.

agricultural worker (alw_i), using data on arable land per capita and land per agricultural worker from World Bank (2012) and elevation data from CIESIN (2010), respectively.

Notice that we define the land intensity of product j using data on land per agricultural worker, whereas we use agricultural land per capita in $\boldsymbol{X}_i$. The motivation for this distinction is that elements of $\boldsymbol{X}_i$ represent the factors that influence exporter i's potential comparative advantage, whereas elements of $\boldsymbol{E}(j)$ represent the ideal conditions under which product j is produced. Products are represented by their observed production conditions, but countries are represented by their potential production conditions.

Defining product requirements as export-weighted averages of country characteristics has the potential of being imprecise. Many important agricultural exporters have varied terrain and climate within their borders. For example, Canada supplied about 20 percent of global wheat exports in 2006. However, while a large share of Canada's total land area is in the boreal climate zone, the country's wheat production is concentrated in temperate regions. A trade-weighted average of climate distributions would thus misrepresent wheat's 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 (Lee et al., 2005). As part of an effort to model the impact of climate change on the agricultural sector, the database provides estimates of 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. We use export-weighted averages of country climate distributions, as we did for land and elevation intensity, to calculate $[trp(j) \quad tmp(j) \quad bor(j)]$ for these products.

The $ns = 900$ products used to evaluate Equation 19 for each importer and its trading partners are drawn from $d\hat{F}_{E_n}(\boldsymbol{E})d\hat{F}\boldsymbol{\nu}_n(\boldsymbol{\nu})$. We construct this density as in Heerman et al. (2015), first using FAO item level import data to estimate $d\hat{F}_{E_n}(\boldsymbol{E})$, the empirical distribution of $\boldsymbol{E}(j)$ across products imported by each market by compiling a list of 1,000 imported items defined by the vector $\boldsymbol{E}(j)$ for each market n. Unique values of $\boldsymbol{E}(j)$ are represented in $d\hat{F}_{E_n}(\boldsymbol{E})$ in proportion to the associated FAO item's share in total imports. That is, if 15 percent of importer n's total agricultural imports consist of the FAO item "wheat," then $E(wheat)$ makes up 150 entries on $d\hat{F}_{E_n}(\boldsymbol{E})$. Next we make uniform draws of $\boldsymbol{E}(j)$ from each country's distribution. The distribution is completed by associating each item on the list with $\nu_n(j) = [\boldsymbol{\nu}_{\boldsymbol{E}}(j) \quad \boldsymbol{\nu}_{\boldsymbol{t}_n}(j)]$ drawn from a standard multivariate normal distribution, effectively generating a "data set" of 900 unique products imported by each market.

In addition to the estimated parameters that define the productivity distribution, computing world equilibrium requires data on labor and land endowments, values for utility and production function parameters, and the elasticity of substitution, σ. Data on arable land in hectares and total labor force are obtained from the World Bank World Development Indicators (World Bank, 2012). Table 2 summarizes all of the structural parameters.

6. Estimated productivity distribution and base model solution

Land Productivity Distribution

Table 3 contains estimates for the land productivity distribution parameters $\boldsymbol{\delta}$, $\boldsymbol{\Lambda}$, and $\boldsymbol{\Sigma_E}$. The total effect of each exporter characteristic in $\boldsymbol{X}_i$ 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 columns 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. The positive mean effect on tropical land share ($\delta_{trp} = 0.7$) implies that having more than the average share of land in a tropical climate increases agricultural market share on average. The positive and larger coefficient on $trp(j)$ ($\lambda_{trp,trp} = 6.86$) implies this effect is increasing for products that are more intensively tropical than average. Negative coefficients imply the advantage of tropical land is decreasing for more intensively boreal products ($\lambda_{trp,bor} = -7.4$) and elevation-intensive products ($\lambda_{trp,elv} = -3.96$).

Figure 1 illustrates the distribution of the total effect of high elevation land across the products in our constructed data set. High elevation land decreases the probability of having the lowest price for some products, but raises it for most. The mean effect of a higher than average amount of land at high elevation acreage is positive ($\delta_{elev} = 1.14$). This implies that having more land at high elevation increases agricultural market share on average. However, this benefit is substantially diminished for products more intensively produced in temperate climates than the average product ($\lambda_{elev,tmp} = -12.32$). In contrast, the benefit is greatly magnified for products that are more intensely boreal than the average product ($\lambda_{elev,bor} = 11.01$). Boreal climates are associated with high elevation, therefore, we expect to see countries with higher than average acreage at high elevations are more likely to specialize in boreal crops. The statistically and economically insignificant value of the estimated coefficient on unobservable product characteristics ($\sigma_{elev} = -0.21$), implies that variation in the effect of high elevation across products is sufficiently explained by the product requirements in $\boldsymbol{E}(j)$.

Estimates for $\hat{\hat{S}}_i^A$ and $\hat{S}_i^M$ are listed in Table A3. These values are normalized to sum to zero and are thus interpreted as average sector-level productivity relative to the average country, and in the case of agriculture, in the average product. Recall that $\hat{\hat{S}}_i^A$ and $\hat{S}_i^M$ are increasing in average technological (and land productivity in the agricultural sector), but decreasing in costs of production c_i^k. Therefore, a country with high average productivity may nevertheless have a small $\hat{S}_i^k$ if it has, e.g., very high wages or land rental rates. Values of $\hat{T}_i^k$ are obtained from $\hat{S}_i^k$ as in Waugh (2010).

Trade Costs

Table 4 contains estimates for the agricultural trade cost distribution parameters $\boldsymbol{\beta^A}$ and $\boldsymbol{\Sigma_t^A}$ and the manufacturing trade cost parameters $\boldsymbol{\beta^M}$. Positive coefficient values in $\boldsymbol{\beta^A}$ and $\boldsymbol{\beta^M}$ imply higher trade costs, but lower expected market share. Elements of $\boldsymbol{\Sigma_t^A}$ capture heterogeneity in the effect of each element of $\boldsymbol{t}_{ni}^A$ across agricultural products and can thus be interpreted like a standard error around the mean effect.

In the agricultural sector, positive mean effects imply that sharing a common language and participating in an RTA increases market share on average, while negative coefficients imply increasing distance tends to decrease it. The negative mean effect of sharing a border ($\beta_b^A = -1.76$) may seem counterintuitive. However, the relatively larger magnitude of the estimated standard error ($\sigma_b = 3.13$) implies sharing a border increases market share for some products and decreases it for others. Sharing a border may reduce trade in individual products for a number of reasons. For example, agricultural policies often systematically advantage domestic producers relative to their close competitors.

Coefficient estimates on the components of trade costs in the manufacturing sector are generally similar to the agricultural sector. Smaller magnitude coefficients on the distance variables suggest in manufactured products are less costly to transport than agricultural products on average. This is sensible since agricultural products are often perishable or otherwise require special handling. The positive and significant effect implies sharing a border unambiguously increases manufactured products market share on average ($\beta_b^M =$ 0.82).

Values of $\widehat{ex}_i^k$ are reported in Table A3. The values are normalized to sum to zero, so positive (negative) values imply that exporter i is a lower (higher)-than-average-cost exporter. Our results suggest that Belgium, Canada and the United States are the lowest-cost exporters of agricultural products. The United States and the Netherlands are the lowest-cost exporters of manufactured products.

Elasticities

Parameter estimates in Tables 3 and 4 allow us to calculate predicted market share (Equation 19) and elasticities using the formulas underlying Equation E1. To see how the

SH gravity model overcomes the limitations of imposing the IIE property highlighted in Arkolakis *et al*. (2012), we show that the predicted elasticities are not a constant proportion of market share, as the standard model predicts (Equation E2).

By way of example, we calculate the ratio of the elasticity to Mexican trade costs to market share in Canada, that is $\frac{\partial \pi_{ni}}{\partial \tau_{nl}} \frac{\tau_{nl}}{\pi_{ni}} / \pi_{nl}$, where l =Mexico, $i \neq$ Mexico and n=Canada. Since the relevant elasticity is a direct elasticity for i=Mexico, we divide the elasticity by $(1 - \pi_{CanMex})$. This ratio would be a the same (equal to θ) for every country in the standard model. In the SH model the ratio varies dramatically depending on characteristics of the exporter and the products they export to Canada. Table 5 reports this ratio for the countries with the largest share of Canadian expenditure on the products in our data set. The SH gravity model predicts that Colombia, Chile and Indonesia, who are more likely to compete with Mexico, would gain disproportionately from higher Mexican trade costs, whereas gains in Canadian and US market share will be proportionately smaller.

General Equilibrium Solution

We use a two-step process similar to that outlined in Levchenko and Zhang (2014) to solve the model. In step one, given a vector of unobserved trade costs ($\bar{\boldsymbol{\xi}}$), the data, the parameters described in Table 3, and an initial guess for a vector of wages, ($\bar{\boldsymbol{w}}$), land rent, ($\bar{\boldsymbol{r}}$), we solve for equilibrium, beginning by solving for $\boldsymbol{p^A}$ and $\boldsymbol{p^M}$ consistent with the guessed values (Equations 7 and 8), and simulating the integral in Equation 8 as:

$$p_n^A = \frac{\gamma}{ns} \left(\sum_{j=1}^{ns} \Omega_n^A (\bar{\boldsymbol{w}}; j)^{\frac{\sigma-1}{\theta}} \right)^{\frac{1}{1-\sigma}} \qquad (21)$$

using the same ns products used to estimate Equation 19.

We then calculate the cost of an input bundle in each tradeable sector (Equation 6), consumer final demand, $X_i^k = \lambda^k(w_i N_i + r_i L_i)$, bilateral market shares (Equations 9 and 10, simulating the integral as above), total demand for each sector (Equation 12), labor allocations (Equation 14) and land rental rates (Equation 15). We adjust the vector of guessed wages until labor market clearing conditions hold. In the next step, $\bar{\boldsymbol{\xi}}$ is adjusted until observed and predicted trade shares are sufficiently close.

7. Examining Trans-Pacific Integration

To explore the effects of Trans-Pacific integration on agricultural trade we run two scenarios based on the tariff reductions agreed under the CPTPP. The benchmark scenario simulates tariff cuts agreed under the CPTPP on the products in our data set among CPTPP members. In the alternative scenario, the United States obtains equivalent access to CPTPP markets and, following Australia, offers free access to the US market on all agricultural products in our model.

We simulate tariff cuts by reducing estimated trade costs product-by-product in the amount of the change in each country's simple average applied MFN tariff and the simple average tariff listed in each country's CPTPP schedule for the tariff lines that make up each of our products at full implementation. We then re-solve the model for a new equilibrium. No changes are made to manufacturing sector trade costs, which includes some products commonly considered agricultural products. As such, the results presented here cannot be interpreted as the likely results of the CPTPP agreement. Rather, they serve to highlight the likely effects of Trans-Pacific integration on the structure of competition among CPTPP participants and the United States in trade in primary agricultural products.

The results reported in this paper should be considered preliminary, given our treatment of existing RTAs and specific tariffs in the CPTPP schedule. These assumptions imply that we neither fully capture nor isolate the effect of the CPTPP. These assumptions are made purely for expedience and will be addressed in later versions of the paper.

Since many members have pre-existing RTAs, CPTPP tariff cuts are not taking place from global MFN levels. Importantly, there are bilateral relationships – such as among the NAFTA countries - where tariffs were largely zero as of 2006 and could thus not be cut much further. To avoid over-estimating the magnitude of the tariff cuts implied by the CPTPP and thus the impact of Trans-Pacific integration, we exclude country pairs that had an RTA prior to 2006 from the modeled tariff cuts. Thus we implicitly assume the CPTPP does not introduce further tariff reductions for countries with pre-existing agreements. Likewise, we do not model tariff cuts under individual RTAs implemented after 2006. This implies that our model assumes that post-2006 agreements do not provide access beyond that offered under the CPTPP.

We have also not modeled product-specific tariff cuts that take the form of specific tariffs in this paper. Neither have we included all cases of expansions in TRQs. This is an important drawback of the results we report here since these policy measures tend to cover import-competing products. Including them in future work will likely increase our estimates of the trade effects of Trans-Pacific integration under the CPTPP.

Preliminary counterfactual results

Table 6 presents the model's predicted changes in export value in response to tariff cuts described above. The first two columns contain the percent change in the value of agricultural exports for each CPTPP member plus the United States. The first column contains the change in global exports. The second contains the percent change within the Trans Pacific region, defined as the CPTPP countries plus the United States. The model predicts that each country's exports increase under the CPTPP tariff cuts, including the United States. US exports benefit indirectly from the lower cost of importing agricultural products as intermediate inputs. Increases in export value are larger within the region. This implies that increased market access in the Trans-Pacific region is the key driver of expanded global exports for these countries.

The largest beneficiaries in terms of regional exports expansion under the CPTPP tariff cuts modeled here are Australia, Canada and Chile. New Zealand sees the smallest increases in exports value, although it should be noted that our definition of the agricultural sector excludes many of the products in which New Zealand is a competitive exporter. Peru's exports expansion is also relatively small under the CPTPP.

The last two columns present ratios of the percent change in exports value under the alternative scenario in which the United States obtains equivalent access to CPTPP markets and offers free access to CPTPP countries in return to the benchmark reported in the first two columns. When these ratios take values greater than one, it indicates that exports value increases more under the alternative scenario. Global exports value expands more for every country except Australia, for which it is roughly unchanged. The largest relative increases are for New Zealand, Peru and the United States. The relative increase in global trade value for these countries is similar to the increase in regional trade value in all three cases. For New Zealand and Peru[6] this implies that the additional access to the United States market is driving their export expansion.

[6] Note that Peru and the United States have an FTA which came into force after 2006.

The final column of Table 6 reveals the model's prediction that given equivalent access to CPTPP markets, Australia, Canada, Chile and Mexico have a particularly large reduction in the regional exports expansion in percentage terms when the United States benefits from the tariff cuts offered under the CPTPP. This suggests these countries are the United States' closest competitors in Trans-Pacific markets for the products in our data set.

8. Summary and conclusions

The preliminary results reported in this paper suggest that Trans-Pacific integration offers a substantial opportunity for increased agricultural exports. *Ad valorem* tariff cuts under the CPTPP on the products included in our dataset increases exports of the agreement's signatories, both regionally and globally. The additional market access embodied by these tariff cuts erodes the competitiveness of the United States in these markets by increasing the relative price of US exports. Nevertheless, US agricultural exports increase on average from CPTPP as it lowers the cost of agricultural products used as imported intermediate inputs and increases demand for food and agricultural products generally as real incomes rise in CPTPP markets.

As expected, with increased access to CPTPP markets, the value of US agricultural exports increases much more than it does under the indirect benefits of the CPTPP. Importantly, in contrast to standard gravity modeling approaches, the SH model is able to capture the difference in the impact on relative demand when the US is involved in Trans-Pacific integration versus when integration proceeds without new US access. The model finds that the percent change in exports value for Australia, Canada, Chile and Mexico is disproportionately larger under the CPTPP without equivalent US market access. This implies these are the United States' closest competitors in the region among CPTPP countries. In contrast, other countries gain relatively more when the US market is integrated. Standard gravity-based models of the agricultural sector miss these distinctions.

There are many limits to the analysis presented here. First, our base model is calibrated with data from 2006, when global trade patterns differed in some important ways, particularly in terms of the nature and degree of competition from Brazil and other rising exporters and the nature and degree of demand from China and other rising importers. The tariff cuts we model to capture the CPTPP are incomplete. Moreover, in our scenario analysis we abstract from the impact of changes in manufacturing tariffs. Future work will address these and other issues.

References

Adao, R., Costinot, A., Donaldson, D. 2017. Nonparametric counterfactual predictions in neoclassical models of international trade. *American Economic Review* 107(3), 633-689.

Anderson, J.E., van Wincoop, E., 2003.Gravity with gravitas: a solution to the border puzzle. *American Economic Review* 93 (1), 170-192.

Anderson, J.E., van Wincoop, E., 2004. Trade costs. *Journal of Economic Literature* 42 (3), 691-751.

Anderson, J.E., Yotov, Y.V. 2010a. The changing incidence of geography. *American Economic Review* 100 (5), 2157-2186.

Anderson, J.E., Yotov, Y.V. 2010b. Specialization: Pro-and anti-globalizing, 1990-2002. NBER Working Paper 16301. NBER, Cambridge, MA.

Anderson, J.E., Yotov, Y.V. 2012. Gold standard gravity. NBER Working Paper 17835. NBER, Cambridge, MA.

Arkolakis, C., Costinot, A., Rodríguez-Clare, A. 2012. New trade models, same old gains? *Amer* Cardamone, P. 2011. The effect of preferential trade agreements on monthly fruit exports to the European Union. *European Review of Agricultural Economics* 38(4), 553-586.

Bagwell, K., Bown, C.P., Staiger, R.W. 2016. Is the WTO passé? *Journal of Economic Literature* 54(4), 1125-1231.

Berry, S., Levinsohn, J, Pakes, A. 1995. Automobile prices in market equilibrium. *Econometrica* 63(4), 841-890.

Burfisher, M.E., Dyck, J., Meade B., Mitchell, L, Wainio, J. Zahnhiser, S., Arita, S., Beckmann, J. 2014. Agriculture in the Trans-Pacific Partnership. Economic Research Report Number 176. Economic Research Service. United States Department of Agriculture, Washington DC.

Burstein, A., Vogel, J. 2010. Globalization, technology, and the skill premium: A quantitative analysis. NBER Working Paper 16459. NBER, Cambridge MA.

Caliendo, L., Parro, F. 2015. Estimates of the trade and welfare effects of NAFTA. *Review of Economic Studies* 82 (1), 1-44.

Cardamone, P. 2011. The effect of preferential trade agreements on monthly fruit exports to the European Union. *European Review of Agricultural Economics* 38(4), 553-586.

Chaney, T., 2008. Distorted gravity: The intensive and extensive margins of international trade. *American Economic Review* 98(4), 1707-1721.

Chevassus-Lozza, E., Latouche, K. 2012. Firms, markets and trade costs: access of French exporters to European agri-food markets. *European Review of Agricultural Economics* 39(2), 257-288.

Chor, D. 2010. Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics* 82(2), 152-167.

Center for International Earth Science Information Network (CIESIN). 2010. *National Aggregates of Geospatial Data Collection: Population, Landscape and Climate Estimates*. CIESIN, Columbia University, NY.

Costinot, A., Donaldson, D., Komunjer, I. 2012. What goods do countries trade? A quantitative exploration of Ricardo's ideas. *Review of Economic Studies* 79(2), 581-608.

Costinot, A., Rodríguez-Clare, A. 2014. Trade theory with numbers: Quantifying the consequences of globalization in G. Gopinath, E. Helpman, and K. Rogoff, eds. *Handbook of International Economics*. North-Holland, Amsterdam.

Dal Bianco, A., Boatto, V.L., Caracciolo, F., Santeramo, F.G., 2016. Tariffs and non-tariff frictions in the world wine trade. *European Review of Agricultural Economics* 43(1), 31-57.

Disdier, A-C., Emlinger, C., Fouré, J. 2015. Atlantic versus Pacific agreement in agrifood sectors: Does the winner take it all? CEPII Working Paper No 2015-10. CEPII, Paris.

Eaton, J., Kortum, S., 2002. Technology, geography, and trade. *Econometrica* 70 (5), 1741-1779.

Feenstra, R.C. 2004. *Advanced International Trade: Theory and Evidence*. Princeton University Press, Princeton, NJ.

Food and Agricultural Organization of the United Nations (FAO). 2013. *FAOSTAT Database*. FAO, Rome.

Freund, C., Moran, T., Oliver, S. 2016. Tariff liberalization, in *Assessing the Trans-Pacific Partnership, Volume 1: Market Access and Sectoral Issues*. Peterson Institute of International Economics, Washington DC.

Gollin, D. 2002. Getting income shares right. *Journal of Political Economy* 110 (2): 458-474.

Head, K., Mayer, T., 2014. Gravity equations: workhorse, toolkit, and cookbook in G. Gopinath, E. Helpman, and K. Rogoff, eds. *Handbook of International Economics*. North-Holland, Amsterdam.

Head, K, Mayer, T., Ries. 2009. How remote is the offshoring threat? *European Economic Review* 53(4), 429-444.

Heerman, K, E.R. 2016. Technology, ecology and agricultural trade. Unpublished working paper.

Heerman, K.E.R., Arita, S., Gopinath, M. 2015. Asia-Pacific integration with China versus the United States: Examining trade patterns under heterogeneous agricultural sectors. *American Journal of Agricultural Economics* 97(5), 1324-1344.

Heerman, K.E.R., Sheldon, I.M. 2017. Gravity and comparative advantage: Estimation of trade elasticities for the agricultural sector. Unpublished working paper. Ohio State University, Columbus, OH.

Heerman, K.E.R., Zahniser, S. 2018. Trade and production impacts of rolling back NAFTA's agricultural preferences: An application of the systematic heterogeneity general equilibrium gravity model. Invited Paper presented at the AAEA/ASSA meetings, Philadelphia, PA.

Hendrix, C., Kotschwar, B. 2016. Agriculture, in *Assessing the Trans-Pacific Partnership, Volume 1: Market Access and Sectoral Issues*. Peterson Institute of International Economics, Washington DC.

Hertel, T. 2013. Global applied general equilibrium analysis using the Global Trade Analysis Project framework in P.B. Dixon and D.W. Jorgenson, eds. *Handbook of Computable General Equilibrium Modeling*. Elsevier, New York.

Jales, M., Josling, T., Nassar, A., Tutwiler, A. 2005. Options for agriculture: From framework to modalities in market access/domestic support/export competition. Trade Policy Issues Paper No. 2. International Agricultural Trade Research Consortium (IATRC). Minneapolis St.Paul, MI.

Jayasinghe, S., Beghin, J.C., Moschini, G. 2009. Determinants of world demand for US corn seeds: The role of trade costs. *American Journal of Agricultural Economics* 92(4), 999-1010.

Kerr, W.R. 2017. Heterogeneous technology diffusion and Ricardian trade patterns. *The World Bank Economic Review*, 1-20, doi: 10.1093/wber/lhx002.

Lee, H-L, Hertel, T., Sohngen, B., Ramankutty, N. 2005. Towards and integrated land use data base for assessing the potential for greenhouse gas mitigation. GTAP Technical Paper No. 25. Center for Global Trade Analysis (GTAP), Department of Agricultural Economics, Purdue University, West Lafayette, IN.

Levchenko, A.A., Zhang, J. 2014. Ricardian productivity diferences and the gains from trade. *European Economic Review* 65: 45-65.

Melitz, M.J., 2003. The impact of trade on intra-industry allocations and aggregate industry productivity. *Econometrica* 71 (6), 1695-1725.

Nevo, A. 2000. A practitioner's guide to estimation of random-coefficients logit models of demand. *Journal of Economics and Management Strategy* 9(4), 513-548.

OECD. 2013. STAN Database. Organization for Economic Cooperation and Development, Paris.

Reimer, J. J., Li, M. 2010. Trade costs and the gains from trade in crop agriculture. *American Journal of Agricultural Economics* 92 (4), 1024–1039.

Ruhl, K. 2008. The International Elasticity Puzzle. Working Paper, University of Texas, Austin, TX.

Shiker, S. 2011. Capital, technology, and specialization in the neoclassical model. *Journal of International Economics* 83(2), 229-242.

Shiker, S. 2012. Predicting the effects of NAFTA: Now we can do it better! *Journal of International and Global Economic Studies* 5(2), 32-59.

Simonovska, I., Waugh, M.E. 2014. The elasticity of trade: Estimates and evidence. *Journal of International Economics* 92 (1), 34–50.

Tombe, T. 2015. The missing food problem: Trade, agriculture, and international productivity differences. *American Economic Journal: Macroeconomics* 7(3), 226-258.

Train, K. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge, MA.

Waugh, M. 2010. International trade and income differences. *The American Economic Review* 100 (5): 2093-2124.

World Bank. 2012. *World Development Indicators*. World Bank, Washington DC.

World Trade Organization (WTO). 2018. *Regional Trade Agreements: Facts and Figures*, WTO, Geneva.

Xu, K. 2015. Why are agricultural goods not traded more intensively: High trade costs or low productivity variation? *World Economy* 38 (11), 1722–1743.

Tables

Table 1: Definition of distance variables

Variable	Distance, miles
Distance 1	[0,375)
Distance 2	[375,750)
Distance 3	[750,1,500)
Distance 4	[1,500,3,000)
Distance 5	[3,000,6,000)
Distance 6	[6,000, maximum]

Table 2: Summary of parameter values

Parameter	Value	Source
$\boldsymbol{\delta}, \boldsymbol{\Lambda}, \boldsymbol{\Sigma_E}$	Table 4	Estimated from Equation 19
$\boldsymbol{\beta^A}, \boldsymbol{\Sigma_t}, \boldsymbol{ex^A}$	Table 3 and Table A3	
$\boldsymbol{\beta^M}, \boldsymbol{ex^M}$	Table 3 and Table A3	Estimated from Equation 20
$\boldsymbol{T}^A, \boldsymbol{T}^M$	*Not reported*	Estimates of $\tilde{\boldsymbol{S}}^A$ and $\boldsymbol{S^M}$
$\lambda^k, \alpha^k, \xi_l^k$	Tables A1 and A2	Input-Output Tables (OECD 2013)
β	0.66	Gollin (2002)
θ	4.12	Simonovska and Waugh (2014)
σ	2.00	Ruhl (2008)

Table 3: Land productivity distribution parameter estimates

Exporter Characteristics ($\boldsymbol{X_i}$)	**Mean Effects** ($\boldsymbol{\delta}$)	**Unobserved Reqs** ($\boldsymbol{\Sigma_E}$)	**Agro-Ecological Requirements** ($\boldsymbol{\Lambda}$) $\boldsymbol{elv(j)}$	$\boldsymbol{alw(j)}$	$\boldsymbol{trp(j)}$	$\boldsymbol{tmp(j)}$	$\boldsymbol{bor(j)}$
ln Arable Land per Ag Worker	0.17***	-0.01	-4.51***	0.42***	1.81***	0.33***	-2.14
High Elevation	1.14***	-0.21	47.96***	0.44***	1.31***	-12.32***	11.01
Tropical Climate Share	0.7***	-0.16**	-3.96***	0.73***	6.86***	0.19	-7.04
Temp. Climate Share	0.19***	-0.03	1.46***	-0.53***	-2.8***	0.7***	2.1
Boreal Climate Share	-0.88***	0.19**	2.5***	-0.2***	-4.06***	-0.89***	4.94

***significant at the 1% level, ** significant at the 5% level, *significant at the 10% level.

Note: Values in this table are inclusive of the term $\theta\alpha_i(1-\beta_i)$

Table 4: Trade cost distribution parameters

	Agriculture		Manufacturing
Country Pair Characteristics	**Mean Effect ($\boldsymbol{\beta^A}$)**	**Unobserved Heterogeneity ($\boldsymbol{\Sigma_t}$)**	**Mean Effect ($\boldsymbol{\beta^M}$)**
Common Border	-1.76***	3.13***	0.82***
Common Language	1.24***	0.95***	1.10***
Common RTA	0.19**	-0.11	0.11
Distance 1	-5.28***	2.36***	-4.54***
Distance 2	-7.67***	2.33***	-4.96***
Distance 3	-7.43***	-0.16	-5.42***
Distance 4	-9.95***	1.37***	-5.71***
Distance 5	-11.56***	-0.04	-7.09***
Distance 6	-12.94***	0.64***	-7.67***

*** significant at the 1% level, ** significant at the 5% level, *significant at the 10% level.

Note: Values in this table are inclusive of the term θ.

Table 5. Trade elasticities are not constant

Source country	$\boldsymbol{\frac{\partial \pi_{ni}}{\partial \tau_{nl}} \frac{\tau_{nl}}{\pi_{ni}} / \pi_{ni}}$ *
Canada	3.47
USA	2.22
Mexico**	-3.70
Chile	5.56
Indonesia	6.30
Colombia	7.03

$*$ n = Canada, l = Mexico, i = Source country

**The elasticity of Mexico with respect to Mexican trade costs is divided by $(1 - \hat{\pi}_{ca,mex})$

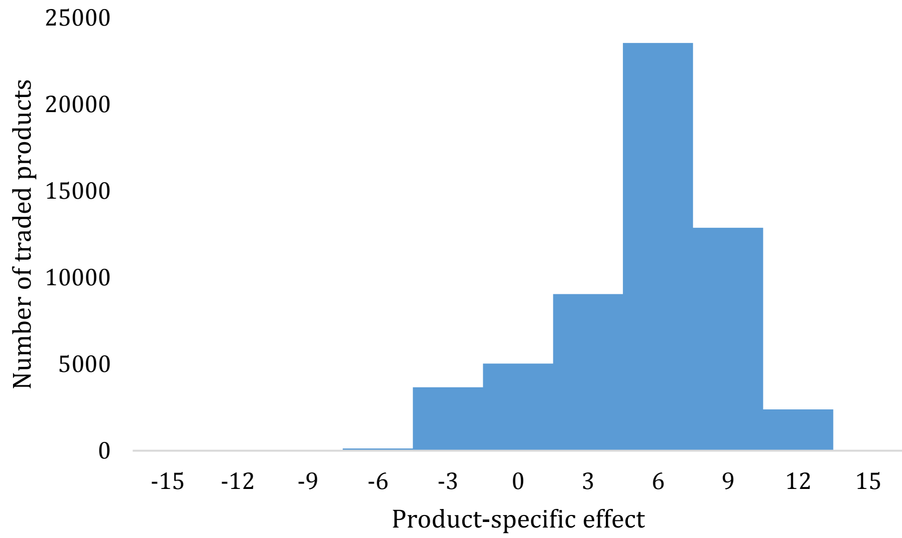
Table 6: Preliminary Results – Agricultural exports responses to agricultural tariff cuts

	% Change in agricultural exports value			
	CPTPP countries only		Ratio: $\frac{CPTT+USA}{CPTPP\ Only}$	
Country	**Global**	**Regional***	**Global**	**Regional***
Australia	0.17	2.29	1.000	0.905
Canada	0.56	2.37	1.002	0.949
Chile	0.09	2.17	1.005	0.790
Japan	0.27	1.94	1.059	0.994
Malaysia	0.15	1.73	1.024	1.002
Mexico	0.42	1.97	1.001	0.631
New Zealand	0.02	0.05	1.344	1.381
Peru	0.23	1.16	1.356	1.133
Vietnam	0.32	1.61	1.032	0.999
United States	0.07	0.27	1.338	1.322

*Regional refers to the CPTPP members in our data set plus the United States

Figures

Figure 1. Frequency plot - High elevation land effect



Appendix Tables

Table A1: Value added and consumption shares

α^A	α^M	α^S	λ^A	λ^M	λ^S
0.49	0.32	0.56	0.05	0.30	0.65

Table A2: Intermediate input shares

ξ_A^A	ξ_M^A	ξ_S^A	ξ_A^M	ξ_M^M	ξ_S^M	ξ_A^S	ξ_M^S	ξ_S^S
0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68

Table A3: Average productivity and exporter cost estimates

Country	$\hat{S}_i^A$	$\widehat{ex}_i^A/\theta$	$\hat{S}_i^M$	$\widehat{ex}_i^M/\theta$
Argentina	0.86***	1.17***	0.11	0.24***
Australia	0.85***	0.3***	-0.1	0.35***
Austria	-1.06***	-0.03	-0.24	0.32***
Belgium	-8.3***	2.96***	-1.83***	0.88***
Bolivia	0.34	-1.54***	0.29*	-1.28***
Brazil	0.7***	0.69***	0.85***	0.4***
Bulgaria	0.08***	-0.11***	-0.27**	-0.26***
Canada	-5.75***	2.79***	-0.35***	0.48
Chile	1.66***	1.21***	0.58***	0.01***
China	2.61***	1.16	1.15**	0.8***
Colombia	1.42***	0***	0.44***	-0.43***
Costa Rica	1.15***	-0.81***	-0.56***	-0.36***
Cote d'Ivoire	0.56	-0.75***	1.08	-1.27**
Czech Republic	0**	-0.48	-0.16***	0.16***
Denmark	0.44***	0.04***	-1.53***	0.53***
Ecuador	1.21***	-0.32***	0.58***	-0.63**
Estonia	2.77	-2.56***	-1.05***	-0.15***
Ethiopia	-0.37***	-0.96***	-0.96	-1.41***
Finland	1.72***	-1.58***	0.1	0.3***
France	-2.96***	1.76***	0.18	0.62***
Germany	-4.87	2.41***	0.21**	0.81***
Ghana	-0.35***	-1.06	-0.4	-0.94***
Greece	1	0.1***	0.13***	-0.24***
Honduras	-0.24***	-1.35***	-1.44**	-0.82
Hungary	2.1	-0.67***	0.45***	-0.07***
Iceland	-0.14***	-2.2***	-0.72***	-0.58***
India	1.13**	0.57***	0.8	0.31***

Country	$\widehat{S}_i^A$	$\widehat{ex}_i^A/\theta$	$\widehat{S}_i^M$	$\widehat{ex}_i^M/\theta$
Indonesia	0.55***	0.78***	0.13***	0.43***
Ireland	2.14***	-1.3	-2	0.63*
Israel	1.58***	0.06***	0.11**	-0.11***
Italy	-3.31***	2***	0.4***	0.57***
Japan	-1.68***	0.75***	1.37***	0.63***
Kazakhstan	0.78**	-1.76***	-0.5	-0.68***
Kenya	-0.51***	-0.7***	0.05	-0.9***
Lithuania	2.64***	-2.13***	-0.07*	-0.35***
Malaysia	-2.76**	1.51***	-0.3***	0.59***
Mexico	0.65***	0.5***	-0.9	0.46***
Morocco	1.41***	-0.88***	-0.06***	-0.38***
Netherlands	-3.12***	2.16***	-0.66***	0.71**
New Zealand	2.8***	0.35***	-0.5	0.16
Norway	2.41***	-2.41***	0.14***	0***
Paraguay	1.48***	-0.67	-0.71***	-0.83***
Peru	1	0.12	0.49*	-0.32*
Poland	-0.2***	0.03**	0.27***	0.11***
Portugal	-1.55***	0.17***	-1.96***	0.43***
Russia	-2.49***	0.16***	0.62	0.25**
Slovakia	3.07***	-2.15***	0.12*	-0.16***
Slovenia	1.63	-2.05***	0.31	-0.4***
South Africa	-0.07***	0.41**	-0.26***	0.32***
South Korea	1.85***	-0.21***	1.01	0.52***
Spain	-3.82***	2.12	0.23***	0.4***
Sri Lanka	1.36***	0.11***	2.2	-0.93***
Sweden	-0.64***	-0.25***	-0.08	0.46***
Switzerland	-2.46	0.31***	0.23*	0.3***
Thailand	-0.27***	0.28***	-0.27***	0.58***
Tunisia	3.04***	-1.13***	1.14*	-0.83***
Turkey	1.32***	0.56***	0.26**	0.17**
Ukraine	1.31***	-0.5***	0.4	-0.13***
UK	-4.05***	2.13	0.05	0.57***
Uruguay	2.68**	-0.12***	0.03***	-0.41***
Venezuela	0.62*	-2.36***	1.11	-0.62*
Vietnam	0.4***	0.35***	-0.03	0.1
USA	-4.36***	3.04***	0.3***	0.9***

***significant at the 1% level, ** significant at the 5% level, *significant at the 10% level