Technology, Ecology and Agricultural Trade

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Dedication

To my father, Mark Richman and to Prof. G. Edward Schuh, who inspired and actively supported my curiosity about economics

Abstract

I present a methodology for parameterizing and solving a probabilistic Ricardian model with two tradable sectors based on Eaton and Kortum (2002), henceforth EK. I make two changes that generate correlation in product-specific agricultural comparative advantage across agro-ecologically similar countries and deliver trade elasticities that are increasing in this correlation. First, I add product heterogeneity stemming from agro-ecological characteristics to the independently distributed productivity differences in production technology advanced by EK. Second, I allow trade costs to vary across products. As in EK, I estimate trade costs using bilateral trade flow data. However, to account for the additional heterogeneity, I use the simulated method of moments estimator pioneered by Berry, Levinsohn and Pakes (1995). The modified model successfully generates large differences in an exporter's elasticity with respect to its close competitors versus those that produce a very different set of agricultural products. This produces substantial differences in the model's predictions for changes to production and trade patterns in response to agricultural liberalization compared to those predicted by EK.

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Chapter 1

Introduction

Changes in bilateral trade policies have direct effects on trade flows between the two countries involved, but also indirect effects on those of their competitors. The total trade effect of a preferential agreement is thus properly described by the magnitude and distribution of the resulting shifts in bilateral trade flows across exporters. However, simplifying assumptions on the structure of production in existing quantitative models of trade result in rather coarse predictions for how patterns of production and trade shift across countries in response to policy-induced changes in costs in the agricultural sector.

A central prediction of trade theory is that opening to trade causes countries to specialize according to comparative advantage. Until recently, most of the empirical economics literature only considered comparative advantage at the sector or industry-level. Recent advances have provided the tools to define comparative advantage at the individual product level in an empirical model by defining technology with heterogeneous productivity across products. These technologies have been embedded in global general equilibrium models, most notably by Eaton and Kortum (2002)[1] and Melitz (2003)[2].

I introduce an analytical and empirical methodology that builds on the probabilistic Ricardian model of Eaton and Kortum (2002)[1], henceforth EK. Here, product-level comparative advantage in the agricultural sector is a function of the interaction between exporter agro-ecological characteristics and product-specific agro-ecological production requirements as well as independently distributed productivity differences arising from a country and sector-specific R&D process. Product-specific trade frictions blunt the trade-promoting force of comparative advantage due to productivity differences. These costs arise from differences in shipping and handling costs and trade policy, among other sources.

The model I present here is the first to my knowledge that integrates non-random sources of comparative advantage into a heterogeneous productivity trade model. It is also the first in this literature I am aware of to incorporate product-specific trade costs. As such, it is the only model built on the EK framework in which changes in the dispersion of tariffs *within sectors* can be analyzed. This feature is essential for meaningful agricultural policy analysis.

Public policy-makers considering a preferential trade agreement are typically at least as concerned with how gains and losses will be distributed across producers within the agricultural sector as they are with its effect on consumer welfare. This framework promises to allow researchers to make more informed predictions for how global production patterns are affected by opening to trade and thus provide better support for those questions. It will also be a useful framework for private sector decision-makers to explore how policy changes affect optimal global input sourcing and marketing decisions and for researchers in other disciplines in global agricultural production patterns.

A Point of Reference: The Model

In the model, I countries engage in bilateral trade. Each country has producers in two tradable sectors: manufacturing and agriculture, and in a non-tradable services sector. The agriculture and manufacturing sectors are each comprised of a unit continuum of products that are differentiated only in terms of their intrinsic characteristics. As in the multi-sector extensions of the EK framework of Caliendo and Parro (2012)[3] and Shikher (2012)[4], the sectors are linked through intermediate inputs.

A sector- and country-specific R&D process generates product-specific technologies that differ in terms of their productive efficiency. As in EK, these productivity differences are independently distributed across products. Unlike EK, there is a second source of productivity differences in the agriculture sector which comes from the coincidence of product-specific agro-ecological production requirements and exporters' agro-ecological characteristics. These productivity differences create comparative advantage within the sector and thus provide a natural explanation for agricultural trade, even among similar countries.

Exporters are assumed to face *ad valorem* trade costs to access foreign markets. These costs are assumed constant within the manufacturing sector as in EK. In contast, I allow trade costs to be product-specific in the agricultural sector. Systematic variation in trade costs across agricultural products is generated by intrinsic product characteristics such as perishability, and by differential policy treatment.

Exporter-level market shares are derived as the aggregate outcomes of revealed product-level comparative advantage. The direct effect of lower bilateral trade costs in the model is an expansion in the set of products an exporter sells to the importing country. The indirect effect on a third countrys market share in the import market depends on the extent to which this expansion eats into the set of products it sells to the importing country.

Key Features of Agricultural Production and Trade

A model that abstracts from non-random sources of agricultural comparative advantage and their distribution across exporters ignores fundamental determinants of the structure of the competitive environment in which agricultural producers operate. It will thus yield imprecise if not misleading predictions for the distribution of trade effects due to a change in bilateral trade barriers.

Individual agricultural products are plants and animals. As such, they vary intrinsically in terms of the amount of moisture, soil type, thermal climate and other environmental conditions in which they are most successfully cultivated. Comparative advantage in a given agricultural product is most likely to emerge in countries whose natural resource endowment has features that coincide with its ideal production conditions. Importantly, environmental conditions are not uniformly distributed across countries. Exporters with similar environmental conditions are more likely to have comparative advantage in similar products in international agricultural markets. The magnitude and distribution of the direct and indirect effects of a change in bilateral trade costs thus depends non-trivially on the pair of countries involved.

The framework I present generates a more complex description of the competitive environment in the agricultural sector by identifying countries likely to compete head to head in global markets in the same agricultural products based on similarities in their agricultural endowments. The model is thus able to generate a more nuanced picture of the effects of policy on global patterns of production and trade. As just one example, the model sensibly predicts that market share of the United States' closest competitor Canada, is over ten-times more responsive to changes in US tariffs than is tropical Costa Rica.

Dispersion of Agricultural Trade Costs

Heterogeneous productivity models with a continuum of goods have provided tools to conceptualize product-specific differences in trade costs. However, these models impose strong assumptions on the distribution of product heterogeneity in order to deliver convenient analytical forms for structural equations, which prevent analysis of anything more complex than changes in average trade costs. However, tariffs, transportation fees and other costs associated with exporting vary significantly and systematically across agricultural products. Agricultural products like fresh berries that are highly perishable have costly handling and transportation requirements while most grains can be shipped in bulk in relatively standard cargo containers. Import tariffs on dairy, cotton, sugar and rice are consistently among the highest in markets around the world.

Moreover, particularly in the case of tariffs and other policy barriers, the distribution of trade costs across products is typically the central focus of policy analysis. Consumers of agricultural policy analysis in the public and private sector are rarely interested in the effects of changes in the average agricultural subsidy or the average tariff. It is almost always the product-specific divergences from average that interest negotiators of trade agreements, agricultural producers and industrial users of agricultural products.

The flexibility of the model I present here, in terms of its ability to incorporate product-specific policy, is therefore a substantial contribution. To my knowledge it is the first heterogeneous productivity model in which changes in the distribution of these costs across products within sectors can be studied.

Imperfect Cross-Country Substitution

In the EK framework, all productivity differences are assumed to be independent across products and trade costs are constant and *ad valorem*. These two assumptions deliver convenient analytical solutions for the model's key structural equations, but they also have counter-intuitive implications. First, they imply that specialization patterns are randomly determined. As an illustrative example, this means that Colombia just happens to be a more competitive coffee exporter than Canada because of the random chance process that assigned it a high productivity coffee technology.

These assumptions are counter-intuitive on their face. More troubling is that they also impose strong restrictions on how trade patterns shift in response to changes in bilateral trade costs. Namely, they imply that the direct effect of bilateral trade liberalization on market share is virtually the same for every pair of countries. Furthermore, they imply that the indirect effect of a change in an exporter's bilateral trade costs is identical for all of its competitors' market shares, regardless of whether they are likely to compete head-to-head in the same products. Arkolakis, Costinot and Rodriguez-Clare (2012)[5] dub these features of the EK framework a "CES import demand system". Importantly, the authors point out that the CES import demand system is also a feature of other quantitative trade models, including those built on the Melitz (2003)[2] or the Armington assumption.

As an example of the peculiar substitution patterns this implies, suppose the United States cuts tariffs on all agricultural products imported from Colombia. The EK model would predict that Colombia will gain market share in the US at the expense of its competitors, who all lose an equal proportion of their US market share. That is, the EK model predicts identical drops in both Canadian and Costa Rican market share in response to lower Colombian tariffs. Basic reasoning, on the other hand, would lead one to expect Costa Rica's market share to fall proportionally more than Canada's.

In the model I introduce here, product-specific comparative advantage is no longer random. It is determined in part by agro-ecological characteristics. Countries with similar characteristics are likely to be competitive in the same products, everything else equal. This generates correlation in comparative advantage across countries and delivers elasticities of substitution (and thus indirect effects) between competing exporters that are increasing in this correlation.

Variation in Intensity of Global Competition across Products

In the EK framework, the intensity of competition is described by the cross-country variation in prices offered in a given market. If countries offer similar prices for the same product, international competition is intense and changes in trade costs are likely to cause shifts in trade patterns. If prices vary widely, it suggests that high-productivity technology or low trade costs are only available to producers in a few countries. In this case, marginal changes in trade costs are less likely to shift trade patterns. The nature of the intensity of competition in products traded between two partners can therefore have sizeable effects on the magnitude of the direct and indirect effects of bilateral liberalization.

Under the EK framework assumptions of independently distributed productivity and constant ad valorem trade costs, the intensity of competition is constant across products. However, this is a strong assumption for global agriculture markets. Some agricultural products require more specific or rare environmental conditions than others. While a soybean seed will yield a crop almost everywhere, cocoa beans can only be grown under very specific conditions that exist in relatively few countries. Basic microeconomic theory thus suggests that cross-country competition for market share is more intense in soybeans than cocoa.

In my model, the dispersion of productivity across countries is product specific. The magnitude of direct and indirect trade effects of bilateral trade liberalization in an import market is determined by the aggregate effect of product-specific sensitivity to trade costs over products consumed in that market.

Simonovska and Waugh (2011)[6] make a significant contribution to the literature on heterogeneous productivity trade models by offering an unbiased estimator for the single parameter that governs the constant dispersion of productivity across products in the EK framework. The authors argue that a crucial advantage of the heterogeneous productivity trade models is that the underlying micro-structure delivers a better basis for estimating this parameter and thus trade elasticities. My approach supports and extends their argument, demonstrating that heterogeneous productivity models can allow for a more complex characterization of elasticity in cases where it is necessary because the strength of comparative advantage varies non-trivially across products.

Estimating Trade Costs and Productivity Distribution Parameters

A central and desirable feature of the EK model is a structural equation that implies a log-linear gravity-like relationship between trade flows, exporter characteristics and trade costs. This equation is used to estimate trade costs and the parameters of the productivity distribution. These are the key parameters describing bilateral trade flows in the general equilibrium model. This basic structure is retained in my model, but the modifications to technology and trade costs complicate the equation such that it can no longer be estimated with linear methods.

I show that the distribution of trade costs and absolute advantage can be obtained from the same structural relationship by specifying it as a random-coefficients logit model. I estimate a set of parameters describing the distribution of trade costs and productivity across agricultural products using methods pioneered in the literature on differentiated products demand systems by Berry, Levinsohn and Pakes (1995)[7], henceforth BLP. This empirical technique allows me to connect the product-level conceptual model to sector-level trade flow data without making strong distributional assumptions, as in EK and others.

In the empirical model, individual products are defined by their agro-ecological production requirements and trade costs. Neither of these is directly observable. However, the BLP methodology only requires information on the *distribution* of production requirements and trade costs across products consumed in each import market.

I assume that information on key product-specific agro-ecological production requirements can be implicitly obtained from the distribution of production across regions. Information on product-specific trade costs can be obtained from disaggregated data on tariffs and other trade policies. Additional unobservable or unquantifiable product-specific requirements and costs are represented by random variables drawn from a parametric distribution.

This paper represents the first time to my knowledge that a gravity-like representation of trade flows has been specified as a random parameters logit model. It is almost certainly unique in its use of the BLP methodology. Its value, however, is not limited to extensions of the EK model. Any model in which the relationship between expenditure shares and trade costs takes the form of a logit probability can be extended in this manner. Arkolakis, Costinot and Rodriguez-Clare (2012)[5] demonstrate that models based on the Armington framework and that of Melitz (2003)[2] can also meet this requirement[1] .

[1] The assumption that the relationship between trade costs and market shares take the logit form

This is not the first time the gravity model has been estimated using a discrete choice methodology. In fact, EK makes note of the similarity between the structural equation from which the log-linear gravity model is derived and the discrete choice literature in a footnote. Anderson (2011)[8] references earlier efforts by Savage and Deutsch (1960)[9] and Leamer and Stern (1970)[10] to develop structural gravity models within the discrete choice framework. However, the context of these models is quite different from what I present here. Anderson describes these models as positing international transactions as a result of the choice of an individual trader, whose decision of the source country to purchase from is influenced by traditional gravity variables.

The model embedded in the EK framework turns this upside down. In a sense, it is the individual product making a "choice" of a source country in which to be produced. This "choice" is influenced by agro-ecological requirements that are non-randomly distributed across countries and idiosyncratic technological productivity available in each country. In the model I present here, buyers are simply responding to the prices that reflect these "choices" made by products.

An Alternative Approach

While the CES import demand system may not provide a reasonable forecast of the responses to changes in agricultural trade costs at the sector level, it will hold for some appropriately-defined subset of products. A reasonable approach might therefore be to break up the agricultural sector into sub-sectors. On its face, this is a more straightforward than the approach I suggest here. However, assuming that sufficiently disaggregated data are even available, identifying the boundaries of these sub-sectors within agriculture would require extensive additional research. For some product types like fruit, the boundaries might be obvious. For others, like grains, oilseeds and livestock products, the degree and manner in which these products will need to be divided into subsectors is less clear. Moreover, the divisions under which the CES import demand system holds are unlikely to be the same in every import market.

The BLP method delivers the considerable benefit that comparative advantage in agriculture can exist product-by-product on the continuum without requiring the researcher to define which countries and products within the agricultural sector are similar

is Assumption R3 in Arkolakis, Costinot and Rodriguez-Clare (2012).

a priori or assume that the set of goods in which a country has comparative advantage is fixed or exogenous. Instead of having the researcher tell the model that tropical countries produce tropical products, the BLP methodology allows the data to tell the researcher.

Policy Analysis

The model I introduce is expressly designed for empirical policy analysis of agricultural markets in an open economy setting. However, the immediate focus of this thesis is to introduce and demonstrate this novel and flexible methodology as clearly as possible. The cost of the model's flexibility is a degree of complexity. In order to focus on the methodology in what follows I keep the specification of the distribution of heterogeneity as lean as possible.

In Chapter 4 I carry out two counterfactual experiments. These experiments are designed to demonstrate the value and flexibility of this approach for policy analysis, but given the highly stylized way in which I present and calibrate the model here, the results they produce should not be used to evaluate the general equilibrium model or be relied upon as serious policy analysis. Future applications of this framework will require a more purposeful specification of the productivity and trade cost distributions.

Background

Previous general equilibrium analyses of the impact of agricultural trade liberalization have largely been conducted using CGE models with an Armington assumption on preferences (see Anderson (2011)[8] for several references). These models assume the set of goods in which each country has comparative advantage is fixed and exogenously determined. The composition of bilateral trade is thus unaffected by liberalization, i.e., changes in trade flows are exclusively at the intensive margin. Sector-level trade patterns are essentially locked-in.

Kehoe (2003)[11] provides perhaps the most compelling source of motivation for my approach. The paper provides an *ex post* evaluation of a set of influential Armington models designed to forecast the effects of the NAFTA. Kehoe reveals that these models did a uniformly poor job predicting the effect NAFTA would have on trade flows. He suggests the mechanism driving trade in these models is faulty, making them inadequate for the study of the effect of trade liberalization on patterns of global production and trade. Kehoe anticipates that a Ricardian approach built on the two country model of Dornbusch, Fischer and Samuelson (1977)[12] may offer a better characterization of the forces that compel two countries to trade and would thus bet better suited to predict the trade effects of liberalization. The EK framework is, in fact, a many-country extension of the Dornbusch, Fisher and Samuelson framework.

My work is most similar to that of Caliendo and Parro (2012)[3] and Shikher (2012)[4], who develop multi-sector extensions of the EK framework explicitly for trade policy analysis. These authors introduce multiple tradable sectors into the EK model by allowing trade costs and average productivity to differ across sectors within countries and linkages among sectors via their intermediate input use. They distinguish sectors by allowing trade costs and the parameters of the productivity distribution to vary across industries. While these models do allow the forces driving competition to differ at the sector level, their approaches are still restrictive because they take no account of intra-sectoral specialization. Unless sub-sectors happen to be defined such that changes in trade flows in response to policy change are proportional to market share, this will produce imprecise predictions for patterns of production and bilateral trade.

Both Shikher (2012)[4] and Caliendo and Parro (2012)[3] evaluate the Ricardian approach by simulating the changes in trade costs that comprise the NAFTA in multi-sector extensions of the EK model. Both papers demonstrate that EK-style models offer superior predictions for the relative magnitudes of the direct trade flow effects of the NAFTA within North America. They demonstrate that their approach offers a substantial improvement over Armington models in its ability to forecast the distribution of trade flow responses across sub-sectors. In both papers the focus is primarily on trade in manufactured goods. Shikher focuses on manufacturing sub-sectors exclusively.

The model I introduce in this thesis contributes to the literature on international trade with heterogeneous productivity on both a conceptual and empirical level. To my knowledge, it is the first contribution to this literature that incorporates non-random sources of comparative advantage within sectors. This allows for at least partially endowment-driven trade.

It is also consistent with a fundamental stylized fact of the effect of trade policy on patterns of trade that is not captured by a CES import demand system. By examining highly disaggregated bilateral trade data Kehoe and Ruhl (2013)[13] document a consistent feature of how the response of trade flows to liberalization varies across products. Namely, the largest percent increase in trade between two countries after bilateral liberalization is in the set of products that were least-traded prior to liberalization. Conversely, the share of the products that were most traded diminishes. The model of agricultural trade I present can convey this pattern. In fact, it is a natural implication of the analytical model.

The empirical contribution of my approach is also significant. The BLP estimation approach allows the researcher to introduce additional information on the drivers of comparative advantage and trade costs, providing a more nuanced analysis. It also opens the door for research on how factor endowments or other natural or economic characteristics of exporters affect intra-sector specialization. This feature may be appealing to researchers interested the link between trade patterns and the environmental conditions in which production takes place. As such, it is worthwhile to explore the model's potential for evaluating the effects of environmental phenomena such as climate change and agricultural trade and production patterns.

The analytical and empirical model I introduce in this paper has been informed by a great deal of work that is not directly referenced herein. A list of further reading that contains the additional resources I consulted while developing this approach is available in Appendix A.

Thesis Structure

In the next chapter, as a point of departure to my contribution, I introduce the standard EK technology and trade cost assumptions that deliver the log-linear gravity-like structural equation which is used to parameterize the general equilibrium model. I show that the EK assumptions place strong restrictions on cross-country substitution patterns and argue that they are counter-intuitive for agricultural trade. I then conduct econometric tests which confirm these restrictions are not supported by agricultural trade data.

In Chapter 3 I modify the EK assumptions on technology and trade costs and derive a structural relationship corresponding to EK's gravity-like model of trade flows. I demonstrate how these changes generate a range of trade elasticities in each import market then estimate the parameters describing bilateral trade patterns by specifying the relationship as a random coefficients logit model.

In Chapter 4 I embed the modified agriculture sector technology and trade cost assumptions into a general equilibrium model with two tradable sectors and conduct two counterfactual experiments. The first calculates simulated general equilibrium elasticities with respect to the United States, Canada, France and Costa Rica in the model I present and in a model that maintains the EK structure for the agricultural sector to compare the predictions of the EK and modified model. The second experiment demonstrates the flexibility of the modified model by exploring the difference between full and partial agricultural trade liberalization, an analysis which cannot be performed in the EK framework since trade costs are assumed constant within sectors.

Chapter 2

Motivation: The Independence of Irrelevant Exporters

In this chapter, as a point of departure to my contribution, I introduce the EK model assumptions on technology and trade costs and derive the gravity-like structural equation that is used to estimate trade costs and absolute advantage. These are the key parameters that describe global production and bilateral trade patterns and their responses to changes in trade costs in the general equilibrium model. I show that the EK assumptions place strong and counter-intuitive restrictions on cross-country substitution patterns, revealing what Arkolakis, Costinot and Rodriguez-Clare (2011)[5] refer to as a CES import demand structure. Finally, I adapt and carry out econometric tests from the discrete choice literature which confirm these restrictions are not supported by agricultural trade data.

2.1 An EK-style Model of Agricultural Trade

The global economy is comprised of I countries. All countries are engaged in bilateral agricultural trade. Exporters are indexed by i and importers by n. The agricultural sector is comprised of a continuum of tradable products differentiated only by their intrinsic properties. Individual agricultural products are indexed by j. In each country, consumers buy agricultural products for final consumption and firms buy them to use as intermediate inputs. All buyers in market n purchase each product from the one source country that offers the lowest price.

Production technology is product-specific within each country, where it is used by many, perfectly-competitive individual producers. An amount $q_i^A(j)$ of product j can be produced in country i with technology that is a Cobb-Douglas function of factors and intermediate inputs:

$$q_i^A(j) = z_i^A(j)(N_i^{A\beta_i^A} L_i^{A(1-\beta_i^A)})^{\alpha_i^A} \mathbf{Q}_i^{A(1-\alpha_i^A)} \tag{2.1}$$

where N_i^A is labor; L_i^A is land; and $\mathbf{Q}_i^A$ is an aggregate of intermediate inputs from agriculture and other sectors of the economy.

The term $z_i^A(j)$ is a productivity-augmenting random variable specific to product j in country i. Technological productivity, $z_i^A(j)$ is independently distributed across products following a Frechet distribution with parameters T_i^A and θ:

$$F_{z_n}^A(z) = exp\{-T_i^A z^{-\theta}\} \tag{2.2}$$

The value of T_i^A is assumed to emerge from the country-specific R&D process described in Eaton and Kortum (1999)[14]. A high value of T_i^A means country i is more likely to have a high draw of $z_i^A(j)$. As such, it represents country i's absolute advantage in the agricultural sector. The parameter $\theta > 1$ governs the dispersion of productivity. A smaller θ implies larger productivity differences.

Producers in exporter i face additional costs $\tau_{ni}^A \geq 1$, to sell a product in import market n. These trade costs are assumed to take the iceberg form, with $\tau_{nn}^A = 1$ and $\tau_{ni}^A \geq \tau_{nj}^A \tau_{ji}^A$. With perfect competition, producers set prices equal to the unit cost of producing the product and selling it in market n. Therefore, the price offered by country i producers to buyers in market n for good j is:

$$p_{ni}^A(j) = \frac{c_i^A \tau_{ni}^A}{z_i^A(j)} \tag{2.3}$$

where c_i^A is the cost of an agricultural input bundle in country i. Buyers in market n purchase product j from the source country that offers the lowest price.

Notice that the sole source of variation in exporter i's price offers comes from productivity differences, $z_i^A(j)$. The productivity dispersion parameter θ fully describes the variation in price offers and thus the force exerted by comparative advantage to promote trade in the face of trade barriers. Larger values of θ imply that productivity differences across countries are small. In this case global competition is intense and the cost advantage provided by a high realization of $z_i^A(j)$ for producers in exporter i is more likely to be overcome by trade costs.

Moreover, the assumption that $z_i^A(j)$ is independently distributed implies that the set of agricultural products in which a county specializes is determined entirely randomly. To allude to how this assumption will produce counter-intuitive predictions in the agricultural sector, consider an illustration: The independence assumption implies that the only reason Colombia specializes in coffee is that its R&D process happened to generate a high efficiency coffee production technology. Such a technology is as least as likely to have manifested in Canada rather than Colombia and would have, in turn, translated directly into comparative advantage for Canadian coffee producers.

Invoking a law of large numbers, EK shows that the share of agricultural expenditure spent on imports from country i is equal to the probability it offers the lowest price. The assumptions on the distribution of $z_i^A(j)$ yield:

$$Pr\left(p_{ni}^A(j) = p_n^A(j)\right) \equiv \pi_{ni}^A = \frac{T_i^A(c_i^A\tau_{ni}^A)^{-\theta}}{\sum_{l=1}^{I} T_l^A(c_l^A\tau_{nl}^A)^{-\theta}} \tag{2.4}$$

where $p_n^A(j) = \min_i\{p_{ni}^A(j)\}$. This expression is normalized by the domestic share of agricultural expenditure π_{nn}^A, and specified to yield a log-linear parametric expression from which trade costs can be estimated.

To specify equation 2.4, EK define:

$$S_i^A \equiv \ln T_i^A - \theta \ln c_i^A \tag{2.5}$$

Trade costs are proxied by variables common to gravity models following EK, Waugh (2010)[15] and others as:

$$ln\tau_{ni}^A = b_{ni}^A + l_{ni}^A + \sum_{r=1}^{6} d_{r_{ni}}^A + ex_i^A + EU_{ni}^A + NAFTA_{ni}^A + \xi_{ni}^A$$

where b_{ni}^A and l_{ni}^A are coefficients on dummy variables indicating that exporter i and market n share a border or common language, respectively; $d_{r_{ni}}^A$ is the coefficient on a dummy variable equal to one if the two countries are in distance category $r \in [1, 6]$;

ex_i^A is a country fixed effect that captures exporter-specific agricultural trade costs;[1] EU_{ni}^A and $NAFTA_{ni}^A$ are coefficients on dummy variables indicating intra-EU and intra-NAFTA trade respectively, and ξ_{ni}^A is a mean-zero error term that is assumed to be orthogonal to the other regressors. Substituting these into equation 2.4, normalizing by π_{nn}^A, and taking logs yields a gravity-like model of agricultural trade flows:

$$ln\left(\frac{\pi_{ni}^A}{\pi_{nn}^A}\right) = S_i^A - S_n^A - \theta\left(b_{ni}^A + l_{ni}^A + \sum_r d_{r_{ni}}^A + ex_i^A + EU_{ni}^A + NAFTA_{ni}^A + \xi_{ni}^A\right) \quad (2.6)$$

This expression is estimated using linear methods with country fixed effects to capture S_i^A and ex_i^A. Estimates of the location parameter of the agricultural productivity distribution T_i^A, are obtained from $\hat{S}_i^A$ using equilibrium relationships. Estimates of τ_{ni}^A and T_i^A are then used to parameterize the agricultural sector in the general equilibrium model.

2.2 Substitution Patterns in the EK Model

The primary disadvantage of the EK model for agricultural policy analysis lies in its strong and often counter-intuitive implications for the elasticity of bilateral trade flows with respect to changes in trade costs. The elasticity defines the percent change in market share that results from a change in bilateral trade costs and as such, the system of bilateral elasticities fully describes the magnitude and distribution of direct and indirect effects of trade liberalization discussed in Chapter 1.

Equation 2.6 displays the elasticity of π_{ni}^A with respect to a change in bilateral trade costs between its competitor country l and the importing country n, holding all prices constant:

$$\frac{\partial \pi_{ni}^A}{\partial \tau_{nl}^A}\frac{\tau_{nl}^A}{\pi_{ni}^A} = \begin{cases} -\theta(1-\pi_{nl}^A) & if\ l = i \\ \theta\pi_{nl}^A & otherwise \end{cases} \quad (2.7)$$

Arkolakis, Costinot and Rodriguez-Clare define this as a CES input demand system and note that it is a feature of models built on the EK framework as well as many of those built on Melitz (2003)[2] and on the Armington assumption. The simplicity of equation 2.7 is one of the most appealing features of the EK model. However, its usefulness for

[1] EK includes importer fixed effect in trade costs, whereas Waugh (2010) demonstrates that an exporter fixed effect is more appropriate.

applied policy analysis is limited if the CES import demand structure does not hold in the data.

In fact, the CES import demand system imposes strong restrictions on both own-country and cross-country market share elasticity with respect to trade costs. Since $(1 - \pi^A_{ni}) \approx 1$ for almost every pair of countries, Equation 2.7 implies that own-country elasticities, which describe the direct effect of a change in bilateral trade costs, are virtually equal to θ for every exporter in every import market. To the extent it varies at all, own-country elasticity is strictly decreasing in π^A_{ni}. This is an unnecessary and possibly inappropriate assumption for agricultural markets.

To see why, consider an example. Côte d'Ivoire is the global leader in cocoa exports and dominates UK cocoa imports. Yet, its total share of the UK agricultural products market is very small. The EK model would predict Côte d'Ivoire's market share is more own-country elastic than e.g., Germany, which has a relatively large share of the UK agricultural products market. Germany's agricultural exports to the UK primarily consist of grains and meats that can be produced competitively by producers in many countries, including domestic producers. The EK model's predictions would thus run counter to basic microeconomic theory, which would suggest German market share should be more elastic than that of Côte d'Ivoire.

Similarly, equation 2.7 suggests that cross-country elasticities, which describe the indirect effects of a change in bilateral trade costs, are miniscule in almost every market for almost every pair of exporters since π^A_{nl} is very small for almost every pair of countries. Moreover, any change in a competing exporter's bilateral trade costs τ^A_{nl}, has the same effect on π^A_{ni} for all $i \neq l$, including the domestic producers market share π^A_{nn}. This is a highly illogical assumption for the agricultural sector.

Consider the following example: Suppose the United States raises its tariffs on all Costa Rican agricultural products. This results in a decline in Costa Rica's market share to the extent that these tariffs mean it no longer offers the lowest price for some of the products it had been exporting. Ecuador and The Netherlands have virtually identical shares of the US agricultural products market. Equation 2.7 thus implies that US buyers will substitute equally toward products from each of these countries. However, Ecuador's climate suggests it is more likely than The Netherlands to offer low prices in agricultural products once exported by Costa Rica. Contrary to the EK model's predictions, one would thus expect agricultural trade flows from Ecuador to increase more than those of The Netherlands in response to higher Costa Rican tariffs.

2.3 The Independence of Irrelevant Exporters

The assumption that cross-country elasticity is symmetric across competitors within an import market, which characterizes the CES import demand system, is identical to one that arises frequently in the discrete choice literature where it is known as the independence of irrelevant alternatives (IIA) property. Under the IIA property, a third country's trade costs are "irrelevant" to the ratio of market shares of any other two competitors.

Tests for the presence of the IIA property are well-established in the discrete choice literature. In what follows, I adapt two such tests that can be based on the results of estimating Equation 2.6. First I discuss the data set I use to conduct these tests. This is the base data set that I will use throughout this thesis.

Data

The data set is comprised of bilateral shares of agricultural expenditure for 42 countries in the year 2000. I selected this sample of countries using information from the World Bank World Development Indicators[16] to assemble a list of the countries with the 50 highest GDP per capita and the 50 highest share of agricultural raw materials in agricultural value added. This yields 93 total countries.

I constructed bilateral market shares using production and trade data from the UN Food and Agriculture Organization (FAO)[17] for the year 2000. FAO production and trade 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. I compiled a set of 177 agricultural items for which data on both bilateral trade and the gross value of production in US dollars are available. Countries for which complete trade and production data was not available for both the agricultural and manufacturing sectors[2] for the year 2000 were dropped from the sample.

[2] The manufacturing sector data is used in the general equilibrium model in Chapter 4.

I also dropped eleven countries that had available trade and production data, but zero bilateral trade flows for more than half of the import markets in the data set. The impact of zero dependent variables on parameter estimates is an important issue for research that relies on the log-linear gravity equation. I do not pursue analysis of the robustness of the results of equation 2.6 to the treatment of zero trade observations here since my focus is on introducing an alternative framework that does not rely on the log-linear gravity model to estimate trade costs. I replace the remaining zero bilateral trade flows with $1 flows.

I aggregate bilateral trade flows and production over the 177 items in my data and use these values to calculate bilateral expenditure shares $\frac{X_{ni}^A}{X_n^A}$, where X_{ni}^A is the total value of the agricultural trade flow from country i to country n. I calculate X_n^A as the sum of total production plus total agricultural imports less total exports of the 177 agricultural products. Domestic shares are calculated as $\frac{X_{nn}^A}{X_n^A} = 1 - \sum_{i \neq n}^{I} \frac{X_{ni}^A}{X_n^A}$.

I assemble the trade cost proxy variables using the CEPII gravity dataset of Head, Mayer and Ries (2010)[18] available for download from www.cepii.fr. The border variable is a dummy variable equal to 1 if two countries share a border. The language variable equals one if at least 9% of the population in both countries speaks a common language. The CEPII data set provides measures of the geodesic distance between two countries. I use the population-weighted average distance between the largest cities of the two countries. As in EK and Waugh (2010)[15], I classify distance into six categories (see Table 2.1).

Table 2.1: Definition of Distance Variables

Variable	Distance, 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]

The final component of the data set is the producer and exporter effects S_i^A and ex_i^A. I normalize these effects so that coefficients sum to zero as in Waugh (2011)[15]. As such, these estimates are interpreted with respect to the average country: Values of S_i^A greater than one indicate that exporter i producers are more competitive in agriculture than the average country. Values of ex_i^A greater than one suggest that country i exporters face higher than average exporter-specific trade costs. Coefficient estimates for producer fixed effects S_i^A are reported in Appendix B and estimates for exporter fixed effects ex_i^A are reported in Appendix C. Coefficient estimates for the remaining variables are presented in Tables 2.2 and 2.3 below.

2.4 Test One: Hausman and McFadden

The first test of whether agricultural trade is consistent with the CES import demand system is suggested by Hausman and McFadden (1984)[19]. The logic of this test is that if a third countrys trade costs are irrelevant to the relative market share of any two other exporters in a given market, i.e., if the CES import demand system holds, then parameter estimates from estimating equation 2.6 on any subset of countries should not be significantly different from those obtained from the full data set.

To see this, let I be the full set of agricultural exporters and let I_S be a subset of those exporters. It is straightforward to show that under the CES demand system:

$$\pi^A_{ni|I} = \pi^A_{ni|I_S} \times \pi^A_{nI_S}$$

where $\pi^A_{ni|I}$ is the probability exporter i offers the lowest price among all global exporters; $\pi^A_{ni|I_S}$ is the probability it offers the lowest price among exporters in subset I_S; and $\pi^A_{nI_S}$ is the probability the lowest price offer in market n comes from an exporter in subset I_S. Therefore:[3]

$$\frac{\pi^A_{ni|I}}{\pi^A_{nn|I}} = \frac{\pi^A_{ni|I_S}}{\pi^A_{nn|I_S}}$$

Define the true value of the coefficients obtained by estimating equation 2.6 as $\boldsymbol{\beta}^*$.[4]

Define a partition of the coefficients $\boldsymbol{\beta}^* = [\boldsymbol{\beta}_1^*, \boldsymbol{\beta}_2^*]$, where $\boldsymbol{\beta}_1^*$ is comprised of the coefficients that vary both within the full data set and the subset I_S and $\boldsymbol{\beta}_2^*$ is comprised of the coefficients that do not vary within subset I_S. That is, $\boldsymbol{\beta}_2^*$ includes fixed effects for

[3] Note that this condition suggests that if the IIA property holds, dropping zero trade observations from the sample when estimating equation (5) will not itself bias the parameter estimates.

[4] $\beta^* = [S^*, b^*, l^*, d^*, ex^*, EU^*, NAFTA^*]$

countries that have been excluded to form I_S as well as $EU_{ni}, NAFTA_{ni}$ if no members are in the subset I_S.

Under standard OLS assumptions the coefficient estimate $\hat{\boldsymbol{\beta}}^I = [\hat{\boldsymbol{\beta}}_1^I, \hat{\boldsymbol{\beta}}_2^I]$, obtained from estimating equation 2.6 on the full set of countries is a consistent estimate of $\boldsymbol{\beta}^*$ and the coefficient estimate $\hat{\boldsymbol{\beta}}^{I_S} \equiv \hat{\boldsymbol{\beta}}_1^{I_S}$ obtained from estimating 2.6 on the subset I_S is a consistent estimate of $\boldsymbol{\beta}_1^*$. If the IIA property holds, there will be no statistically significant difference between $\hat{\boldsymbol{\beta}}_1^I$ and $\hat{\boldsymbol{\beta}}_1^{I_S}$. If not $\hat{\boldsymbol{\beta}}_1^{I_S}$ is not a consistent estimate of $\boldsymbol{\beta}_1^*$. Small and Hsiao (1985)[20] show that under the null hypothesis that the IIA property holds, the test statistic:

$$H = \left(\hat{\boldsymbol{\beta}}_1^{I_S} - \hat{\boldsymbol{\beta}}_1^I\right)' \left(\frac{\hat{\boldsymbol{\Sigma}}}{I}\right)^{-1} \left(\hat{\boldsymbol{\beta}}_1^{I_S} - \hat{\boldsymbol{\beta}}_1^I\right)$$ [5]

follows a chi-square distribution with degrees of freedom equal to the rank of the matrix:

$$\hat{\boldsymbol{\Sigma}} = \frac{I}{I_S} cov(\hat{\boldsymbol{\beta}}_1^{I_S}) - cov(\hat{\boldsymbol{\beta}}_1^I)$$

The first step in carrying out this test is to define the subset of exporters I_S. With 42 exporters in my data set there are thousands of possible candidates. Unfortunately there is no formal theory to determine which countries should be excluded in order to define I_S for the optimal test.

Small and Hsiao (1985)[20] suggest choosing a subset by eliminating close substitutes. I hypothesize that countries that are close substitutes in an import market are similar in terms of their agro-ecological features and distance from the import market. These countries are most likely to compete head-to-head for market share in the same products and therefore have larger cross-country trade elasticities.

I run the Hausman and McFadden test twice, removing two subsets of countries that I expect to have relatively large cross-country trade elasticities. For the first test I create a subset I_S that excludes the South American countries that produce mainly tropical products. Results are reported in Table 2.2 under Test 1. Next I run the test, forming I_S by excluding Indonesia and Malaysia and report the results under Test 2. Both of these tests soundly reject the null hypothesis that the IIA property holds in the agricultural trade data.

[5] Small and Hsiao (1984) present this test statistic, which adjusts the Hausman and McFadden statistic for differences in sample size between I and I_S.

Table 2.2: Hausman-McFadden Test Results

Null Hypothesis: $\hat{\boldsymbol{\beta}}_1^I = \hat{\boldsymbol{\beta}}_1^{I_S}$

		Test 1	**Test 2**	**Test 3**
Test Statistic	-	3929.34	21337.14	8477.52
Selected Variables	$\hat{\boldsymbol{\beta}}_1^I$	$\hat{\boldsymbol{\beta}}_1^{I_S}$	$\hat{\boldsymbol{\beta}}_1^{I_S}$	$\hat{\boldsymbol{\beta}}_1^{I_S}$
Border	0.75*	0.72	0.83*	1.29**
Language	1.49***	1.19***	1.61***	1.63***
EU	-2.62***	-2.52***	-2.54***	-1.99***
NAFTA	-1.64	-1.98	-1.35	-2.11
Distance 1	-5.89***	-5.34***	-6.21***	-6.07***
Distance 2	-8.47***	-7.84***	-8.70***	-8.90***
Distance 3	-10.27***	-9.91***	-10.45***	-10.75***
Distance 4	-11.87***	-11.7***	-12.02***	-12.02***
Distance 5	-13.91***	-14.22***	-13.97***	-14.08***
Distance 6	-15.00***	-14.95***	-15.07***	-15.21***

*Significance at the 10% level; **Significance at the 5% level; ***Significance at the 1% level

The Hausman-McFadden test is easy to understand and execute, but it has significant drawbacks. The most obvious is that there is no formal procedure for determining which countries should be excluded to create the subset I_S for the optimal test. This is especially troubling since the value of the test statistic varies widely depending on which countries are removed to create the set I_S. This test also has well-documented technical drawbacks when $I > 3$. In particular, the matrix $\hat{\mathbf{\Sigma}}$ may not be positive definite and the computed value of the test statistic may even be negative.

To explore the robustness of my results I ran the test on every possible subset of $I-3$ countries. Of the 10,660 total tests generated by this process, just over half yielded positive values of the test statistic. Of the 5,397 remaining tests, only seven fail to reject the null hypothesis of IIA. I include the results of the test on the subset of countries that excludes France, Germany and Poland under Test 3 in the final column of Table 2.2.

2.5 Test Two: McFadden and Train

McFadden and Train (2000)[21] describe an alternative test of the IIA assumption that can be used to evaluate whether the CES import demand system applies to agricultural trade. The idea behind this test is that if all heterogeneity in price offers is independently distributed, market shares should be uncorrelated across exporters and deviations from average trade costs will not have a statistically significant impact on bilateral market share. The formal hypothesis of the test is that equation 2.4 adequately describes market share in the data, against the alternative that comparative advantage is not independently distributed across products.

To conduct the test, results from estimating 2.6 are used to calculate predicted bilateral market shares:

$$\hat{\pi}_{ni}^{A} = \frac{exp\{\hat{S}_i^A - \theta(\hat{b}_{ni}^A + \hat{l}_{ni}^A + \sum_{r=1}^{6} \hat{d}_{rni}^{\,A} + \hat{ex}_i^A + \hat{EU}_{ni}^{A} + NA\hat{F}TA_{ni}^{A})\}}{\sum_{l=1}^{I} exp\{\hat{S}_l^A - \theta(\hat{b}_{nl}^A + \hat{l}_{nl}^A + \sum_{r=1}^{6} \hat{d}_{rnl}^{\,A} + \hat{ex}_l^A + \hat{EU}_{nl}^{A} + NA\hat{F}TA_{nl}^{A})\}}$$

These estimates are then used to construct artificial variables from trade costs, which take the form:

$$z_{ni} = \frac{1}{2}(t_{ni} - t_n)^2$$

where $t_n = \sum_{l=1}^{I} t_{nl}\hat{\pi}^A_{nl}$ and t_{ni} is a trade cost proxy variable. McFadden and Train show that if the coefficients on these artificial variables are jointly insignificant, the null hypothesis cannot be rejected.

I calculate artificial variables for the trade cost proxy variables border, language, distance and RTA and then estimate:

$$ln\left(\frac{\pi^A_{ni}}{\pi^A_{nn}}\right) = S^A_i - S^A_n - \theta(b^A_{ni} + l^A_{ni} + \sum_{r=1}^{6} d^A_{r_{ni}} + ex^A_i + EU^A_{ni} + NAFTA^A_{ni} + \xi^A_{ni}) + \sum_{d=1}^{10}(z_{ni_d} - z_{nn_d})\beta_d$$

where z_{ni_d} is the artificial variable constructed from the d^{th} element of the vector of trade cost proxy variables for exporter i in market n and β_d is a coefficient. Regression results are reported in Table 2.3.

2.6 Conclusion

The assumption, maintained in the standard EK framework, that the sole source of product-specific comparative advantage is independently-distributed technological productivity differences has strong implications for trade elasticities. Importantly, these elasticities are counter-intuitive as a description of how bilateral agricultural trade responds to changes in trade costs. Tests based on the gravity-like equation that describes the pattern of product-specific comparative advantage in the EK model convincingly reject the CES import demand system as a representation of trade elasticities in the agricultural sector. In the next chapter I modify the EK assumptions that yield equation 2.7 to allow for a more flexible structure of elasticities.

Table 2.3: McFadden and Train Test Results

Null Hypothesis: Artificial variables are jointly = 0

Test Statistic: F = 2.01, p-value = 0.0286

Selected Variables	EK Model	Test Model
Border	0.75*	-1.97
Language	1.49***	-2.85
EU	-2.62***	-6.28**
NAFTA	-1.64	-2.29
Distance 1	-5.89***	-11.01**
Distance 2	-8.47***	-17.45**
Distance 3	-10.27***	-21.22
Distance 4	-11.87***	-143.19***
Distance 5	-13.91***	-29.51*
Distance 6	-15.00***	-24.56
Artificial Variables		
Z_Border		5.91
Z_Language		9.33**
Z_EU		8.09
Z_NAFTA		2.72
Z_Distance 1		12.07
Z_Distance 2		18.67
Z_Distance 3		22.1
Z_Distance 4		263.45***
Z_Distance 5		31.43
Z_Distance 6		19.14

Chapter 3

A New Way to Model Product Heterogeneity

In Chapter 2 I performed tests which found that the CES import demand system implied by the EK assumptions on technology and trade costs is inconsistent with agricultural trade data. In this chapter I make two modifications to the EK framework. First, I introduce a product-specific term into each country's agricultural production technology that captures how well an exporter's agro-ecological characteristics suit an individual product. This term induces correlation in comparative advantage among countries with similar agro-ecological characteristics and generates cross-country elasticities that are increasing in this correlation. Second, I allow trade costs to vary deterministically across products. In this way, cross-country correlation is further increasing in "gravity".

Next, I derive a structural relationship between bilateral trade flows and trade costs corresponding to the gravity-like Equation 2.6 under these modifications. The resulting equation is specified as a random coefficients logit model. The density of productivity and trade costs across products is captured in the econometric model by interactions between variables representing exporter characteristics and variables representing product-specific production requirements and trade costs. The model is used to estimate trade costs and the parameters of the agricultural productivity distribution. These are the key parameters describing trade patterns in the general equilibrium model, which I will introduce in Chapter 4.

My estimation methodology draws heavily on techniques pioneered in the discrete choice literature, particularly those of Berry, Levinsohn and Pakes (1995)[7] (BLP). Their approach allows the data to identify which countries are likely to be closest substitutes rather than forcing the researcher to do so a priori via carefully-defined sub-sectors as discussed in Chapter 1. It also opens the door to evaluate the effect of the dispersion of tariffs and other trade-distorting policies across products within the agricultural sector on the patterns of global production and trade. This is a singular contribution in itself. I estimate a more complex model of product-level comparative advantage using the same sector-level bilateral market shares I used in the EK-style model in Chapter 2 as the dependent variable.

3.1 Two Modifications of the EK Assumptions

To capture the role of agro-ecological endowments in shaping specialization patterns within the agricultural sector, I modify the agriculture sector technology by allowing land productivity to vary across products:

$$q_i^A(j) = z_i^A(j)(N_i^{\beta_i^A}(a_i(j)L_i)^{1-\beta_i^A})^{\alpha_i^A}\mathbf{Q}_i^{A^{1-\alpha_i^A}} \tag{3.1}$$

This technology is identical to Equation 3.1 with the exception of $a_i(j)$, which represents the productivity of exporter i land in product j production.[1] I assume $a_i(j)$ follows a parametric density that is a deterministic function of exporter i's agro-ecological characteristics and product j's agro-ecological production requirements. The value $a_i(j)$ thus reflects the suitability of exporter i's natural environment for product j production. For example, countries with volcanic soil and tropical climate will tend to have higher values of $a_i(j)$ for pineapple, which thrives in volcanic soil and tropical climate. Importantly, countries with similar agro-ecological characteristics will have high values of $a_i(j)$ for a similar set of products. This term thus captures the tendency for countries with similar agro-ecological attributes have comparative advantage in a similar set of agricultural products.

I maintain the EK assumption that $z_i^A(j)$ is a random variable representing technological productivity arising from exporter i's R&D process, and that it follows an

[1] This is like the human-capital-adjusted labor used throughout the economics literature.

independent, Frechet distribution. I further assume it is independent of $a_i(j)$. This means an exporter is equally likely to have a high realization of $z_i^A(j)$ in a product for which its agro-ecological environment is unsuitable as it is for a product it is well-suited to produce.

Cost-minimizing producers of product j in exporter i have unit production costs:

$$C_i^A(j) = \frac{\tilde{a}_i(j)c_i^A}{z_i^A(j)}$$

where $\tilde{a}_i(j) = a_i(j)^{-\alpha_i^A(1-\beta_i^A)}$. As in EK, exporters face iceberg trade costs when selling product j in import market n. Unlike EK, I allow these costs to vary across products, following a parametric density that is a deterministic function of product-specific policies and marketing requirements. I assume $\tau_{ni}^A(j)$ is independent of both $a_i(j)$ and $z_i^A(j)$ and I maintain the assumptions that $\tau_{ni}^A(j) \leq \tau_{nk}^A(j)\tau_{ki}^A(j)$ and $\tau_{nn}^A(j) = 1$.

With perfect competition, the price offered by exporter i in market n for agricultural product j is:

$$p_{ni}^A(j) = \frac{\tilde{a}_i(j)c_i^A\tau_{ni}^A(j)}{z_i^A(j)} \tag{3.2}$$

As in EK, buyers in market n purchase each product from the source country that offers the lowest price. In contrast to the EK framework where technology is the only source of heterogeneity, high realizations of $z_i^A(j)$ may not translate into comparative advantage in market n if exporter i's environment is unsuitable for product j or if $\tau_{ni}^A(j)$ is particularly high. For example, the Canadian R&D process may indeed deliver a high-productivity technology for cultivating coffee beans, but without the appropriate climate and terrain, Canada is still unlikely to be a competitive coffee exporter. Similarly, without high import tariffs specific to sugar, tropical countries might be revealed to have comparative advantage in exporting sugar to US and European markets.

As in the EK model, exporter i's share of market n agricultural products expenditure is equivalent to the probability it offers the lowest price for an agricultural product in market n.[2] To arrive at an expression that corresponds to Equation 2.4, first note that

[2] I show this formally in Appendix D.4.

the probability exporter i offers the lowest price for product j in market n is:[3]

$$Pr(p_{ni}^A(j) \leq p_{nl}^A(j)\ \forall l) = \pi_{ni}^A(j) = \frac{T_i^A \left(\tilde{a}_i(j) c_i^A \tau_{ni}^A(j)\right)^{-\theta}}{\sum_{l=1}^{I} T_l^k (\tilde{a}_l(j) c_l^A \tau_{nl}^A(j))^{-\theta}} \tag{3.3}$$

This product-specific probability is a function of the global distribution of land productivity and trade costs for product j. Exporter i's total share of market n agricultural expenditure is the unconditional probability it offers the lowest price for any agricultural product. Since land productivity and trade costs are independently distributed, this is:

$$\pi_{ni}^A = \int \frac{T_i^k (\tilde{a}_i c_i^A \tau_{ni}^A)^{-\theta}}{\sum_{l=1}^{I} T_l^k (\tilde{a}_l c_l^A \tau_{nl}^A)^{-\theta}} dF_{\tilde{a}_n}(\tilde{\mathbf{a}}) dF_{\tau_n}(\boldsymbol{\tau}) \tag{3.4}$$

where $dF_{\tilde{a}_n}(\tilde{a}) dF_{\tau_n}(\tau)$ is the joint density of $\tilde{\mathbf{a}} = [\tilde{\mathbf{a}}(0) \ldots \tilde{\mathbf{a}}(1)]$ and $\boldsymbol{\tau}_n^A = \left[\boldsymbol{\tau}_n^A(0), \ldots, \boldsymbol{\tau}_n^A(1)\right]$[4] across products consumed in market n.

Equation 3.4 corresponds to Equation 2.4 and will likewise serve as the model from which I estimate trade costs and productivity parameters. Unlike Frechet-distributed technological productivity, the integral over land productivity and trade costs has no analytical solution. And unlike Equation 2.4, this expression cannot be log-linearized. However, $dF_{\tilde{a}_n}(\tilde{\mathbf{a}}) dF_{\tau_n}(\boldsymbol{\tau})$ is a parametric density for which I can specify Equation 3.4 to estimate parameters. Before I specify the model of bilateral trade flows based on 3.4 and describe the estimation procedure, I first highlight a few implications of the modified model.

First, while the mechanism generating trade in this model is Ricardian in the sense that differences in productivity generate comparative advantage, it also has elements of endowment-based trade. The model predicts, for example, that countries that are "tropical-climate-abundant" will tend to specialize in agricultural products that are "tropical-climate-intensive" because they will tend to have high values of $a_i(j)$ for tropical products. However, this does not produce complete specialization in a bilateral relationship at the sector-level or even within a sub-sector defined by production requirements. Ricardian differences in technological productivity defined by realizations of $z_i^A(j)$ and even small differences in values of $a_i(j)$ can create comparative advantage

[3] I derive this expression in Appendix D.2.
[4] $\tilde{\mathbf{a}}(j) = [\tilde{a}_1(j), \ldots, \tilde{a}_I(j)]$, $\boldsymbol{\tau}_n^A(j) = \left[\tau_{n1}^A(j), \ldots, \tau_{nI}^A(j)\right]$

and thus incentives for agricultural trade even between two countries that are both tropical-land-abundant.

Second, in my model the force of comparative advantage is product-specific. As I discussed in Chapter 1, the force of comparative advantage is determined by the variation in price offers across countries. In the EK model this variation is entirely captured by θ. However, as I argued elsewhere, a single, constant measure of the force that comparative advantage exerts over bilateral trade barriers cannot be expected to fully capture the competitive intensity faced by agricultural producers.

In the modified model, deterministic differences in agro-ecological endowments $a_i(j)$, and trade costs also create variation in price offers. As an example, products like some tropical fruits or spices have very specialized production requirements. As such, there may be fewer countries in which these products can be competitively produced. This is characterized by extreme values of $a_i(j)$. The resulting variation in price offers across exporters will be greater for these products than for e.g., soybeans which can be produced under many different agro-ecological conditions. Similarly, extreme realizations of $\tau^A_{ni}(j)$, for example a geographical indication recognized by trading partners, may also increase the variation in price offers across countries.

As a final note, a wide range of values and calibration methods have been proposed for the parameter θ (see Simonovska and Waugh (2011)[6]). As such, it is arguably an additional advantage of the modified model that the measurement of the effects of lower bilateral trade costs is less reliant on this parameter.

3.2 Elasticity in the Modified Model

The elasticity of exporter i's share of market n agricultural expenditure with respect to competitor l's trade costs in the modified model is:

$$\frac{\partial \pi^A_{ni}}{\partial \tau^A_{nl}} \frac{\tau^A_{nl}}{\pi^A_{ni}} = \begin{cases} \frac{-\theta}{\pi^A_{ni}} \int \pi_n i^A(j)(1 - \pi^A_{ni}(j)) dF_{\tilde{a}}(\tilde{\mathbf{a}}) dF_{\tau_n}(\boldsymbol{\tau}) & if\ l = i \\ \frac{\theta}{\pi^A_{ni}} \int \pi^A_{ni}(j) \pi^A_{nl}(j) dF_{\tilde{a}}(\tilde{\mathbf{a}}) dF_{\tau_n}(\boldsymbol{\tau}) & otherwise \end{cases} \tag{3.5}$$

In contrast to the CES import demand system described by Equation 2.7, elasticity with respect to a given exporter's trade costs varies across competitors. Sensitivity to changes in a competitor's trade costs is product-specific: The probability Ecuador offers the lowest price for bananas in the US market may be highly sensitive to changes in Costa Rican trade costs, whereas the probability it offers the lowest price for oranges may be less so. Sector-level elasticity is a weighted average of product-specific sensitivities, where the weights are based on each product's share of market n agricultural expenditure.

The modified model is consistent with a key fact of trade liberalization highlighted in Kehoe and Ruhl (2013)[13]. Namely, that the products that are the least-traded between two countries tend to realize the biggest increase in their share of exports after bilateral liberalization. To see this, note from Equation 3.3 that the elasticity of $\pi_{ni}^{A}(j)$ with respect to $\tau_{ni}^{A}(j)$ is $\theta(1-\pi_{ni}^{A}(j))$, which is decreasing in market share. This means that when $\tau_{ni}^{A}(j)$ declines, the direct effect on the probability of offering the lowest price is largest for products with the smallest probability prior to liberalization.

Unlike in the CES import demand system, own-country trade elasticity is not determined solely by market share. Own-country trade elasticity from Equation 3.5 can be written:

$$\frac{\partial \pi_{ni}^{A}}{\partial \tau_{ni}^{A}} \frac{\tau_{ni}^{A}}{\pi_{ni}^{A}} = -\theta((1-\pi_{ni}^{A}) - \frac{1}{\pi_{ni}^{A}} var(\pi_{ni}^{A}(j))) \tag{3.6}$$

The magnitude of own-country elasticity is decreasing in the extent to which the probability its producers offer the lowest price varies across products. In the previous chapter I argued that the intensity of international price competition varies across products in systematic and non-trivial ways using the illustration of the dominance of Côte d'Ivoire producers in global cocoa trade. In the EK framework, an exporter is equally likely to offer the lowest price in any given agricultural product, so $var(\pi_{ni}^{A}(j)) = 0$ and the relative magnitude of the direct effect of a change in bilateral trade costs is determined only by π_{ni}^{A}.

In the modified model, on the other hand, $var(\pi_{ni}^{A}(j))$ also depends on variation in the suitability of its agro-ecological characteristics $a_i(j)$ and trade costs $\tau_{ni}^{A}(j)$. Exporters with extreme values of $a_i(j)$ or $\tau_{ni}^{A}(j)$ for some products will tend to have a larger $var(\pi_{ni}^{k}(j))$ in any market that imports these products. Thus we expect the direct effect of lowering bilateral agricultural tariffs to be smaller for exporters that specialize in products for which competition outside of its borders is not intense or for which non-tariff trade costs remain high. This is consistent with basic micro-economic theory.

The modified model also induces variation in cross-country elasticity that is stifled under the CES import demand system. Cross-country elasticity captures the indirect effect of a change in τ_{ni}^A across exporter i's competitors. Country i's partial equilibrium cross-country elasticity with respect to exporter l in market n from Equation 3.5 can be written:

$$\frac{\partial \pi_{ni}^A}{\partial \tau_{nl}^A} \frac{\tau_{nl}^A}{\pi_{ni}^A} = \frac{\theta}{\pi_{ni}^A}(cov(\pi_{ni}^A(j), \pi_{nl}^A(j)) + \pi_{ni}^A \times \pi_{nl}^A) \qquad l \neq i \tag{3.7}$$

In the EK framework - and all other models with a CES import demand system - all countries are perfect substitutes so $cov(\pi_{ni}^A(j), \pi_{nl}^A(j)) = 1$. The cross-country elasticity is identical for all competitors and the magnitude is primarily determined by θ. In contrast, in the modified model cross-country elasticity is larger for country pairs with large $cov(\pi_{ni}^A(j), \pi_{nl}^A(j))$. Such countries are more likely to be competing head-to-head in the same products. I refer to these countries as close substitutes.

Since $z_i^A(j)$ is independently distributed across products, covariance in $\pi_{ni}^A(j)$ comes entirely from $a_i(j)$ and $\tau_{ni}^A(j)$. Costa Rica's probability of offering the lowest price for product j in the US market, $\pi_{USA,CRI}^A(j)$, will tend to co-vary more strongly with that of Ecuador than The Netherlands since Ecuador is more agro-ecologically similar to Costa Rica. On the other hand, an East African country may be just as similar to Costa Rica as Ecuador in terms of its agro-ecological endowment, but its market share will nevertheless be less sensitive because of larger costs of exporting to the United States.

3.3 Specification

In this section I specify Equation 3.4 as a random coefficients logit model. The primary distinction between my approach and the simple log-linear model delivered by the EK framework is that I estimate parameters that describe the distribution of production and trade costs across products, whereas the EK approach essentially estimates a degenerate distribution for these costs. Since the focus of this work is on introducing the random coefficients methodology rather than on its application to a particular policy issue, I keep the specification as simple as possible. Future applications will take a more methodical approach.

I begin by defining

$$S_i^A \equiv ln(T_i^A) - \theta ln(c_i^A) \tag{3.8}$$

as in EK. Next I specify land productivity, $\tilde{a}_i(j)$ as a parametric function of exporter agro-ecological characteristics and product-specific agro-ecological requirements:

$$ln(\tilde{a}_i(j)) = \mathbf{X}_i\boldsymbol{\delta} + \mathbf{X}_i(\mathbf{E}(j)\boldsymbol{\Lambda})' + \mathbf{X}_i(\boldsymbol{\nu}_{\mathbf{E}}(j)\boldsymbol{\Sigma}_E)' \tag{3.9}$$

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

I define $\mathbf{X}_i = \begin{bmatrix} AL_i & trop_i & temp_i & bor_i \end{bmatrix}$, where AL_i is log arable land area, and the remaining elements are the shares of total land area in tropical, temperate, and boreal climate zones. I normalize the climate share variables so their coefficients sum to zero[22]. Defining product-specific production requirements is less straightforward. While I refer to $\mathbf{E}(j)$ as "observable" production requirements I cannot actually observe them. Fortunately, the BLP methodology only requires information on the distribution of these requirements across agricultural products, which I obtain implicitly from the distribution of production across countries as follows.

I define $\mathbf{E}(j) = \begin{bmatrix} trop(j) & temp(j) & bor(j) \end{bmatrix}$, where elements of $\mathbf{E}(j)$ are the intensity of product j's cultivation in each climate zone. This vector represents the ideal climate for product j. I refer to e.g., $trop(j)$ as the tropical land intensity of product j production. I assume $\mathbf{E}(j)$ is distributed across products following the empirical distribution of product requirements for products defined at the "item" level by the FAO, which is the most disaggregated agricultural production data available to me. I assume unobservable agro-ecological requirements $\boldsymbol{\nu}_E(j)$, follow a standard multivariate normal distribution.

I specify product-specific trade costs as:

$$ln(\tau_{ni}^A(j)) = \mathbf{t}_{ni}\boldsymbol{\beta} + ex_i^A + \mathbf{t}_{ni}(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t)' + \xi_{ni}^A \tag{3.10}$$

where $\mathbf{t}_{ni}$ is the 1×10 vector of proxy variables for trade costs used in Chapter 2;[5] $\boldsymbol{\beta}$ is a vector of coefficients on those proxy variables; ex_i^A is an exporter-specific trade cost; $\boldsymbol{\nu}_{t_n}(j)$ is a 1×10 vector of standard normal random variables representing unobserved product-specific trade costs in import market n; $\boldsymbol{\Sigma}_t$ is a scaling matrix; and ξ_{ni}^A captures unobservable or unquantifiable bilateral trade costs that are invariant across products and orthogonal to the regressors.

Note that variables from data on product-specific trade policies could be included here in a matrix that interacts with elements of $\mathbf{t}_{ni}$ in the same way that $\mathbf{E}(j)$ interacts with $\mathbf{X}_i$ in the land productivity distribution specification. This could include product-specific tariff data or other measures of agricultural protection disaggregated across products at any level. It can also include other policies, such as product-specific agricultural price supports, that either increase or decrease unit production costs. The framework I present here can thus be used to conduct studies similar to the highly influential Armington-based CGE models used to evaluate various proposals for multilateral trade reform in the Doha Round of WTO negotiations in Anderson and Martin (2006)[23], Hertel and Winters (2005)[24], Bouët, Mevel, and Orden (2006)[25] and many others.

Using Equations 3.9 and 3.10 in 3.4 I get the modified model of trade flows, which corresponds to Equation 2.6:

$$\pi_{ni}^A = \int \frac{exp\{\tilde{S}_i^A + \mathbf{X}_i(\mathbf{E}(j)\boldsymbol{\Lambda})' + \mathbf{X}_i(\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)' - \theta\mathbf{t}_{ni}\boldsymbol{\beta} - \theta ex_i - \theta\mathbf{t}_{ni}(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t)'\}}{\sum_{l=1}^{I} exp\{\tilde{S}_l^A + \mathbf{X}_l(\mathbf{E}(j)\boldsymbol{\Lambda})' + \mathbf{X}_l(\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)' - \theta\mathbf{t}_{nl}\boldsymbol{\beta} - \theta ex_l - \theta\mathbf{t}_{nl}(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t)'} d\hat{F}_{E_n}(\mathbf{E}) d\hat{F}_{\nu_n}(\boldsymbol{\nu}) \tag{3.11}$$

where $\tilde{S}_i^A \equiv S_i^A + \mathbf{X}_i\boldsymbol{\delta}$ and $d\hat{F}_{E_n}(\mathbf{E})d\hat{F}_{\nu_n}(\boldsymbol{\nu})$ is the estimated density of products imported into market n defined jointly by their climate and unobserved agro-ecological requirements and trade costs. Since the integral in 3.11 does not have an analytical solution, simulation techniques are required to estimate the parameters.

Before I discuss the estimation procedure, I first demonstrate how this specification generates more sensible predictions for the response of trade and production patterns to policy change. Recall from Equation 3.7 that cross-country trade elasticity is increasing in the covariance of $\pi_{ni}^A(j)$. To illustrate how this specification generates covariance

[5] These are dummy variables indicating that the countries share a border or language, their distance, and whether they are members of the EU or NAFTA FTAs.

among similar exporters, I separate the terms in Equation 3.3 into those that are invariant across products, denoted δ^A_{ni}, and those that vary, denoted $\mu^A_{ni}(j)$:

$$\begin{aligned}\delta^A_{ni} &\equiv S^A_i + \mathbf{X}_i\boldsymbol{\delta} - \theta\mathbf{t}_{ni}\boldsymbol{\beta} - \theta ex^A_i \qquad and \\ \mu^A_{ni}(j) &\equiv \mathbf{X}_i(\mathbf{E}(j)\boldsymbol{\Lambda})' + \mathbf{X}_i(\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)' - \theta\mathbf{t}_{ni}(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t)'\end{aligned}$$

The probability country i offers the lowest price for product j can then be written in these terms:

$$\pi^A_{ni}(j) = \frac{\delta^A_{ni} + \mu^A_{ni}(j)}{\sum_{l=1}^{I} \delta^A_{nl} + \mu^A_{nl}(j)}$$

and the covariance between the price offers of exporter i and exporter l in market n is:

$$\begin{aligned}cov(\mu^A_{ni}(j), \mu^A_{nl}(j)) &= \sum_{k,q}\sum_{m,p} \lambda_k m \lambda_q p \mathbf{X}_{i,k}\mathbf{X}_{l,q} cov(\mathbf{E}_m(j), \mathbf{E}_p(j)) \\ &+ \sum_k \sigma^2_k \mathbf{X}_{i,k}\mathbf{X}_{l,k} + \sum_d \sigma^2_{t,d}\mathbf{t}_{ni,d}\mathbf{t}_{nl,d}\end{aligned} \tag{3.12}$$

The first two sums describe covariance arising from the degree to which the exporters are agro-ecologically well-suited for producing similar agricultural products. The last captures covariance due to "gravity." The parameter values $\boldsymbol{\Lambda}$, $\boldsymbol{\Sigma}_E$ and $\boldsymbol{\Sigma}_t$ are weights defining the influence of each term on covariance.

3.4 Estimation

I estimate equation 3.11 using the simulated method of moments approach introduced by BLP and detailed in Nevo (2000)[26] and Train (2009)[27]. To numerically evaluate the integral, I use the "smooth simulator" suggested by Nevo (2000):

$$\pi^A_{ni} = \frac{1}{ns}\sum_{j=1}^{ns} \frac{exp\{\tilde{S}^A_i + \mathbf{X}_i(\mathbf{E}(j)\boldsymbol{\Lambda})' + \mathbf{X}_i(\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)' - \theta\mathbf{t}_{ni}\boldsymbol{\beta} - \theta ex_i - \theta\mathbf{t}_{ni}(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t)'}{\sum_{l=1}^{I} exp\{\tilde{S}^A_l + \mathbf{X}_l(\mathbf{E}(j)\boldsymbol{\Lambda})' + \mathbf{X}_l(\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)' - \theta\mathbf{t}_{nl}\boldsymbol{\beta} - \theta ex_l - \theta\mathbf{t}_{nl}(\boldsymbol{\nu}_{t_n}(j)\boldsymbol{\Sigma}_t)'} \tag{3.13}$$

where ns is a large number. The general approach of the BLP method is to compute the probability of offering the lowest price at the product-level $\pi^A_{ni}(j)$ for a given set of parameter values and then aggregate over all products purchased in a given import market to obtain the predicted sector-level market share. Parameters values are chosen to minimize the difference between observed and expected sector-level market share.[6]

I use the minimum distance procedure suggested by Nevo (2000)[26] to obtain $\hat{\boldsymbol{\delta}}$ from $\hat{\tilde{S}}_i^A$. By definition:

$$\tilde{S}_i^A = \mathbf{X}_i \boldsymbol{\delta} + S_i^A$$

Estimates of $\boldsymbol{\delta}$ and S_i^A are then obtained from:

$$\hat{\boldsymbol{\delta}} = (\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\,\hat{\tilde{S}}^A$$

where $\mathbf{V}$ is the covariance matrix of the $\tilde{S}_i^A$ estimates and estimates of S_i^A are obtained as the residuals from this estimation.

Data

In addition to the market shares and trade cost proxy variables I assembled to estimate Equation 2.6 in Chapter 2, estimating 3.11 requires data on exporter characteristics $\mathbf{X}_i$, the distribution of product-specific climate requirements $\mathbf{E}(j)$ across products, and the density of agricultural products imported by each country. I obtain data on the distribution of each country's total land area across climate zones $\begin{bmatrix} trop_i & temp_i & bor_i \end{bmatrix}$ from the GTAP Land Use Database [28] and data on total arable land (AL_i) from the World Bank World Development Indicators [16].

The vector of observable production requirements $\mathbf{E}(j) = \begin{bmatrix} trop(j) & temp(j) & boreal(j) \end{bmatrix}$] is estimated for products at the FAO item level as a production-weighted distribution of climate across all 42 countries. For example the tropical cultivation intensity for FAO item j is estimated as:

$$trop(j) = \sum_{i=1}^{I} \omega_i(j) trop_i$$

where $\omega_i(j)$ is country i's share of global item j production value. The estimate of $\mathbf{E}(j)$ for each of the 130 FAO agricultural items traded among the countries in my data set is listed in Appendix E.

I use FAO item level import data to estimate $\hat{F}_{E_n}(\mathbf{E})$, the empirical distribution of $\mathbf{E}(j)$ across products imported by each market.[7] To do so I first compile a list of 100

[6] The process could be improved by using additional moments such as sub-sector-level market shares as well.

[7] See Appendix E.

products imported by each market and defined by $\mathbf{E}(j)$. Unique values of $\mathbf{E}(j)$ are included in this list in proportion to their 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 $\mathbf{E}(wheat)$ makes up 15 entries the list that represents $\hat{F}_{E_n}(\mathbf{E})$. The distribution $\hat{F}_{E_n}(\mathbf{E})\hat{F}_{\nu_n}(\boldsymbol{\nu})$ is completed by associating each product with the corresponding value of $\boldsymbol{\nu}_n(j) = [\boldsymbol{\nu}_E(j)\ \ \boldsymbol{\nu}_{t_n}(j)]$ drawn from a standard multivariate normal distribution for each item. I draw $ns = 100$ values of $(\mathbf{E}(j),\, \boldsymbol{\nu}_n(j))$ at random from these distributions effectively generating a "data set" of 100 products imported by each market.

Results: Production Cost Parameters

In this section I will first present the parameter estimates that describe the distribution of production costs across agricultural products. I will briefly discuss their interpretation and present a few key implications for the structure of competition in the agricultural sector before moving on to trade cost estimates. Recall that unit production costs are specified as follows.

$$ln(C_i^A(j)) = S_i^A + \mathbf{X}_i \times \left[\boldsymbol{\delta} + (\mathbf{E}(j)\boldsymbol{\Lambda})' + (\boldsymbol{\nu}_E(j)\boldsymbol{\Sigma}_E)'\right] \tag{3.14}$$

This exposition underscores that differences in production requirements $[\mathbf{E}(j)\ \ \boldsymbol{\nu}_E(j)]$ generate variation in the effect of exporter agro-ecological characteristics $\mathbf{X}_i$, on production costs. Table 3.1 contains the parameter estimates that describe this variation, i.e., $\hat{\boldsymbol{\delta}}$,[8] $\hat{\boldsymbol{\Lambda}}$, and $\hat{\boldsymbol{\Sigma}}_E$.

Coefficients on all climate variables are normalized to sum to zero. As such, 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 distribution in my sample is 23% tropical, 64% temperate and 13% boreal. The average distribution of cultivation across climates for products in my sample is 10% tropical, 80% temperate and 10% boreal.

As an example of how to interpret the coefficient estimates in Table 3.1, consider the effect of an exporter's share of land in a tropical climate zone ($trop_i$). The negative

[8] These coefficients are estimated by regressing values of $\hat{\hat{S}}_i^A$ obtained from Equation 3.11 on $\mathbf{X}_i$ as suggested in Nevo (2000)[26].

Table 3.1: Production Cost Distribution Parameter Estimates

Exporter Characteristics	Mean Effect (δ)	Climate Requirements (Λ)		Unobserved Requirements (Σ_E)
		Tropical	Temperate	
ln Arable Land (AL_i)	-0.07***	-1.14***	-1.23***	0.04***
	(0.01)	(0.05)	(0.04)	(0.004)
Tropical Climate Share ($trop_i$)	-2.64***	4.12***	7.93***	-0.03
	(0.12)	(0.35)	(0.29)	(0.1)
Temperate Climate Share ($temp_i$)	1.61***	-0.03	-4.02***	0.19**
	(0.12)	(0.33)	(0.28)	(0.1)
Boreal Climate Share (bor_i)	1.03***	-4.09***	-3.92***	-0.16
	(0.19)	(0.46)	(0.41)	(0.17)

mean coefficient estimate on the share of tropical land indicates that market share in the average product is decreasing in the extent to which an exporter has a larger-than-average share of tropical land. However, the large and positive estimates of $\lambda_{trop,trop} = 4.12$ and $\lambda_{trop,temp} = 7.93$ imply that this disadvantage is reversed for products that are more intensively tropical or temperate than the average product. It might seem odd that the value of tropical land share increases more with the temperate intensity of production than the tropical intensity of production, but this is in part a reflection of the temperate climate intensity of the average product. The statistically insignificant estimate for σ_{trop} suggests that the climate-based differences in production requirements defined here adequately capture the variation in the effect of tropical land share across products.

The left panel of Figure 3.1 displays the distribution of the total effect of tropical climate share: $\delta_{trop} + \mathbf{E}(j)\boldsymbol{\lambda}_{trop} + \boldsymbol{\nu}(j)\boldsymbol{\sigma}_{trop}$ across the 130 traded items. The figure illustrates that the total effect is positive for a large number of products even though the mean effect is negative. In contrast to the effect of tropical land, a larger than average share of boreal climate increases market share in the average product, but the benefit is severely diminishing in both tropical and temperate climate cultivation intensity. The right panel of Figure 3.1 illustrates the distribution of the total value of the boreal coefficient: $\delta_{bor} + \mathbf{E}(j)\boldsymbol{\lambda}_{bor} + \boldsymbol{\nu}(j)\boldsymbol{\sigma}_{bor}$, across all 130 traded items. Despite the positive mean effect, the coefficient on boreal land share is negative for all but a few products.

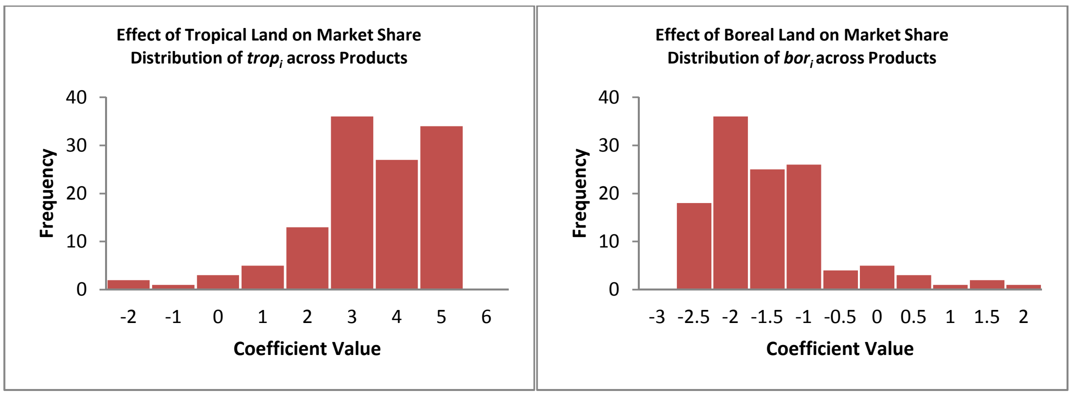

Figure 3.1: Distribution of Climate Effects Across Products

The only climate share characteristic for which unobserved heterogeneity is statistically significant is $temp_i$. This suggests that the distribution of production requirements across three climate zones is inadequate to explain how the value of temperate land share varies across products. This is unsurprising given that the average country is characterized by a large share of temperate land and the average product is intensively cultivated in temperate climate zones. A more precise measure of the relationship between exporter agro-ecological characteristics and trade patterns will thus require either additional refinements to the temperate land characteristic or additional variables representing non-climate production requirements that influence the differential value of temperate land across products. This will be particularly important in applications where trade between countries with a large share of temperate land is central to the analysis.

In Figure 3.2, I demonstrate that the modified model predicts exporters will specialize in products for which their agro-ecological characteristics are well-suited. This is in contrast to the EK model, where specialization is randomly determined by realizations of $z_i^A(j)$. Figure 3.3 is a relative frequency distribution of $\tilde{S}_i^A + \mathbf{X}_i(\mathbf{\Lambda E}(j))$ for i=Costa Rica, The United States, and Turkey for j= coffee, tea and spice products. This value can be interpreted as a measure of the country's absolute advantage in product j. Values of "competitiveness" closer to zero indicate greater absolute advantage.

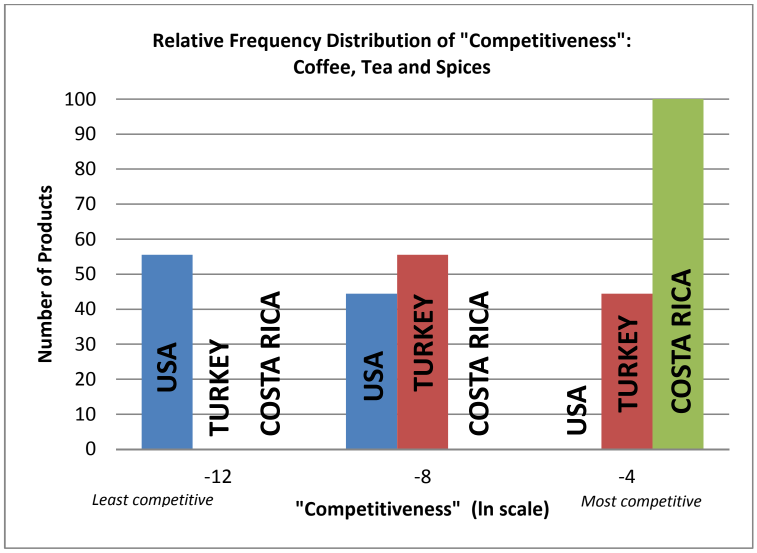

Figure 3.2: "Competitiveness" in Coffee, Tea and Spices

Estimates of $\tilde{S}_i^A$ suggest that the United States and Turkey both have an absolute advantage over Costa Rica in the average agricultural product.[9] However, Figure 3.3 illustrates the model's prediction that Costa Rica is more competitive than the United States in all coffee, tea and spice products, and more competitive than Turkey in most of them. I list the values of $\hat{\tilde{S}}_i^A$ obtained from Equation 3.11 in Appendix B. Recall that these values are interpreted as the competitiveness in the average product compared to the *average country*.

Results: Trade Costs

Table 3.2 contains parameter estimates for the distribution of trade costs across agricultural products. Coefficients in the first column capture the average effect of each trade cost component on market share. Positive coefficients imply the effect decreases trade costs, but increases market share. The second column contains coefficient estimates on the product-specific heterogeneity around each trade cost component, Σ_t. These values can be interpreted like a standard deviation of the distribution of each effect across

[9] $\hat{\tilde{S}}_{TUR}^A = 4.30$, $\hat{\tilde{S}}_{USA}^A = 2.38$, $\hat{\tilde{S}}_{CRI}^A = -6.27$

products.

The third column of Table 3.2 contains coefficient estimates from the model I estimated in Chapter 2. Notice that the mean effect estimates from the modified model are broadly similar in magnitude to the EK estimates, and all have the same sign.

It is perhaps surprising that the signs on $NAFTA$ and EU are negative in both models, implying that membership in these FTAs increases agricultural trade costs on average. This result can be rationalized by the product-specific interpretation of trade cost effects in the modified model. Indeed, there are many agricultural products for which no member country of EU or NAFTA will be agro-ecologically well-suited: The lowest price offer for green coffee beans in France certainly has a very low probability of coming from producers in another EU member state!

Importantly, the large magnitude of $\hat{\sigma}_{NAFTA}$ and $\hat{\sigma}_{EU}$ indicates a great deal of variation in the effect of membership in these FTAs across products. This suggests additional variables describing product-specific policies or other product-specific costs are needed to more precisely describe the distribution of the effects of NAFTA and EU membership. This can be accomplished by introducing interaction terms between $\mathbf{t}_{ni}$ and observable product-specific trade costs such as tariff rates just like the interaction between $\mathbf{X}_i$ and $\mathbf{E}(j)$ in the productivity distribution.

A notable departure from the EK model is that the mean effect of distance among countries in closest proximity to each other is larger than the mean effect of the second-closest distance category. However, the large and statistically significant value of $\sigma_{D1} = -3.26$ suggests that the total effect of distance in this category varies considerably across products and is likely to have a smaller effect on trade costs than distance in the second category for many products. As with the RTA variables, this suggests additional information on product-specific trade costs should be incorporated for more precise predictions of the effect of distance on trade among neighboring countries.

I report estimates of the exporter-specific trade cost ex_i^A, in Appendix C. Recall that these values are interpreted with respect to the average country: Exporters with coefficients greater than one face higher than average agricultural trade costs and vice versa. Coefficient estimates from the modified model are highly correlated with and of broadly similar magnitude to those obtained under the EK framework in Chapter 2. As in the EK-style model of manufacturing trade in Waugh (2010)[15], exporter-specific

Table 3.2: Trade Cost Distribution Parameters

Exporter Characteristic	Modified Model: Mean (β)	Modified Model: Unobserved Heterogeneity (σ_t)	EK Model Coefficient
Common Border	0.54*	0.93***	0.75*
	(-0.35)	(-0.33)	(-0.56)
Common Language	1.30**	-0.48**	1.49***
	(-0.29)	(-0.21)	(-0.35)
Distance 1	-8.82***	-3.26***	-5.89***
	(-0.21)	(-0.29)	(-0.7)
Distance 2	-7.75***	-0.78***	-8.47***
	(-0.34)	(-0.26)	(-0.44)
Distance 3	-9.57***	0.6***	-10.27***
	(-0.31)	(-0.24)	(-0.32)
Distance 4	-11.33***	0.63***	-11.87***
	(-0.32)	(-0.2)	(-0.32)
Distance 5	-14.09***	-1.14***	-13.91***
	(-0.32)	(-0.33)	(-0.18)
Distance 6	-14.38***	0.1	-15.00***
	(-0.23)	(-0.34)	(-0.17)
Intra-EU	-5.68***	-2.76***	-2.62***
	(-0.19)	(-0.2)	(-0.47)
Intra-NAFTA	-14.92***	-8.21***	-1.64***
	(-0.28)	(-0.58)	(-1.63)

trade costs tend to be higher for developing countries. However, it is notable that the highest exporter-specific costs in agriculture are associated with former members of the Soviet Union and Communist Bloc.

3.5 Partial Equilibrium Elasticity Estimates

I calculate trade elasticities by simulating the integral in Equation 3.5 using the same ns individual products I used to estimate the model. For example, the elasticity of substitution of exporter i with respect to exporter l in market n is computed:

$$\frac{\partial \hat{\pi}_{ni}^{A}}{\partial \hat{\tau}_{nl}^{A}} \frac{\partial \hat{\tau}_{nl}^{A}}{\partial \hat{\pi}_{ni}^{A}} = \frac{\theta}{\hat{\pi}_{ni}^{k}} \left(\frac{1}{ns} \sum_{j=1}^{ns} \hat{\pi}_{ni}^{k}(j) \hat{\pi}_{nl}^{k}(j) \right) \tag{3.15}$$

using the coefficient estimates above to calculate $\hat{\pi}_{ni}^{k}(j)$ and $\hat{\pi}_{ni}^{A}$.[10]

Unlike under the CES import demand system implied by the EK framework, cross-country elasticity with respect to each exporter varies significantly across competitors in each import market. A measure of the extent of this variation is the ratio of the maximum to the minimum value of Equation 3.15 with respect to each exporter's trade costs. Since the value of this max-min ratio is exactly one in the EK model, the extent to which it exceeds one is a measure of the additional variation across competitors detected by the modified model. The max-min ratio for any exporter will naturally vary across import markets due to differences in bilateral trade costs and the composition of imported products. I report the median value across import markets for each exporter in Table 3.3. The modified model predicts over 17-times more variation in sensitivity to US trade costs in the median market! Even for Chile, which displays the least variation in elasticity, the modified model delivers more than twice the variation as the EK model.

These results confirm that the modified model will generate more nuanced predictions for the effect of changes in trade costs on bilateral trade patterns than the EK model. However, the model should also predict sensible directions for shifts in bilateral trade flows. The relative magnitudes of indirect effects are described by the pattern of cross-country elasticities across competitors. Recall from Equation 3.7 that these elasticities are increasing in the covariance generated by similarity in agro-ecological characteristics and trade costs.

[10] I set $\theta = 4.12$, the benchmark estimate from Simonvska and Waugh (2011).[6]

Table 3.3: Increase in Cross-Country Elasticity Variation from Modified over EK Model
Median over import markets

Exporter	Maximum Elasticity/ Minimum Elasticity	Exporter	Maximum Elasticity/ Minimum Elasticity
USA	17.22	Uruguay	8.28
France	16.01	Austria	7.43
Colombia	14.78	Ecuador	7.16
Russia	14.27	Poland	6.98
Argentina	13.87	Netherlands	6.9
Germany	13.77	Canada	6.6
Sweden	12.47	Denmark	6.37
UK	12.44	Finland	5.65
Costa Rica	12.14	Romania	4.94
Czech Republic	12.1	South Africa	4.57
Malaysia	11.64	Turkey	4.4
Thailand	10.97	India	4.27
Slovenia	10.62	Estonia	4.18
Portugal	10.55	Israel	3.65
Italy	10.53	Slovakia	3.3
Spain	10.07	Iran	3.15
Kenya	9.73	New Zealand	2.91
Hungary	9.43	Mexico	2.89
Indonesia	8.81	Japan	2.66
Brazil	8.76	Australia	2.41
Ireland	8.66	Chile	2.18

As an informal test of the model's strength in identifying close substitutes, recall the EK model's prediction that Ecuador and The Netherlands will have an identical response to a change in Costa Rican trade costs in the US market. Table 3.4 displays US market share elasticities with respect to Costa Rican trade costs in the modified model relative to those predicted by the EK framework in Chapter 2 for Ecuador and The Netherlands, as well as for their competitors with the largest and smallest elasticities. First, the modified model predicts Ecuador is more than twice as sensitive to changes in Costa Rican trade costs as The Netherlands. Second, notice that relative elasticities reported in Table 3.4 are all greater than one. This suggests that the EK approach under-predicts the size of the trade response to changes in Costa Rican trade costs for all of its competitors in the US market.

Table 3.4: Elasticity of US Market Share with respect to Costa Rican Trade Costs
Modified model predictions relative to EK predictions

Exporter	Modified Model Elasticity/ EK Elasticity
Colombia	14.15
Ecuador	7.00
The Netherlands	3.65
Russia	2.06

I explore the model's predictions more broadly in Table 3.5, which is a matrix of the elasticities predicted by the modified model relative to those predicted by the framework in Chapter 2 for selected countries. Since relative elasticities vary across import markets, I report the median value. Each row contains an exporter's elasticity of market share with respect to the competitor in the column's trade costs in the median market.

Relative cross-country elasticity ranges from 0.85 for Costa Rica's median relative elasticity with respect to Canadian trade costs to 30.78 for Italy's median relative elasticity with respect to Spain. This is sensible: One expects Costa Rica to be relatively unaffected by Canadian trade costs, whereas Italy and Spain are likely to be close substitutes in many markets. This result also means that the EK model would tend to drastically under-predict the response of Italy's trade flows to changes in Spain's trade costs The modified model predicts Italian market share is nearly 40-times more elastic to Spanish trade costs than the EK-style model from Chapter 2! Similarly, the EK model over-predicts changes in Costa Rican trade flows in response to Canadian trade costs. Elasticity estimates from the modified model suggest that the EK model under-predicts the magnitude of the response to changes in trade costs for just under one-third (31%) of all bilateral trade flows.

While the pattern of cross-country elasticity says a lot about how the model functions, the magnitude of the direct effect is typically the primary object of interest for policy-makers. The direct effect is defined by own-country trade costs elasticities. Table 3.5 does not reveal a great deal of variation in median own-country trade cost elasticities across exporters. However, examining individual import markets reveals a great deal more.

The modified model does overcome the restriction imposed by the CES import demand system that own-country elasticity is strictly decreasing in market share. For example, Japanese products represent a much smaller share of US agricultural expenditure than Brazilian products (0.0001% vs. 0.0051%). However, Japanese agricultural exports to the United States tend to have intrinsic characteristics associated with Japan's technological, cultural and agro-ecological environment, whereas those exported by Brazil do not. This can be characterized by high values of $a_i(j)$ or $\tau_{ni}^{A}(j)$ for many Japanese products. Basic microeconomic theory thus suggests Japan's own-country elasticity should be less than Brazil's, despite its smaller market share. Indeed, the modified model predicts smaller magnitude own-country elasticity for Japan: the ratio of Japan's own-country trade cost elasticity relative to Brazil's in the US market is 0.6467 in the modified model compared to 1.0003 in the EK model.

3.6 The Structure of Competition Faced by US Producers

The modified model can provide insight into the structure of global competition faced by an individual country's agricultural producers. In this section I will examine what the model suggests about the United States' competitors. There are two dimensions to consider: The first is which competitors are most sensitive changes in US trade costs. The second is which competitors' trade costs US market share is most sensitive to. These two sets of countries will likely have a great deal of overlap. The first consists

Table 3.5: Modified Model Elasticity Relative to EK Elasticity

Elasticity of Exporters Market Share (row) to Competitors Trade Costs (column), Median Market

	Competitor													
Exporter	Argentina	Australia	Brazil	Canada	CostaRica	Colombia	Ecuador	France	Indonesia	Italy	Malaysia	Mexico	Spain	USA
Argentina	*1.00*	7.45	3.09	3.64	9.27	2.4	3.1	9.1	2.04	6.95	2.31	5.17	11.11	5.55
Australia	6.91	*1.00*	3.23	3.25	5.73	3.16	3.52	6.45	3.51	6.98	4.43	5.32	7.15	4.17
Brazil	7.21	4.63	*1.00*	3.42	5.23	11.63	7.59	5.64	5.5	7.79	9.02	4.27	6.76	2.94
Canada	5.93	4.98	3.32	*1.00*	5.18	1.73	1.82	5.52	2.18	5.16	5.3	8.66	4.91	8.03
Costa Rica	1.95	3.67	9.54	0.85	*1.00*	15.23	13.36	2.36	7.97	2.72	16.54	4.26	2.62	0.88
Colombia	2.42	3.65	9.26	2.64	5.23	*1.00*	11.31	3.31	7.41	3.04	13.84	4.20	3.88	2.31
Ecuador	3.22	3.90	8.52	1.25	5.12	8.66	*1.00*	3.49	6.11	3.59	12.92	4.47	4.05	1.18
France	10.60	7.54	4.66	3.41	8.92	2.13	3.96	*1.00*	2.37	23.47	2.26	4.74	29.79	4.66
Indonesia	2.66	3.99	7.21	1.56	4.41	8.33	9.30	3.78	*1.00*	7.48	11.57	3.63	3.49	1.27
Italy	7.47	6.74	4.25	3.23	5.87	2.53	3.93	23.83	2.76	*1.00*	3.61	4.74	30.78	3.30
Malaysia	1.94	3.61	7.78	3.56	3.79	9.53	11.34	2.58	8.19	3.33	*1.00*	3.95	2.64	2.22
Mexico	5.16	5.59	5.01	3.67	5.43	4.62	5.23	4.66	4.99	6.59	6.40	*1.00*	5.71	3.14
Spain	7.80	6.67	5.05	3.28	8.38	2.42	4.86	50.11	3.19	30.25	3.21	5.07	*1.00*	4.07
USA	6.08	5.23	1.92	9.32	5.06	1.35	1.77	5.66	1.99	3.91	3.29	5.14	4.29	*1.00*

of countries that are most likely to have low price offers the same goods, i.e., close substitutes. The second set will include close substitutes, but will also be influenced by the size of competitor's market share.

The last column of Table 3.5 contains median relative elasticities with respect to US trade costs. These results suggest, sensibly, that Canada is the closest substitute for the United States, while there will be relatively few agricultural products for which the United States and Costa Rica will compete head-to-head. Importantly, the CES import demand system cannot produce this distinction. Costa Rica's median relative market share response to changes in US trade costs is only about 90% of that predicted by the EK model, whereas Canada's is *more than eight times larger*.

Examining elasticities with respect to US trade costs across import markets reveals that South Africa, Argentina, Russia and Canada tend to have the largest elasticities with respect to US trade costs. The indirect effect of a bilateral trade liberalization between the US and any given import market is thus expected to diminish the market share of these countries the most. Costa Rica, Malaysia, and Colombia tend to have the smallest elasticities with respect to US trade costs and would thus be expected to experience negligible changes in agricultural market share in response to bilateral trade liberalization between the US and any given import market.

Now consider the second dimension of the competitive structure facing US agricultural producers. In the EK model, elasticity is proportional to the competitor's market share, so the United States is always most sensitive to the country with the largest market share. In the modified model, the set of competitors whose trade costs the US market share is most sensitive to is influenced both by the competitor's market share and its similarity in comparative advantage. To make this clear, I re-write equation 3.7:

$$\frac{\partial \pi^A_{nUSA}}{\partial \tau^A_{nl}} \frac{\tau^A_{nl}}{\pi^A_{nUSA}} = \theta \left(\pi^A_{nl} + \frac{cov\left(\pi^A_{nUSA}(j), \pi^A_{nl}(j)\right)}{\pi^A_{nUSA}} \right) \quad l \neq USA$$

The bottom row of Table 3.5 contains the median relative elasticity of US market share with respect to each competitor. The modified model predicts that the response of US market share to Canadian trade costs is more than six-times larger than that predicted by the EK model and merely six-tenths as large with respect to Ecuador in the median market. Looking across all import markets, the modified model predicts that US market share tends to be most sensitive to changes in Canadian, French, Italian and Argentine trade costs.

3.7 Conclusions

In this chapter I made two modifications to the EK framework for trade and production in the agricultural sector. First, I introduced a factor into the EK production technology that allows agro-ecological characteristics to influence patterns of comparative advantage within the sector. Second, I allowed trade costs to vary across agricultural products according to a parametric distribution. These two changes generate correlation in patterns of specialization among countries with similar agro-ecological and "gravity" characteristics, yielding a more nuanced picture of how bilateral trade and production patterns respond to trade costs than the EK model, which assumes a CES import demand system.

Next, I demonstrated that the structural equation used to estimate trade costs and productivity distribution parameters in the EK framework can serve the same role in the modified framework when specified as a random coefficients logit model. The additional data requirements to estimate these parameters are minimized by using the BLP methodology. This approach allows a discrete choice model to be estimated using only sector-level market share data and information on the distribution of product-specific production requirements and trade costs. The statistical significance of the coefficients describing the distribution of land productivity suggests that agro-ecology is a fundamental driver of bilateral trade and production patterns, and that heterogeneity in trade costs cannot be ignored. This is further support for rejecting the CES import demand system inherent in the EK model, as described in Chapter 2.

The modified model not only improves the precision with which a probabilistic Ricardian model can predict shifts in trade patterns in response to policy, it also allows the researcher to include information that the EK structure cannot admit. In particular, while I have not done so here, trade costs can be specified to include variables like product-specific tariffs or other trade-distorting policies that are unevenly applied across products. This feature alone offers a substantial improvement over the standard EK model for agricultural policy analysis.

In future work I will explore alternative specifications for exporter characteristics and product requirements to improve the precision of the model's market share predictions. In particular, the statistical significance on unobserved heterogeneity around the effect of an exporter's share of temperate climate suggests that additional product requirements are necessary to more precisely explain its relationship to market share. Alternatively, it may be necessary to more sharply define agro-ecological characteristics within the temperate climate zone. The model's precision could be similarly enhanced by allowing non-random factors to influence the distribution of trade costs.

In the next chapter I introduce the modified model assumptions on technology and trade costs into a general equilibrium model. The more nuanced picture of substitution patterns described by trade elasticities in the modified model will substantially improve its value as a tool for evaluating the impact of a change in trade policy on the structure of the agricultural sector.

Chapter 4

General Equilibrium

In this chapter I embed the modified agriculture sector technology and trade cost assumptions introduced in Chapter 3 into a general equilibrium model with two tradable sectors. I maintain the EK framework discussed in Chapter 2 for the manufacturing sector. I solve for global equilibrium in the modified model as well as in a model where the EK assumptions are maintained for both tradable sectors. I refer to this second model as the EK model, although strictly speaking it is an extension of the model in Eaton and Kortum (2002)[1] to multiple tradable sectors as in Shikher (2012)[4].

The base solutions for global equilibrium are nearly identical in the modified model and the EK model. It is their implications for the response of trade and production patterns to changes in trade costs that differ—and these differences are even more dramatic in general equilibrium than what is suggested by the partial equilibrium elasticities in Chapter 3. I highlight these differences by calculating simulated general equilibrium elasticities with respect to changes in the trade costs of the United States and three of its competitors: Canada, France and Costa Rica. According to the results in Chapter 3, Canada is the United States' closest substitute and France is among the countries whose trade costs affect US market share most. Costa Rica, on the other hand, tends to have comparative advantage in a different set of agricultural products than the United States. A change in its bilateral trade costs with a given market is therefore expected to have a relatively minimal effect on US market share.

Consistent with the findings in Chapter 3, the general equilibrium model with the modified agricultural sector predicts the increase in US market share from higher Canadian or French trade costs will tend to be larger than the median competitor, whereas US market share elasticity with respect to Costa Rican trade costs is small relative to the median in every import market. In contrast, the predictions of the EK model do not discriminate between competitors that are close agricultural substitutes and those that are not: US market share elasticity is virtually equal to the median for each exporter in every import market. These divergent results suggest that ignoring the findings in Chapter 2, viz., that the CES import demand system does not describe agricultural trade, generates a misleading picture of the effect of policy on production and trade patterns. The EK model is thus insufficient for analysis of global agricultural markets.

I highlight the other key advantage of the modified model in a second experiment. Unlike the EK model, the modified model can be used to evaluate the trade and welfare effects of changes in the dispersion of trade costs within the agricultural sector. This is essential for applied agricultural policy analysis—it is the central issue in most global policy debates. The policies that affect agricultural imports and exports are far from uniformly distributed across products. Moreover, a distinct set of agricultural commodities are systematically subject to high trade barriers. This characterization implies that analyzing the effects of changes in the average barrier to agricultural trade is of little practical value.

To demonstrate how the model can be used to evaluate differences in the dispersion of tariffs in a very simple way, I compare the trade and welfare effects of full agricultural trade liberalization versus a partial liberalization that leaves just two commodities highly protected. I simulate full agricultural "trade liberalization" by setting the average bilateral agricultural trade cost equal to bilateral trade costs in the manufacturing sector. This represents an average cut of 92% in agricultural trade costs. To simulate partial liberalization, I maintain high trade barriers from the base parameterization on cotton lint and cattle meat.

I find that the losses under partial relative to full liberalization are substantial and unevenly distributed across countries. The countries that suffer the biggest losses in real income from partial liberalization are Thailand, Indonesia and Ecuador. Cotton represents a substantial portion of the estimated distribution of imported products in all three of these countries, while their agro-ecological characteristics differ from the estimated requirements for cotton production.

Finally, the emphasis in this thesis is on introducing the analytical and empirical methodology of the modified model under the simplest possible specification. The results of the equally simplified counterfactual experiments should not be taken as formal policy analysis or as an evaluation of the model's performance. Rather, the experiments are a demonstration of the type of analysis that could be performed with a more tailored calibration.

4.1 Modified 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, and one non-tradable sector, services. Tradable sectors are each comprised of a continuum of products indexed by $j \in [0,1]$ produced by many perfectly competitive producers. Individual products are distinguished only by their intrinsic characteristics. 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 agricultural production. All production is constant returns to scale and markets are perfectly competitive.

Trade occurs as buyers in market n seek to purchase each product from the source country that offers the lowest price. Three variables determine which country's producers offer the lowest price for an individual product in each market: factor prices, bilateral trade costs, and product-specific productivity. Factor prices are determined in equilibrium and bilateral trade costs are exogenous. 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:

$$q_i^k(j) = z_i^k(j)\Big(N_i^{\beta_i^k}\,(a_i(j)L_i)^{1-\beta_i^k}\Big)^{\alpha_i^k}\mathbf{Q}i^{k^{1-\alpha_i^k}} \quad k = A, M \quad \beta_i^M = 1\forall i$$

where $z_i^k(j)$ is an independent random variable following a country and sector-specific Frechet distribution as in Equation 2.2; $a_i(j)$ is country i, product j-specific land productivity as described in Chapter 3; and $\mathbf{Q}_i^k$ is an aggregate of intermediate inputs from all three sectors combined in a Cobb-Douglas fashion as in Caliendo and Parro (2012)[3]:

$$Q_i^k = Q_i^{A^{\xi_A^k}} Q_i^{M^{\xi_M^k}} Q_i^{S^{\xi_S^k}} \qquad \sum_{l=A,M,S} \xi_l^k = 1$$

where 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 $\sigma > 0$:

$$Q_i^k = \left(\int_0^1 q_i^k(j)^{\frac{(\sigma-1)}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} \qquad k = A, M \tag{4.1}$$

The services sector produces a homogeneous good using only labor with productivity z_i^S.

Exporters incur "iceberg" trade costs when selling products outside the domestic market. In the agricultural sector, trade costs are product-specific and follow the parametric distribution described in Chapter 3. Trade costs are constant for all manufactured products as in the EK framework. With perfect competition the prices offered for product j, by exporter i in market n are therefore:

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

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

$$c_i^k = \kappa_i^k w_i^{\alpha_i^k \beta_i^k + (1-\alpha_i^k)\xi_S^k} r_i^{\alpha_i^k(1-\beta_i^k)} p_i^{A^{(1-\alpha_i^k)\xi_A^k}} p_i^{M^{(1-\alpha_i^k)\xi_M^k}} \tag{4.2}$$

where κ_i^k is a constant.[1]

Buyers in market n purchase each product from the exporter with the lowest price offer. The price actually paid for product j in market n is therefore:

$$p_n^k(j) = min_i\{p_{ni}^k(j)\}$$

Given the aggregation technology buyers use to assemble individual goods from each sector, a unit price index for sector k is:[2]

$$p_n^k = \left(\int_0^1 p_n^k(j)^{-(\sigma-1)} dj \right)^{1/(1-\sigma)} = \left(\int_0^1 p^{(1-\sigma)} dG_n^k(p) dp \right)^{1/(1-\sigma)}$$

---

[1] $\kappa_i^k =$ $\alpha_i^k {\beta_i^k}^{-\alpha_i^k \beta_i^k} \left(\alpha_i^k(1-\beta_i^k)\right)^{-\alpha_i^k(1-\beta_i^k)} \left(z_i^S \xi_S^k(1-\alpha_i^k)\right)^{-(1-\alpha_i^k)\xi_S^k} \left(\xi_A^k(1-\alpha_i^k)\right)^{-(1-\alpha_i^k)\xi_A^k} \left(\xi_M^k(1-\alpha_i^k)\right)^{-(1-\alpha_i^k)\xi_M^A}$

[2] See Appendix D for details.

Using the price distributions for agricultural products, $G_n^A(p)$,[3] this becomes:

$$p_n^A = \gamma \left(\int \Omega_n^A(j)^{\frac{(\sigma-1)}{\theta}} dF_{a_n}(\tilde{\mathbf{a}}) dF_{\tau_n}^A(\boldsymbol{\tau}) \right)^{\frac{1}{1-\sigma}} \tag{4.3}$$

Where $\Omega_n^A(j) = \sum_{l=1}^{I} T_l^A \left(\tilde{a}_l(j) c_l^A \tau_{nl}^A(j)\right)^{-\theta}$; $\gamma = \Gamma\left[\frac{\theta+1-\sigma}{\theta}\right]^{\frac{1}{(1-\sigma)}}$, and $\Gamma(\cdot)$ is the gamma function, so the parameters satisfy $\theta > 1 - \sigma$; and $dF_{a_n}(\tilde{\mathbf{a}}) dF_{\tau_n}^A(\boldsymbol{\tau})$ is the joint density of $\tilde{\mathbf{a}} = [\tilde{\mathbf{a}}_1, \ldots, \tilde{\mathbf{a}}_I]$ and $\boldsymbol{\tau}_n^A = \left[\boldsymbol{\tau}_{n1}^A, \ldots, \boldsymbol{\tau}_{nI}^A\right]$[4] over all agricultural products consumed in import market n described in Chapter 3. Caliendo and Parro (2012)[3] and Shikher (2012)[4] show that the price index under the EK framework that describes the manufacturing sector is:

$$p_n^M = \gamma \Omega_n^{M \frac{-1}{\theta}} \tag{4.4}$$

where $\Omega_n^M = \sum_{l=1}^{I} T_l^M (c_l^M \tau_{nl}^M)^{-\theta}$.

The share of import market n's expenditure on sector k products is equivalent to the probability exporter i offers the lowest price, denoted π_{ni}^k. As I showed in Chapter 3, for agriculture this is:

$$\pi_{ni}^A \equiv \int \frac{T_i^A (\tilde{a}_i c_i^A \tau_{ni}^A)^{-\theta}}{\Omega_n^A(j)} dF_{a_n}(\tilde{\mathbf{a}}) dF_{\tau_n}^A(\boldsymbol{\tau}) \tag{4.5}$$

For the manufacturing sector, since land is not used in production and since I have assumed trade costs are constant:

$$\pi_{ni}^M = \frac{T_i^M (c_i^M \tau_{ni}^M)^{-\theta}}{\Omega_n^M} \tag{4.6}$$

as in Equation 2.4.

4.2 Equilibrium

Equilibrium consists of factor prices w_i and r_i; price indices for tradable goods p_i^A and p_i^M; 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. Equations 4.5 and 4.6 define equilibrium trade shares and Equations 4.3 and 4.4 define equilibrium price indices.

[3] I derive this distribution in Appendix D. $G_n^M(p)$ is derived in EK.

[4] $\tilde{\mathbf{a}}_1 = [\tilde{a}_1(0), \tilde{a}_1(1)]$, $\boldsymbol{\tau}_{n1}^A = [\tau_{n1}^A(0), \tau_{n1}^A(1)]$

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

$$u_i(Q) = Q_i^{A^{\lambda_i^A}} Q_i^{M^{\lambda_i^M}} Q_i^{S^{\lambda_i^S}}$$

subject to the budget constraint: $w_i N_i + r_i L_i$. Here Q_i^k is the sector k aggregate defined by Equation 4.1. This utility function implies that consumers spend a constant share λ_i^k of their total income on products from sector k.

In solving the model, I make use of expressions for agricultural output and expenditure in terms of wages, exogenous labor endowments and parameters as in Dekle, Eaton and Kortum (2008)[29]. I begin with the tradable products market clearing and trade balance conditions:

$$Y_i^k = \sum_{n=1}^{I} \pi_{ni}^k X_n^k = X_i^k - D_i^k \qquad k = A, M \tag{4.7}$$

where Y_i^k is country i's gross sector k production and X_i^k is country i's gross absorption of sector k goods. Under the trade balance condition country i may be a net importer of sector k goods in the amount D_i^k, however economy-level trade balance requires $D_i^A + D_i^M = 0$. Sectoral trade deficits are exogenous and $\sum_{i=1}^{I} D_i^k = 0$.

Individual products are purchased by consumers for final consumption and by producers as intermediate inputs. Total demand for sector k goods in country i is:

$$X_i^k = \lambda_i^k X_i + (1 - \alpha_i^k)(\xi_k^M Y_i^M + \xi_k^A Y_i^A) \tag{4.8}$$

where X_i is total final absorption and $(1 - \alpha_i^k)(\xi_k^M Y_i^M + \xi_k^A Y_i^A)$ is demand for sector k intermediate inputs.

Substituting Equation 4.8 in Equation 4.7 yields:

$$Y_i^M = \frac{\lambda_i^M X_i + (1 - \alpha_i^A)\xi_M^A Y_i^A - D_i^M}{1 - (1 - \alpha_i^M)\xi_M^M} \quad \textit{and} \quad Y_i^A = \frac{\lambda_i^A X_i + (1 - \alpha_i^M)\xi_A^M Y_i^M - D_i^A}{1 - (1 - \alpha_i^A)\xi_A^A} \tag{4.9}$$

With perfect competition, value-added equals factor payments in each sector:

$$V_i^k = w_i N_i^k + r_i L_i^{k}\,{}^{5} \tag{4.10}$$

[5] $L_i^M = L_i^S = 0$

Exporter is GDP is therefore:

$$Y_i = w_i N_i + r_i L_i = w_i N_i + \alpha_i^A (1 - \beta_i^A) Y_i^A$$

where the first equality follows from the labor market clearing condition and the second follows from the agricultural producer's problem.

Substituting Equation 4.9 for the manufacturing sector and the trade balance condition $X_i = Y_i$ into the agricultural sector, Equation 4.9 yields an expression for agricultural output in terms of the total value of labor, the exogenous agricultural sector deficit D_i^A and model parameters:

$$Y_i^A = \kappa_{1i}^A w_i N_i + \kappa_{2i}^A D_i^A \tag{4.11}$$

where the κ terms are functions of parameters.[6] Similarly, for the manufacturing sector:[7]

$$Y_i^M = \kappa_{1i}^M w_i N_i + \kappa_{2i}^M Y_i^A + \kappa_{3i}^M D_i^A \tag{4.12}$$

where Y_i^A is calculated as in 4.11. Substituting this into the market clearing condition yields an equation for manufacturing sector expenditure:

$$X_i^M = \kappa_{1i}^M w_i N_i + \kappa_{2i}^M Y_i^A + \kappa_{4i}^M D_i^A \tag{4.13}$$

4.3 Data and Calibration

Computing world equilibrium requires data on labor and land endowments and values for the utility function parameters λ_i^k; production function parameters κ_i^k, α_i^k, β_i^k, ξ_l^k, T_i^k and θ; trade costs τ_{ni}^k and land productivity a_i; and the elasticity of substitution parameter σ. Data on arable land in hectares and total labor force is obtained from the World Bank World Development Indicators. Values for $a_i(j)$ and $\tau_{ni}^A(j)$ in the modified model are estimated as in Chapter 3. Values for τ_{ni}^A in the EK model are estimated as in Chapter 2.

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6 $\kappa_{1i}^A = \frac{\lambda_i^A(1-(1-\alpha_i^M)\xi_M^M)+\lambda_i^M(1-\alpha_i^M)\xi_A^M}{(1-(1-\alpha_i^M)\xi_M^M-(1-\alpha_i^A)\xi_A^A)-(\lambda_i^A(1-(1-\alpha_i^M)\xi_M^M)+\lambda_i^M(1-\alpha_i^M)\xi_A^M)\alpha_i^A(1-\beta_i^A)}$,
$\kappa_{2i}^A = \frac{(1-\alpha_i^M)\xi_A^M-(1-(1-\alpha_i^M)\xi_M^M)}{(1-(1-\alpha_i^M)\xi_M^M-(1-\alpha_i^A)\xi_A^A)-(\lambda_i^A(1-(1-\alpha_i^M)\xi_M^M)+\lambda_i^M(1-\alpha_i^M)\xi_A^M)\alpha_i^A(1-\beta_i^A)}$,
$\kappa_{3i}^A = \frac{\lambda_i^A(1-(1-\alpha_i^M)\xi_M^M)+\lambda_i^M(1-\alpha_i^M)\xi_A^M)\alpha_i^A(1-\beta_i^A)+((1-\alpha_i^M)\xi_A^M-(1-\alpha_i^A)\xi_A^A}{(1-(1-\alpha_i^M)\xi_M^M-(1-\alpha_i^A)\xi_A^A)-\alpha_i^A(1-\beta_i^A)(\lambda_i^A(1-(1-\alpha_i^M)\xi_M^M)+\lambda_i^M(1-\alpha_i^M)\xi_A^M)}$

7 $\kappa_{1i}^M = \frac{\lambda_i^M}{1-(1-\alpha_i^M)\xi_M^M}$, $\kappa_{2i}^M = \frac{\lambda_i^M\alpha_i^A(1-\beta_i^A)+(1-\alpha_i^A)\xi_M^A}{1-(1-\alpha_i^M)\xi_M^M}$, $\kappa_{3i}^M = \frac{1}{1-(1-\alpha_i^M)\xi_M^M}$, $\kappa_{4i}^M = \frac{1-\alpha_i^M}{1-(1-\alpha_i^M)}$

To estimate manufacturing trade costs τ_{ni}^M, I assemble bilateral market shares following the procedure described in Chapter 2 using data on production and trade data from the CEPII TradeProd database, described in de Sousa et al (2012)[30]. Using a concordance between FAO item codes and the HS classification provided by the FAO, I confirm that there is no overlap in the products that comprise the agricultural and manufacturing sector data. I use OLS to estimate manufacturing sector trade costs as in Chapter 2 from:

$$ln\frac{\pi_{ni}^M}{\pi_{nn}^M} = S_i^M - S_n^M - \theta\left(b_{ni}^M + l_{ni}^M + \sum_{r=1}^{6} d_{r_{ni}}^M + ex_i^M + EU_{ni}^M + NAFTA_{ni}^M + \xi_{ni}^M\right) \qquad (4.14)$$

Estimates for S_i^M are reported in Appendix B. Estimates for ex_i^M are reported in Appendix C. The remaining parameter estimates from this equation are reported in Appendix F.

As in EK, I obtain estimates of T_i^k in the modified model from $\hat{\tilde{S}}_i^A$ and $\hat{S}_i^M$, the coefficients on producer fixed effects from Equations 3.13 and 4.14. Estimates of T_i^A for the EK model are obtained from S_i^A estimates from Equation 2.6. The methodology is detailed in Appendix G.

Value-added α_i^k, intermediate inputs shares ξ_l^k, and consumption shares λ_i^k are obtained from input-output tables for the early 2000's from the OECD-STAN database[31]. Input-output tables are available for 30 countries. I assign the average value for each parameter to the remaining countries. The values of α_i^k, ξ_l^k, and λ_i^k used for each country are listed in Appendix H. I set $\beta_i^A = 0.66$, the mean estimate of labor's share in production in Gollin (2002)[32]. I set $\sigma = 2.0$ as in Ruhl (2008)[33] and $\theta = 4.12$, the baseline estimate from Simonovska and Waugh (2011)[6]. Finally, I set $z_i^S = 1$ and $D_i^A = 0$, leaving them as free parameters.

4.4 Solution

I use the same approach to solve for equilibrium in both the modified and EK models. The only difference is that I use equation 4.3 and 4.5 to solve for the agricultural price index and market shares in the modified model and equations 4.4 and 4.6 for the agriculture and manufacturing sectors in the EK model.

To solve for equilibrium given the structural parameter values in Table 4.1, I first guess a vector of wages $\bar{\mathbf{w}} = [\bar{w}_1, \ldots, \bar{w}_I]$. Let $Y_i^A(\bar{\mathbf{w}})$ be the solution to Equation 4.11

Table 4.1: Sources and Values for Structural Parameters

Parameter	Source	Value
$\tilde{a}_i(j)$, T_i^A, $\tau_{ni}^A(j)$, τ_{ni}^A	Estimates from Equation 3.11 for the modified model; Estimates from Equation 2.6 for the EK model	See Tables 2.2 3.1, 3.2 and Appendix B, C and G
T_i^M, τ_{ni}^M	Estimates from Equation 4.14	See Appendix B, C, F and G
λ_i^k, α_i^k, ξ_l^k	Input-Output tables [31]	See Appendix H
β_i	Gollin (2002) [32]	0.66
z_i^S	–	$1 \ \forall \ i$
D_i^k	–	$D_i^A = D_i^M = 0 \ \forall i$
θ	Simonovska and Waugh (2011) [6]	4.12
σ	Ruhl (2008) [33]	2.00

consistent with the guessed wage vector and country i's total labor endowment. I use the following equilibrium condition from the agricultural producer's problem with each country's total arable land endowment to solve for land rent associated with $Y_i^A(\bar{\mathbf{w}})$:

$$r_i L_i = \alpha_i^A (1 - \beta_i^A) Y_i^A \tag{4.15}$$

Given $\bar{\mathbf{w}}$, sectoral price indices are $2 \times I$ equations in $2 \times I$ unknowns. Therefore, I can solve for the agriculture and manufacturing sector price indices in each country given the guessed wages and calibrated parameters. I simulate the integral in the modified model agricultural price index as:

$$p_n^A = \frac{\gamma}{ns} \left(\sum_{j=1}^{ns} \Omega_n^A(j)^{\frac{\sigma-1}{\theta}} \right)^{\frac{1}{1-\sigma}}$$

using the same ns products I used to estimate trade costs and productivity distribution parameters in Chapter 3. Let $p_i^A(\bar{\mathbf{w}})$, $p_i^M(\bar{\mathbf{w}})$, and $r_i(\bar{\mathbf{w}})$ be the solution for price indices and land rent for each country consistent with the guessed wages. I use these, along with $\bar{\mathbf{w}}$ to solve for the cost of an input bundle in each sector from equilibrium condition 4.2.

I then use the resulting $c_i^A(\bar{\mathbf{w}})$ and $c_i^M(\bar{\mathbf{w}})$ with the estimates of $\tau_{ni}^A(j)$, and $\tilde{a}_i(j)$, to solve for agricultural market shares $\pi_{ni}^A(\bar{\mathbf{w}})$ using Equation 3.4 for the modified model, simulating the integral as in Equation 3.11. Correspondingly, I use estimates of τ_{ni}^A from Chapter 2 to solve for agricultural trade shares using Equation 2.4 for the EK model. I solve for manufacturing sector market shares in both models using $\hat{\tau}_{ni}^M$ in Equation 4.6.

Substituting Equations 4.11 and 4.12 into the country i manufacturing sector goods market clearing condition yields a system of I equations that relate the value of labor in each country to its value in all other countries.

$$\kappa_{1i}^M w_i N_i + \kappa_{2i}^M Y_i^A + \kappa_{3i}^M D_i^A = \sum_{n=1}^{I} \left(\kappa_{1n}^M w_n N_n + \kappa_{2n}^M Y_n^A + \kappa_{4n}^M D_n^A \right) \tag{4.16}$$

If Equation 4.16 holds under the guessed value $\bar{\mathbf{w}}$, the solution is attained. If not, the vector of wages is adjusted until it does. To complete the equilibrium solution, I calculate labor shares for each sector according to Equation 4.10.

Base solutions for each model are reported in Appendix I. As expected, the equilibrium solutions are nearly the same, with the sole and unsurprising exception of the agricultural price index. Differences between the two models' predictions for trade shares and GDP are not significantly different from zero and both models predict identical distributions of labor across sectors.

Predicted bilateral market shares in both models fit observed market shares well, but predictions for other aggregate measures are weakly correlated with the data. Since the base solutions are highly correlated with each other, this suggests model performance could be improved by adjusting the calibration of structural parameters other than trade costs. There are several degrees of freedom available in the model for such adjustment.

4.5 Simulated General Equilibrium Elasticities

The primary difference between the EK and modified model is in their implications for changes in equilibrium outcomes in response to changes in structural parameters. To examine these differences I calculate general equilibrium elasticities with respect to US, French, Canadian and Costa Rican trade costs and compare the predicted magnitudes and distribution of direct and indirect effects in the two models. General equilibrium elasticities for a given exporter are calculated by simulating a 1% increase in its agricultural trade costs and then calculating the percent change in each competitor's agricultural market share over the base solution.

The variation in sensitivity across competitors observed in partial equilibrium elasticities in Chapter 3 increases in general equilibrium. General equilibrium effects magnify the difference between the elasticity of the closest and most distant competitors observed in partial equilibrium. This is in stark contrast to the EK model's by now familiar prediction that the market share adjustment in response to any of these three is virtually identical for every competitor. Unlike in partial equilibrium, the EK model does generate some variation in general equilibrium elasticities of substitution across competitors, however it is negligible. The variation in cross-country general equilibrium elasticity as measured by the standard deviation with respect to US trade costs ranges from a minimum of 1,230 times the standard deviation in the EK model in the Costa Rican market to several thousand times the standard deviation in the EK model in many other markets.

As in partial equilibrium, comparing the cross-country elasticities generated by the EK and modified models reveals considerable differences in the magnitude of the indirect effects of changes in trade costs predicted by each model. The EK model will tend to over-predict the indirect effects of changes in Canadian and French trade costs and under-predict the indirect effects of changes in US and Costa Rican costs. The relative magnitudes are particularly divergent in the case of Costa Rica, for which the elasticities predicted by the modified model are vastly greater than those predicted by the EK model in every import market.

Table 4.2 compares the indirect effects of changes in Canadian, French, and Costa Rican costs on US market share to their effects on the median competitor in select import markets. The first column under each exporter contains the elasticity of US market share with respect to the exporter's trade costs, relative to the median value predicted by the modified model. The second column contains the US elasticity relative to the median predicted by the EK model. It is immediately clear that the modified model generates a much more nuanced picture of the magnitude and direction of production and trade shifts in response to a bilateral policy change. These results reaffirm that the EK model generates very little variation in cross-trade elasticities across competitors.

The relative elasticities in Table 4.2 demonstrate that the modified model consistently predicts the US is a closer substitute for Canada and France than it is for Costa Rica. US market share is more elastic than the median country to changes in Canadian trade costs in every market except the domestic market and more elastic than the median to French trade costs in all but a few. In contrast, US market share is far less sensitive than the median exporter to changes in Costa Rican trade costs in every import market.

Table 4.2 also suggests how trade driven by natural endowment differences as opposed to trade driven by random technological productivity differences has different implications for the distribution of indirect effects across competitors. Notice that the few import markets in which the United States is less sensitive than the median with respect to changes in French trade costs are those that are the most agro-ecologically similar to either France or the United States. In such markets, the comparative advantage of US and French producers is less likely to be driven by relatively high values of

Table 4.2: The Elasticity of US Market Share Relative to the Median Exporter

	Canada		Costa Rica		France	
	Modified Model	EK Model	Modified Model	EK Model	Modified Model	EK Model
Canada	-	-	0.09	1.00	0.82	1.00
Chile	7.67	1.00	0.00	1.00	7.23	1.00
Costa Rica	1.43	1.00	-	-	1.42	1.00
Czech Republic	15.02	1.00	0.00	1.00	12.32	1.00
Ecuador	3.32	1.00	0.34	1.00	3.15	1.00
Finland	14.2	1.00	0.01	1.00	3.63	1.00
Hungary	13.83	1.00	0.00	1.00	7.55	1.00
Ireland	6.60	1.00	0.07	1.00	0.76	1.00
Israel	3.08	1.00	0.47	1.00	2.51	1.00
Japan	14.90	1.00	0.00	1.00	5.22	1.00
Malaysia	1.28	1.00	0.13	1.00	1.06	1.00
Mexico	56.25	1.00	0.25	1.00	0.20	1.00
Poland	14.86	1.00	0.01	0.95	4.56	1.00
Portugal	26.35	1.00	0.00	1.00	14.48	1.00
South Africa	7.15	1.00	0.00	0.98	0.62	1.00
Spain	17.48	1.00	0.03	1.00	1.25	1.00
Turkey	13.04	1.00	0.01	0.85	1.12	1.00
UK	18.67	1.00	0.02	1.00	0.67	1.00
Uruguay	6.68	1.00	0.02	1.00	6.62	1.00
USA	0.19	0.80	0.26	0.80	0.73	0.80

$a_i(j)$ and more likely to be driven by relatively high realizations of $z_i^A(j)$. The United States and France are not necessarily closer substitutes for each other than any other competitor as a source for products in which the advantage is primarily technological. On the other hand, the markets in which US elasticity with respect to Costa Rican costs is highest relative to the median are those in which incentives to trade with Costa Rica are least likely to derive from agro-ecological differences.

4.6 Full vs. Partial Agricultural Liberalization

In this section I explore the effects of full versus partial agricultural trade liberalization using the modified model. The ability to simulate changes in product-specific trade costs as opposed to average costs only is critical for applied agricultural policy analysis, in which implications of changes in the dispersion of trade costs are of central interest. Such an experiment cannot be carried out using the EK model since trade costs are of necessity assumed constant across products.

I simulate agricultural trade liberalization by setting average bilateral trade costs in the agricultural sector equal to bilateral manufacturing trade cost estimates. This represents an average cut in agricultural trade costs of 92%. To simulate partial liberalization I add the difference between average agricultural and manufacturing trade costs back for just two products: cotton lint and cattle meat. I maintain product-specific deviations from average in order to allow for non-policy differences in trade costs across products such as transport and handling requirements.

The implicit claim behind this experiment is that manufacturing trade is as close to free trade as it is possible to achieve, and that any difference in average trade costs between sectors represents barriers that could potentially be reduced. This is admittedly a simplified way to contemplate agricultural liberalization. The results will be highly influenced by the degree to which a country is an efficient manufactured products exporter. Moreover, by calibrating the model with $D_i^k = 0$, I have effectively imposed sector-by-sector trade balance. Sector-level specialization will therefore be limited.

Total agricultural trade increases dramatically under both full and partial liberalization. This is illustrated in Table 4.3 which compares the increase in agricultural imports under the two scenarios for selected import markets.[8] I denote domestic market share under the base solution, full liberalization and partial liberalization respectively as $\pi_{nn}^{A^*}$, $\pi_{nn}^{A^F}$ and $\pi_{nn}^{A^P}$. The first column displays the import penetration ratio under full liberalization relative to the base solution. The model predicts that trade liberalization increases the share of imports in agricultural expenditure by nearly 100 times in Ireland and South Africa and over 100 times in Kenya and New Zealand.

The second column compares the increase in trade under full agricultural liberalization to the increase when just cotton lint and cattle meat are left unprotected, as revealed by the ratio of import penetration under partial liberalization relative to full liberalization. The difference between the import share of agricultural expenditure is negligible for just under half of the import markets in the data. For others the difference is highly significant. In particular, the share of imports in agricultural expenditure falls by more than one-third in Indonesia, Ecuador and Thailand under partial liberalization. This can be traced to the importance of cotton in these three countries' estimated import distributions and the fact that their ecological characteristics differ substantially from cotton's estimated agro-ecological production requirements.

Table 4.3: Increase in Ag Trade - Full vs. Partial Liberalization

	Increase in Ag Imports over Base Solution	
Country	Full Liberalization $\left(\frac{1-\pi_{nn}^{A^F}}{1-\pi_{nn}^{A^*}}\right)$	Partial /Full Liberalization $\left(\frac{1-\pi_{nn}^{A^P}}{1-\pi_{nn}^{A^F}}\right)$
Indonesia	32.01	0.54
Ecuador	50.29	0.65
Thailand	6.15	0.66
Chile	15.30	0.79
South Africa	96.79	0.93
Netherlands	35.19	0.99
Italy	7.49	1.00
Costa Rica	2.23	1.00
Austria	27.50	1.00

[8] Full results are listed in Appendix J.

Table 4.4 examines the difference between full and partial agricultural liberalization from the perspective of countries as exporters.[9] The results demonstrate that it is important to capture product-specific deviations from average trade costs in order to understand the impact of trade policy on agricultural trade and production patterns. Leaving just two commodities highly protected implies significant shifts in sources of agricultural products.

The first column illustrates the magnitude of selected exporters' increase in foreign agricultural market share. It contains the average percent increase in π_{ni}^{A} $(i \neq n)$ in moving from the base solution to full liberalization. The biggest increases are generally among the poorest countries in the sample and Central and East European countries. For example, Table 4.4 indicates that agricultural trade liberalization increases Malaysia's average share of foreign agricultural expenditure more than 900% over the base solution. This is indeed a dramatic increase, but bear in mind that initial values of π_{ni}^{A} tend to be very small the median domestic market share in the base solution is 0.88. Moreover, because of the structure of this experiment, the relative magnitude of these gains is influenced in part by initial differences in agricultural and manufacturing sector trade costs.

The second column compares the average percent increase in each exporter's foreign market share under partial relative to full liberalization. These results suggest that agricultural producers in some countries may gain more from partial than full liberalization, while others experience significantly smaller increases in foreign market share when trade liberalization is uneven across products.

Full agricultural trade liberalization results in significant shifts in production and trade patterns from the base solution. The degree to which agricultural market share has been re-allocated across exporters in a given market can be measured by the rank correlation between exporter market shares in a given importer in the base solution and after liberalization. Table 4.5 reports the Spearman rank correlation coefficient between market shares of foreign producers in the base solution and after full liberalization for each import market. A smaller value of the correlation coefficient implies greater reallocation of agricultural expenditure across exporters. The largest reallocations in market share across exporters are in Iran, Portugal, Malaysia and The Netherlands.

[9] The full results are listed in Appendix J.

Table 4.4: Increase in Average Foreign Market Share - Full vs. Partial Liberalization

	Ave. % Change in π_{ni}^{A} from Base Solution, $(i \neq n)$	
Exporter	Full Liberalization	Partial /Full Liberalization
Costa Rica	384.07	0.95
Thailand	413.55	0.98
Malaysia	902.61	1.00
USA	68.92	1.00
Italy	192.5	1.00
Netherlands	165.44	1.01
Colombia	245.63	1.02
Ecuador	192.12	1.02

Shifts in agricultural import patterns due to agricultural liberalization are smallest in Central and East European countries.

Table 4.5: Size of Shifts in Bilateral Ag Trade Patterns

Import Market	Rank correlation $\pi_{ni}^{A*}, \pi_{ni}^{A^F}$	Import Market	Rank correlation $\pi_{ni}^{A*}, \pi_{ni}^{A^F}$
Iran	0.50	Germany	0.75
Portugal	0.53	Turkey	0.75
Malaysia	0.53	Hungary	0.75
Netherlands	0.56	Czech Republic	0.75
Denmark	0.56	Brazil	0.76
Canada	0.57	Poland	0.77
Russia	0.57	Mexico	0.77
New Zealand	0.59	Slovakia	0.77
Israel	0.59	Austria	0.79

While the results in the preceding table suggest that producers in a handful of countries may benefit from partial liberalization, Table 4.6 shows that consumer gains in terms of real income are uniformly smaller under partial liberalization relative to full liberalization. The first column lists the percent increase in real income under full agricultural liberalization for selected countries.[10] While the increase is small for most countries, considering that agricultural products only represent an average of 5% of

[10] The full results are listed in Appendix J.

consumption expenditure, these gains are not insubstantial.

The second column of Table 4.6 contains the ratio of real income gains under partial relative to full liberalization. These results demonstrate that the ability of the modified model to simulate changes in the structure of trade costs more complex than cuts to average costs is a significant asset. The distribution of product-specific trade costs has important consequences for the distribution welfare gains from trade liberalization across countries. For many countries, leaving cotton lint and cattle meat highly protected has a negligible impact on gains from liberalization while for others particularly Indonesia and Thailand the loss in real income from partial liberalization is substantial.

Table 4.6: Increase in Real Income from Ag Liberalization

	Percent Change in Real Income over Base Solution	
Country	Full Liberalization	Partial /Full Liberalization
Indonesia	16.16%	0.78
Thailand	10.14%	0.85
Netherlands	4.22%	1.00
Malaysia	3.41%	0.99
Italy	2.63%	1.00
Chile	0.62%	0.99
Ecuador	0.51%	0.96
Costa Rica	0.39%	1.00
USA	0.37%	1.00

4.7 Conclusion

The modified model provides a much richer picture of the competitive structure facing agricultural producers around the world than existing general equilibrium models of international trade. This generates more precise predictions of the effects of policy on patterns of bilateral trade and production in addition to the traditional measures of welfare gains.

An equally, if not more important contribution of the methodology I have introduced here is its ability to handle changes in the distribution of tariffs or other policies within a sector. I am unaware of any other model in the literature on heterogeneous productivity trade models that has this feature. The results of the simulated partial agricultural liberalization confirm that the distribution of tariff cuts can have non-trivial effects on the distribution of both trade and welfare gains from trade liberalization across countries, even in this very simplistic and stylized model.

Future work will focus on applications of the framework I have introduced here. The model is expressly intended for applied policy analysis, including but not limited to evaluations of preferential trade agreements at the regional and multilateral level. This is its most obvious use, but it can also be specified to evaluate any taxes, subsidies or other policy or non-policy factors that affect the costs of producing or trading agricultural products. The model may also be used to examine the extent to which the existing structure of agricultural policy instruments restricts the realization of agricultural comparative advantage through international trade, and the extent to which these restrictions fall disproportionately on developing countries as in the influential work of Anderson and Martin (2006)[23], Hertel and Winters (2005)[24], Bouët, Mevel and Orden (2006) [25] and many others.

Improved forecasts for shifts in trade and production patterns have significant value beyond the world of policy-making. The structure presented here may be useful to industrial users and traders of agricultural commodities to analyze how changes in the agricultural production cost structure might alter optimal sourcing and marketing decisions. Additionally, researchers with an interest in the connection between agriculture and the environment may find this framework's ability to more precisely predict shifts in production patterns useful in evaluations of the environmental consequences of policies, technologies and other factors that influence agricultural production costs.

Central to a successful application of this framework will be a more careful calibration and specification of land productivity and trade cost distributions. The primary advantage of this framework is the flexibility of its treatment of the agricultural production structure. However, along with that flexibility comes a degree of complexity, which I have attempted to minimize in this work.

Pursuant to refining the values of structural parameters, it will be useful to evaluate the model in the context of a historical agricultural policy reform. Two of the most attractive candidates for such an exercise are the North American Free Trade Agreement (NAFTA) and the periodic fundamental reforms of the European Union's Common Agricultural Policy. Existing *ex post* evaluations of models constructed to forecast the trade and welfare effects of the NAFTA by Kehoe (2003)[11], Caliendo and Parro (2012)[3] and Shikher (2012)[4] among others make it a particularly attractive candidate for such an evaluation since they offer a ready counter-example.

Although it is beyond the scope of this paper, non-random or non-independent sources of product heterogeneity may also influence patterns of trade in the manufacturing sector. It seems likely, for example, that mining and the manufactured food and beverages industries are likely to have similar natural endowment-based sources of comparative advantage that play a key role in driving production and trade patterns. The model's robustness to the assumptions on the manufacturing sector, even when agricultural trade is the focus, should thus be examined. At a minimum, it would be worthwhile to use the tests introduced in Chapter 2 to examine whether the CES import demand system holds in the manufacturing sector as a whole or at the sub-sector level.

Even if the CES import demand system holds for the manufacturing sector as a whole, it would be useful to explore the interactions between agriculture and the industries for which its outputs represent a large share of intermediate inputs. A finer classification of the manufacturing sector may have important consequences for predictions of the response of bilateral trade and production patterns to changes in agricultural trade costs. Moreover, Arkolakis, Costinot and Rodriguez-Clare (2012)[5] point out that models with inter-sectoral linkages find that gains from trade liberalization are increasing in the share of intermediate goods in production. Such a modification would therefore almost certainly amplify predicted gains from agricultural trade liberali-zation.

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Appendix B

Producer Fixed Effects Estimates

Table B.1: Coefficient Estimates: S_i^k

Country	Agriculture: EK Model ($\hat{S}_i^A$)	Agriculture: Modified ($\hat{\hat{S}}_i^A$)	Manufacturing ($\hat{S}_i^M$)
Argentina	3.16***	2.32***	0.29*
Australia	2.30***	-0.10	-0.90***
Austria	-0.06*	-1.53***	0.04
Brazil	1.30***	0.98**	0.38**
Canada	-1.45***	-1.81***	0.13
Chile	0.38**	-0.22	-0.33**
Colombia	-1.62***	1.35***	0.16
Costa Rica	-3.24***	2.56***	-1.66***
Denmark	-0.61	-1.81***	-0.26*
Ecuador	-1.25***	2.70***	0.18
Estonia	0.14**	1.59***	-0.47***
Finland	-1.56**	-2.96***	0.14
France	1.33***	-1.04**	0.29*
Germany	-1.26	-2.34***	0.02
Hungary	1.73***	1.22**	-0.46***

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Table B.1 – continued from previous page

	Agriculture		
Country	EK Model ($\hat{S}_i^A$)	Modified ($\hat{\hat{S}}_i^A$)	Manufacturing ($\hat{S}_i^M$)
India	2.31	3.38***	0.88***
Indonesia	-0.32***	0.49	-0.52***
Iran	2.25***	3.42***	2.70***
Ireland	0.15***	0.08	-0.98***
Israel	-1.24***	0.14	1.04***
Italy	0.59***	-1.88***	0.25*
Japan	-4.57***	-4.76***	1.31***
Kenya	-0.89***	2.53***	0.51***
Malaysia	-0.84***	0.38	-0.80***
Mexico	0.56	0.45	-1.27***
Netherlands	-2.60***	-2.84***	-1.27***
New Zealand	0.47***	0.49	-0.18
Czech Republic	1.14***	-0.03	0.06
Poland	1.45***	-1.33**	0.50***
Portugal	-1.31	-2.26***	0.06
Romania	2.42***	2.79***	0.51***
Russia	2.55***	-1.97***	0.11
Slovenia	-1.21	1.07**	0.04
Slovakia	0.91***	2.01***	-0.31*
South Africa	1.92***	0.62	0.00
Spain	1.15***	-1.14**	0.20
Sweden	-3.66***	-3.62***	-0.07
Thailand	-1.81***	1.11**	-0.72***
Turkey	3.43***	1.80***	0.32*
UK	-1.91**	-2.75***	0.01
USA	1.77***	-1.08**	0.50***
Uruguay	0.35***	1.98***	-0.42**

Appendix C

Exporter Fixed Effects Estimates

Table C.1: Coefficient Estimates: ex_i^k

	Agriculture ($\hat{ex}_i^A$)		
Country	EK Model	Modified	Manufacturing ($\hat{ex}_i^M$)
Argentina	2.06***	3.67***	-0.17
Australia	4.45***	4.05***	1.51***
Austria	0.46	-1.01	0.41*
Brazil	3.69***	2.68***	1.13***
Canada	6.28***	8.93***	1.03***
Chile	3.09***	2.72***	-0.37*
Colombia	-0.99	-2.04	-2.54***
Costa Rica	-1.92	-3.22	-1.43***
Denmark	3.73***	2.85***	0.55**
Ecuador	-3.13	-2.80	-3.78***
Estonia	-8.47	-7.67	-2.24***
Finland	-3.41	-4.38	0.79***
France	5.21***	4.82***	2.08***
Germany	5.21***	5.88***	3.04***
Hungary	-2.83	-2.57	-0.25

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Table C.1 – continued from previous page

	Agriculture ($\hat{ex}_i^A$)		
Country	EK Model	Modified	Manufacturing ($\hat{ex}_i^M$)
India	-0.20	2.18***	-0.08
Indonesia	3.76***	2.48***	1.69***
Iran	-4.36	-1.44	-5.86***
Ireland	-2.80	-3.37	1.51***
Israel	-0.85	-2.31	-2.08***
Italy	5.55***	4.45***	2.17***
Japan	1.09*	1.91***	2.24***
Kenya	-3.51	-3.66	-6.30***
Malaysia	-0.33	-3.80	2.27***
Mexico	0.63	1.62**	1.85***
Netherlands	5.50***	4.66***	2.85***
New Zealand	1.22*	1.27*	-0.40*
Czech Republic	-4.54	-5.32	-0.73***
Poland	-4.24	-5.33	-1.03***
Portugal	2.63***	1.55**	-0.55**
Romania	-5.81	-3.95	-2.17***
Russia	-2.58	-3.68	0.37*
Slovenia	-9.83	-9.85	-1.85***
Slovakia	-10.57	-9.69	-1.51***
South Africa	1.39**	1.71***	0.24
Spain	5.21***	4.59***	1.26***
Sweden	0.22	0.84	1.53***
Thailand	1.68**	2.33***	1.99***
Turkey	-0.03	0.56	-0.59**
UK	4.61***	4.97***	2.21***
USA	7.03***	8.13***	3.11***
Uruguay	-4.29	-2.75	-1.91***

Appendix D

Detailed Derivation of π_{ni}^{A} and p_n^A, Modified Model

D.1 Market n agriculture sector price distribution

Claim: The prices of agricultural products purchased in market n are distributed following:

$$G_n^A(p) = 1 - \int exp\{-\sum_{m=1}^{I} T_m^k(\tilde{a}_m(j)c_m^k\tau_{nm}^k(j))^{-\theta}p^{\theta}\}dF_{a_n}(\tilde{\mathbf{a}})dF_{\tau_n}^k(\boldsymbol{\tau})dp$$

Proof: First, the probability country i offers a price less than p for product j in market n is:

$$\begin{aligned} Pr\left(p_{ni}^A(j) \leq p\right) &= Pr\left(\frac{\tilde{a}_i(j)c_i^A\tau_{ni}^A(j)}{z_i^A(j)} \leq p\right) \\ &= 1 - F_{z_i}^A\left(\frac{\tilde{a}_i(j)c_i^A\tau_{ni}^A(j)}{p}\right) \\ &= 1 - exp\{-T_i^A(\tilde{a}_i(j)c_i^A\tau_{ni}^A(j))^{-\theta}p^{\theta}\} \equiv G_{ni}^A(p(j)) \end{aligned}$$

The price actually paid for product j is:

$$p_n^A(j) = min_i\{p_{ni}^A(j)\}$$

Therefore, $p_n^A(j) \leq p$ unless all countries' price offers are greater than p. Given the density of $\tilde{a}(j) = [\tilde{a}_1(j), \ldots, \tilde{a}_I(j)]$ and $\tau_n^A(j) = \left[\tau_{n1}^A(j), \ldots, \tau_{nI}^A(j)\right]$:

$$\begin{aligned} Pr\left(p_n^A(j) > p\right) &= Pr\left(p_{nl}^A(j) > p \;\; \forall l\right) \\ &= \prod_{l=1}^{I}\left(1 - G_{ni}^A(p(j))\right) \\ &= \prod_{l=1}^{I} exp\{-T_l^A(\tilde{a}_l(j)c_l^A\tau_{nl}^A(j))^{-\theta}p^{\theta}\} \end{aligned}$$

The probability product j is purchased at a price less than p in market n is therefore:

$$Pr\left(p_{nl}^A(j) \leq p \;\; \forall l\right) = 1 - exp\{-\sum_{l=1}^{I} T_l^A(\tilde{a}_l(j)c_l^A\tau_{nl}^A(j))^{-\theta}p^{\theta}\}$$

Since $\tilde{a}_i(j)$, $\tau_{ni}^A(j)$ and $z_i^A(j)$ follow independent distributions in each country, the distribution of agricultural prices in market n is the integral of this expression over the density of $\tilde{\mathbf{a}} = [\tilde{\mathbf{a}}(0), \ldots, \tilde{\mathbf{a}}(1)]$ and $\boldsymbol{\tau}_n^A = \left[\boldsymbol{\tau}_n^A(0), \ldots, \boldsymbol{\tau}_n^A(1)\right]$ over all products purchased in market n. Therefore,

$$G_n^A(p) = 1 - \int exp\{-\sum_{l=1}^{I} T_l^A(\tilde{\mathbf{a}}_l(j)c_l^A\tau_{nl}^A(j))^{-\theta}p^{\theta}\}dF_{a_n}(\tilde{\mathbf{a}})dF_{\tau_n}^A(\tau)$$

D.2 Exporter i share of agricultural products purchased in market n

Claim: The share of agricultural products purchased from exporter i in market n is:

$$\bar{\pi}_{ni}^A = \int \frac{T_i^A(\tilde{a}_i(j)c_i^A\tau_{ni}^A(j))^{-\theta}}{\Omega_n^A(j)}dF_{a_n}(\tilde{\mathbf{a}})dF_{\tau_n}^k(\boldsymbol{\tau})$$

Proof: By invoking a law of large numbers as in EK, the unconditional probability that exporter i offers the lowest price for an agricultural product in market n is also the fraction of goods that market n buyers purchase from country i producers. The probability that the lowest offer for product j comes from exporter i is the probability all of its competitor offer higher prices. Let $p_{ni}^A(j) = p^*$.

$$Pr\left(p_{nl}^A(j) > p^* \;\; \forall l \neq i\right) = \prod_{l \neq i} Pr(p_{nl}^A(j) > p^*) = exp\{-\sum_{l \neq i} T_l^A(\tilde{a}_l(j)c_l^A\tau_{nl}^A(j))^{-\theta}p^{*\theta}\}$$

Now, integrating over all possible realizations of $p^A_{ni}(j)$:

$$Pr\left(p^A_{nl}(j) > p^A_{ni}(j) \;\; \forall l \neq i\right) = \int exp\{-\sum_{l\neq i} T^A_l(\tilde{a}_i(j)c^A_l\tau^A_{nl}(j))^{-\theta}p^\theta\}dG^A_{ni}(p(j))$$

Note:

$$dG^A_{ni}(p(j)) = e^{-T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}p^\theta}\theta T^k_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}p^{\theta-1}$$

Therefore:

$$Pr\left(p^A_{nl}(j) > p^A_{ni}(j) \;\; \forall l \neq i\right) = \frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}\int_0^\infty exp\{-\Omega^A_n(j)p^\theta\}\Omega^A_n(j)\theta p^{\theta-1}dp$$

Notice that the expression under the integral is $dG^k_n(p)$, so this is:

$$Pr\left(p^A_{nl}(j) > p^A_{ni}(j) \;\; \forall l \neq i\right) = \frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}$$

The unconditional probability exporter i offers the lowest price in market n is then:

$$\bar{\pi}^A_{ni} = \int \frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}dF_{a_n}(\tilde{\mathbf{a}})dF^k_{\tau_n}(\boldsymbol{\tau})$$

D.3 Market n agricultural price index

Claim:

$$p^A_n = \gamma\left(\int \Omega^A_n(j)^{\frac{\sigma-1}{\theta}}dF_{a_n}(\tilde{\mathbf{a}})dF^A_{\tau_n}(\boldsymbol{\tau})\right)^{\frac{1}{1-\sigma}}$$

Proof: A standard unit price index given the CES technology with which agricultural products are aggregated by country n buyers (Equation 4.11) is:

$$p^A_n = \left(\int_0^1 p^A_n(j)^{-(\sigma-1)}dj\right)^{\frac{1}{1-\sigma}}$$

This can be written:

$$p^A_n = \left(\int_0^\infty p^{1-\sigma}dG^A_n(p)dp\right)^{\frac{1}{1-\sigma}} = \left(\int_0^\infty\int_0^1 p^{1-\sigma}e^{-\Omega^A_n(j)p^\theta}\theta\Omega^A(j)p^{\theta-1}dF_{a_n}(\tilde{\mathbf{a}})dF^A_{\tau_n}(\boldsymbol{\tau})dp\right)^{\frac{1}{1-\sigma}}$$

where $\Omega^A_n(j) = \sum_{l=1}^{I} T^A_l(\tilde{a}_l(j)c^A_l\tau^A_{nl}(j))^{-\theta}$.

Define $x = \Omega_n^A(j)p^\theta$, then $dx = \theta\Omega_n^A(j)p^{\theta-1}$ and $p^{1-\sigma} = \left(\frac{x}{\Omega_n^A(j)}\right)^{\frac{1-\sigma}{\theta}}$. Then:

$$p_n^A = \left(\int_0^\infty \int_0^1 \left(\frac{x}{\Omega_n^A(j)}\right)^{\frac{1-\sigma}{\theta}} e^x dx dF_{a_n}(\tilde{\mathbf{a}}) dF_{\tau_n}^A(\boldsymbol{\tau})\right)^{\frac{1}{1-\sigma}}$$

Using the definition of the gamma function, $\Gamma(z) = \int_0^\infty t^{z-1}e^t dt$:

$$p_n^A = \gamma \left(\int \Omega^A(j)^{\frac{\sigma-1}{\theta}} dF_{a_n}(\tilde{\mathbf{a}}) dF_n^A(\boldsymbol{\tau})\right)^{\frac{1}{1-\sigma}}$$

where $\gamma = \Gamma\left[\frac{1-\sigma+\theta}{\theta}\right]^{\frac{1}{1-\sigma}}$ so we must have $\theta > (\sigma - 1)$.

D.4 Exporter i share of market n agricultural expenditure

Claim: The unconditional probability exporter i offers the lowest price for an agricultural product in market n is equal to the fraction of market n agricultural expenditure spent on products from country i:

$$\bar{\pi}_{ni}^A = \pi_{ni}^A \equiv \frac{X_{ni}^A}{X_n}$$

Proof: Bilateral trade shares in expenditure terms are:

$$\pi_{ni}^A = \frac{X_{ni}^A}{X_n^A} = \frac{\bar{\pi}_{ni}^A \bar{X}_{ni}^A}{\sum_{l=1}^{I} \bar{\pi}_{nl}^A \bar{X}_{nl}^A}$$

where $\bar{X}_{ni}^A$ is market n's average expenditure per good on agricultural products from exporter i. Cost-minimizing buyers purchase individual agricultural products to satisfy:

$$q_n^A(j) = \left(\frac{p_n^A(j)}{p_n^A}\right)^{-\sigma} Q_n^A$$

where p_n^A is the price index and Q_n^A is the total quantity of agricultural products purchased in market n. Multiply the right-hand side by $\frac{p_n^A(j)}{p_n^A} \times \frac{p_n^A}{p_n^A(j)} = 1$ and we get:

$$p_n^A(j)q_n^A(j) = \left(\frac{p_n^A(j)}{p_n^A}\right)^{1-\sigma} p_n^A Q_n^A \quad \Leftrightarrow \quad X_n^A(j) = \left(\frac{p_n^A(j)}{p_n^A}\right)^{1-\sigma} X_n^A$$

Therefore, average spending per agricultural good from country i in country n is:

$$\bar{X}^A_{ni} = \int_0^1 X^A_n(j)dj = X^A_n \int_0^\infty \left(\frac{p}{p^A_n}\right)^{1-\sigma} d\tilde{G}^A_{ni}(p)$$

The function $\tilde{G}^A_{ni}(p)$ is the distribution of agricultural price offers made by exporter i and accepted in market n. I claim that $\tilde{G}^A_{ni}(p) \equiv G^A_n(p)\ \forall i$. To see this, note that if country n buys good j from country i, then country i must be the low–cost supplier: $p^A_{ni}(j) = p^A_n(j)$. Suppose $p^A_n(j) = q(j)$. The probability country i is the low–cost supplier of product j is the probability that all other suppliers have prices higher than $q(j)$:

$$Pr\left(p^A_{nl}(j) > q(j)\ \ \forall l \neq i\right) = exp\{-\sum_{l\neq i} T^A_l(\tilde{a}_l(j)c^A_l\tau_n l^A(j))^{-\theta}q(j)^\theta\}$$

Integrating over this for all possible realizations of $p^A_{ni}(j) \leq q(j)$:

$$\begin{aligned}
\int_0^{q(j)} exp\{-\sum_{l\neq i} T^A_l(\tilde{a}_l(j)c^A_l\tau^A_{nl}(j))^{-\theta}p(j)^\theta\}dG^A_{ni}(p(j)) &= \\
\frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)} \int_0^{q(j)} exp\{-\Omega^A_n(j)p(j)^\theta\}\Omega^A_n(j)\theta p(j)^{\theta-1}dp(j) &= \\
\frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}G^A_n(q(j))
\end{aligned}$$

The probability country i offers the lowest price for good j in market n is $\frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}$. Therefore, the probability good j is purchased for a price less than or equal to $q(j)$ conditional on it having been purchased from exporter i is:

$$\tilde{G}^A_{ni}(p(j)) = \frac{\frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}G^A_n(q(j))}{\frac{T^A_i(\tilde{a}_i(j)c^A_i\tau^A_{ni}(j))^{-\theta}}{\Omega^A_n(j)}} = G^A_n(q(j))$$

Notice, this does not depend on exporter i. Even though the variation price offers varies across countries based on their distributions of $\tilde{a}_i(j)$ and $\tau^A_{ni}(j)$, the variation in offers actually accepted by market n is the same for every country. The unconditional probability that an agricultural product was purchased for a price less than or equal to

$q(j)$, conditional on its having been purchased from exporter i is the integral over all possible realizations of $q(j)$:

$$\tilde{G}_{ni}^{A}(p) = \int_{0}^{1} G_{n}^{A}(p(j))dj = \int_{0}^{\infty} G_{n}^{A}(q)dF_{a_n}(\tilde{a})dF_{\tau_n}^{A}(\boldsymbol{\tau})dq \equiv G_{n}^{A}(p)$$

Therefore:

$$\bar{X}_{ni}^{A} = X_{n}^{A} \int_{0}^{\infty} \left(\frac{p}{p_{n}^{A}}\right)^{1-\sigma} dG_{n}^{A}(p) \ \ \forall i$$

Therefore, the average price offer accepted by market n buyers is the same for all exporters, and:

$$\pi_{ni}^{A} = \bar{\pi}_{ni}^{A} = \int \frac{T_{i}^{A}(\tilde{a}_{i}(j)c_{i}^{A}\tau_{ni}^{A}(j))^{-\theta}}{\Omega_{n}^{A}(j)} dF_{a_n}(\tilde{\mathbf{a}})dF_{\tau_n}^{k}(\boldsymbol{\tau}) = \int \pi_{ni}^{A}(j)dF_{a_n}(\tilde{\mathbf{a}})dF_{\tau_n}^{k}(\boldsymbol{\tau})$$

Appendix E

Agricultural Production Requirements

Observable production requirements $E(j) = \begin{bmatrix} trop(j) & temp(j) & boreal(j) \end{bmatrix}$ represent the ideal climate for product j cultivation. This ideal climate is estimated as a production–weighted distribution across all 42 countries in my data set for the 130 agricultural FAO items traded among the countries in my data and for which year 2000 production and trade data are both available. For example:

$$trop(j) = \sum_{i=1}^{I} \omega_i(j) \times trop_i \tag{E.1}$$

where $\omega_i(j)$ is country i's share of global product j production value. The table below lists the agricultural items included in my data set and their estimated climate distribution.

Table E.1: Agricultural Items and their Climate Production Requirements

Item	$trop(j)$	$temp(j)$	$bor(j)$
Alfalfa for forage and silage	0.27	0.73	0.00
Almonds, with shell	0.04	0.81	0.15
Anise, badian, fennel, corian.	0.02	0.64	0.34

Continued on next page

Table E.1 – continued from previous page

Item	$trop(j)$	$temp(j)$	$bor(j)$
Apples	0.09	0.81	0.10
Apricots	0.00	0.98	0.02
Arecanuts	0.47	0.50	0.03
Artichokes	0.11	0.84	0.04
Asparagus	0.08	0.73	0.19
Avocados	0.02	0.93	0.05
Bacon and Ham	0.00	0.90	0.10
Bananas	0.02	0.92	0.07
Barley	0.02	0.73	0.25
Beans, dry	0.18	0.71	0.10
Beans, green	0.11	0.85	0.04
Beeswax	0.43	0.46	0.11
Blueberries	0.00	0.89	0.11
Brazil nuts, with shell	0.47	0.45	0.09
Broad beans, horse beans, dry	0.05	0.80	0.15
Buffalo meat	0.73	0.24	0.03
Cabbages and other brassicas	0.13	0.78	0.09
Canary seed	0.00	0.84	0.16
Carrots and turnips	0.17	0.72	0.11
Cashew nuts, with shell	0.13	0.74	0.13
Castor oil seed	0.55	0.38	0.07
Cattle meat	0.06	0.78	0.16
Cauliflowers and broccoli	0.11	0.81	0.08
Cereals, nes	0.01	0.71	0.28
Cherries	0.01	0.89	0.1
Chestnuts	0.13	0.72	0.15
Chick peas	0.07	0.80	0.13
Chicken meat	0.21	0.65	0.14
Chillies and peppers, dry	0.18	0.60	0.21

Continued on next page

Table E.1 – continued from previous page

Item	$trop(j)$	$temp(j)$	$bor(j)$
Chillies and peppers, green	0.10	0.87	0.03
Cloves	0.10	0.85	0.05
Cocoa beans	0.01	0.94	0.05
Coconuts	0.26	0.65	0.10
Coffee, green	0.01	0.94	0.05
Copra	0.07	0.92	0.01
Cotton lint	0.06	0.89	0.05
Cottonseed	0.12	0.77	0.11
Cow milk, whole, fresh	0.01	0.86	0.13
Cucumbers and gherkins	0.07	0.72	0.21
Currants	0.01	0.77	0.22
Dates	0.06	0.90	0.04
Duck meat	0.12	0.82	0.06
Eggplants (aubergines)	0.24	0.71	0.05
Flax fibre and tow	0.02	0.84	0.14
Fruit Fresh Nes	0.03	0.94	0.03
Fruit, tropical fresh nes	0.25	0.60	0.15
Game meat	0.00	0.95	0.05
Garlic	0.15	0.79	0.06
Ginger	0.46	0.51	0.03
Goose and guinea fowl meat	0.02	0.96	0.02
Gooseberries	0.00	1.00	0.00
Grapefruit (inc. pomelos)	0.00	0.95	0.04
Grapes	0.05	0.88	0.07
Groundnuts, with shell	0.37	0.57	0.07
Hen eggs, in shell	0.13	0.75	0.12
Honey, natural	0.05	0.91	0.04
Hops	0.01	0.91	0.08
Horse meat	0.14	0.76	0.10

Continued on next page

Table E.1 – continued from previous page

Item	$trop(j)$	$temp(j)$	$bor(j)$
Kiwi fruit	0.00	0.98	0.02
Leeks, other alliaceous veg	0.05	0.81	0.14
Leguminous vegetables, nes	0.27	0.72	0.01
Lemons and limes	0.01	0.97	0.02
Lentils	0.09	0.80	0.10
Lettuce and chicory	0.04	0.84	0.11
Linseed	0.00	0.63	0.37
Maize	0.11	0.75	0.14
Maize, green	0.01	0.93	0.07
Mangoes, mangosteens, guavas	0.05	0.94	0.01
Mat	0.03	0.86	0.11
Meat nes	0.34	0.58	0.07
Mixed grain	0.00	0.95	0.05
Mushrooms and truffles	0.14	0.74	0.12
Natural rubber	0.13	0.74	0.14
Nutmeg, mace and cardamoms	0.03	0.90	0.07
Nuts, nes	0.07	0.82	0.10
Oats	0.06	0.59	0.35
Oilseeds, Nes	0.11	0.78	0.12
Olive oil, virgin	0.01	0.89	0.10
Onions (inc. shallots), green	0.15	0.69	0.17
Onions, dry	0.50	0.46	0.04
Oranges	0.02	0.95	0.03
Other bird eggs,in shell	0.01	0.95	0.04
Other melons (inc.cantaloupes)	0.04	0.83	0.12
Palm kernels	0.31	0.66	0.03
Palm oil	0.04	0.91	0.05
Papayas	0.06	0.93	0.00
Peaches and nectarines	0.01	0.96	0.03

Continued on next page

Table E.1 – continued from previous page

Item	$trop(j)$	$temp(j)$	$bor(j)$
Pears	0.03	0.90	0.07
Peas, dry	0.08	0.64	0.28
Pepper (Piper spp.)	0.01	0.89	0.10
Pig meat	0.06	0.81	0.13
Pineapples	0.02	0.95	0.03
Pistachios	0.00	0.95	0.04
Plantains	0.00	0.97	0.03
Plums and sloes	0.02	0.86	0.12
Poppy seed	0.22	0.73	0.04
Potatoes	0.04	0.83	0.13
Pulses, nes	0.12	0.72	0.16
Pumpkins, squash and gourds	0.02	0.85	0.13
Rabbit meat	0.01	0.75	0.23
Raisins	0.02	0.85	0.13
Rapeseed	0.04	0.66	0.30
Raspberries	0.13	0.41	0.45
Rice, paddy	0.08	0.78	0.14
Rubber Nat Dry	0.94	0.05	0.01
Rye	0.00	0.91	0.09
Sesame seed	0.01	0.91	0.08
Sheep meat	0.08	0.84	0.08
Sorghum	0.03	0.86	0.11
Soybeans	0.05	0.92	0.02
Spices, nes	0.04	0.86	0.10
Spinach	0.03	0.86	0.10
Strawberries	0.03	0.83	0.15
Sunflower seed	0.01	0.92	0.07
Sweet potatoes	0.11	0.85	0.04
Tangerines, mandarins, clem.	0.01	0.91	0.08

Continued on next page

Table E.1 – continued from previous page

Item	$trop(j)$	$temp(j)$	$bor(j)$
Tea	0.01	0.85	0.15
Tobacco, unmanufactured	0.02	0.92	0.06
Tomatoes	0.07	0.81	0.12
Triticale	0.00	0.95	0.04
Turkey meat	0.03	0.80	0.17
Vegetables fresh nes	0.30	0.64	0.06
Walnuts, with shell	0.04	0.91	0.05
Watermelons	0.02	0.91	0.07
Wheat	0.03	0.77	0.20
Wine	0.05	0.86	0.10
Wool, greasy	0.20	0.76	0.04

Appendix F

Manufacturing Sector Trade Cost Parameter Estimates

The following table contains parameter estimates for the trade cost proxy variables in the manufacturing sector. Producer fixed effects S_i^M can be found in Appendix B, and exporter fixed effects ex_i^M can be found in Appendix C.

Table F.1: Manufacturing Sector Trade Cost Parameters

Variable	Coefficient Estimate
Border	0.58
Language	0.91
Distance 1	-3.53
Distance 2	-4.47
Distance 3	-5.16
Distance 4	-5.33
Distance 5	-6.78
Distance 6	-7.34
EU	-0.61
NAFTA	0.12

Appendix G

Obtaining Estimates of T_i^k

Equations 2.5 and 3.8 imply:

$$T_i^k = e^{S_i^k}\left(\kappa_i^k w_i^{\alpha_i^k\beta_i^k+\xi_{S_i}^k(1-\alpha_i^k)} r_i^{\alpha_i^k(1-\beta_i^k)} p_i^{A\xi_A^k(1-\alpha_i^k)} p_i^{M\xi_M^k(1-\alpha_i^k)}\right)^{\theta}$$

Thus, to obtain an estimate of T_i^k, I first need estimates of wages, land rent and tradable product price indices for each country. To obtain estimates of for T_i^k for the modified model I use data on bilateral market shares and labor endowments to solve for wages using equation 4.16. I use the estimated wages with data on arable land endowments to obtain estimates for land rental rates from equation 4.15. I solve for prices using equations 4.3 and 4.4 using estimated trade costs and produce fixed effects to calculate:

$$\hat{\Omega}_n^k = \sum_{i=1}^{I} e^{\hat{S}_i^k}\hat{\tau}_{ni}^k$$

I use the same ns products I used to estimate the model in Chapter 3 to simulate the integral in Equation 4.3 as follows, where the calculation of $\hat{\Omega}_{ni}^A(j)$ is analogous to $\hat{\Omega}_n^k$.

$$\hat{p}_{ni}^A = \frac{\gamma}{ns}\left(\sum_{j=1}^{ns}\Omega_n^A(j)^{\frac{\sigma-1}{\theta}}\right)^{\frac{1}{1-\sigma}}$$

I use $\hat{\mathbf{w}}$, $\hat{\mathbf{r}}$, $\hat{\mathbf{p}}^A$, and $\hat{\mathbf{p}}^M$ along with the calibrated parameter values to solve Equation 3.11. Note that since I calibrate $z_i^S = 1$, differences in service sector productivity are not included in the calculation of κ_i^k. Under this interpretation I am obtaining estimates of $\frac{T_i^k}{z_i^S}$ rather than T_i^k. Estimates are listed in Table G.1 on the following page.

Table G.1: Average Productivity Estimates

Country	Modified Model $\frac{T_i^A}{T_{USA}^A}$	Modified Model $\frac{T_i^M}{T_{USA}^M}$	EK Model $\frac{T_i^A}{T_{USA}^A}$	EK Model $\frac{T_i^M}{T_{USA}^M}$
Japan	2.084	46.015	6.149	126.211
Italy	1.948	0.488	3.337	1.119
Ireland	1.778	1.181	3.156	3.035
France	1.24	0.271	1.624	0.649
USA	1.000	1.000	1.000	1.000
Germany	0.657	0.608	0.473	1.343
Austria	0.612	0.767	1.019	1.983
Finland	0.246	1.435	0.5	3.641
Netherlands	0.189	0.112	0.18	0.262
UK	0.175	0.625	0.145	1.506
Denmark	0.137	1.022	0.187	2.654
Spain	0.134	0.102	0.28	0.25
Israel	0.13	0.81	0.272	2.138
New Zealand	0.127	0.168	0.141	0.415
Slovenia	0.112	1.45	0.136	3.822
Malaysia	0.105	0.09	0.253	0.242
Hungary	0.089	0.011	0.098	0.026
Czech Republic	0.085	0.028	0.135	0.071
Canada	0.041	1.084	0.02	2.447
Sweden	0.039	1.097	0.059	2.733
Slovakia	0.025	0.009	0.024	0.02
Poland	0.021	0.02	0.033	0.053
Chile	0.014	0.012	0.029	0.031
South Africa	0.013	0.017	0.027	0.044
Portugal	0.012	0.029	0.029	0.076
Estonia	0.012	0.015	0.014	0.036

Continued on next page

Table G.1 – continued from previous page

Country	Modified Model $\frac{T_i^A}{T_{USA}^A}$	Modified Model $\frac{T_i^M}{T_{USA}^M}$	EK Model $\frac{T_i^A}{T_{USA}^A}$	EK Model $\frac{T_i^M}{T_{USA}^M}$
Argentina	0.011	0.008	0.011	0.018
Australia	0.007	0.028	0.011	0.07
Turkey	0.004	0.011	0.009	0.028
Mexico	0.003	0.003	0.005	0.009
Brazil	0.002	0.005	0.004	0.014
Romania	0.002	0.003	0.003	0.008
Uruguay	0.001	0.003	0.000	0.013
Thailand	0.001	0.004	0.001	0.01
Russia	0.000	0.001	0.001	0.003
Indonesia	0.000	0.000	0.000	0.001
Iran	0.000	161.104	0.000	404.152
Costa Rica	0.000	0.003	0.000	0.008
Colombia	0.000	0.000	0.000	0.001
Ecuador	0.000	0.000	0.000	0.001
India	0.000	0.000	0.000	0.001
Kenya	0.000	0.000	0.000	0.000

Appendix H

Calibrated Production and Utility Function Parameters

H.1 Production Function Parameters

Table H.1: Value Added Shares

Country	α^A	α^M	α^S
Argentina*	0.49	0.32	0.56
Australia	0.50	0.35	0.54
Austria	0.47	0.35	0.57
Brazil	0.53	0.31	0.61
Canada	0.41	0.36	0.58
Chile*	0.49	0.32	0.56
Colombia*	0.49	0.32	0.56
Costa Rica*	0.49	0.32	0.56
Denmark	0.42	0.39	0.56
Ecuador*	0.49	0.32	0.56
Estonia	0.40	0.23	0.48
Finland	0.55	0.3	0.56

Continued on next page

Table H.1 – continued from previous page

Country	α^A	α^M	α^S
France	0.48	0.27	0.59
Germany	0.48	0.33	0.6
Hungary	0.34	0.21	0.53
India	0.78	0.28	0.60
Indonesia	0.49	0.32	0.56
Iran*	0.49	0.32	0.56
Ireland	0.49	0.33	0.53
Israel*	0.49	0.32	0.56
Italy	0.63	0.29	0.55
Japan	0.55	0.30	0.61
Kenya*	0.49	0.32	0.56
Malaysia*	0.49	0.32	0.56
Mexico*	0.49	0.32	0.56
Netherlands	0.44	0.30	0.55
New Zealand	0.40	0.32	0.50
Czech Republic	0.43	0.25	0.45
Poland	0.34	0.32	0.52
Portugal	0.54	0.27	0.54
Romania	0.52	0.34	0.54
Russia	0.54	0.38	0.60
Slovenia	0.45	0.50	0.61
Slovakia	0.39	0.25	0.44
South Africa	0.49	0.34	0.61
Spain	0.61	0.28	0.56
Sweden	0.49	0.32	0.56
Thailand*	0.49	0.32	0.56
Turkey	0.64	0.39	0.66
UK	0.42	0.38	0.50
USA	0.39	0.36	0.60

Continued on next page

Table H.1 – continued from previous page

Country	α^A	α^M	α^S
Uruguay*	0.49	0.32	0.56

Table H.2: Intermediate Input Shares

Country	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
Argentina*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Australia	0.24	0.35	0.41	0.09	0.57	0.34	0.01	0.26	0.73
Austria	0.43	0.29	0.28	0.06	0.64	0.30	0.01	0.26	0.73
Brazil	0.34	0.42	0.24	0.13	0.65	0.22	0.01	0.41	0.58
Canada	0.31	0.36	0.33	0.06	0.67	0.27	0.02	0.26	0.72
Chile*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Colombia*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Costa Rica*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Denmark	0.30	0.33	0.37	0.13	0.61	0.26	0.01	0.22	0.77
Ecuador*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Estonia	0.29	0.34	0.37	0.10	0.68	0.22	0.01	0.30	0.69
Finland	0.44	0.20	0.36	0.08	0.67	0.25	0.00	0.33	0.67
France	0.34	0.40	0.26	0.06	0.63	0.31	0.01	0.23	0.76
Germany	0.18	0.38	0.44	0.04	0.64	0.32	0.00	0.21	0.79
Hungary	0.27	0.47	0.26	0.06	0.74	0.20	0.02	0.37	0.61
India	0.48	0.28	0.24	0.15	0.54	0.31	0.04	0.40	0.56
Indonesia	0.28	0.48	0.24	0.20	0.57	0.23	0.04	0.44	0.52
Iran*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Ireland	0.35	0.46	0.19	0.07	0.49	0.44	0.01	0.24	0.75
Israel*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Italy	0.33	0.39	0.28	0.05	0.62	0.33	0.01	0.27	0.72
Japan	0.25	0.37	0.38	0.04	0.62	0.34	0.02	0.27	0.71
Kenya*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68

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Table H.2 – continued from previous page

Country	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
Malaysia*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Mexico*	0.33	0.37	0.03	0.08	0.62	0.30	0.01	0.31	0.68
Netherlands	0.28	0.35	0.37	0.08	0.68	0.24	0.00	0.24	0.76
New Zealand	0.33	0.26	0.41	0.18	0.47	0.35	0.02	0.26	0.72
Czech Republic	0.33	0.44	0.23	0.06	0.72	0.22	0.01	0.28	0.71
Poland	0.42	0.31	0.27	0.09	0.58	0.33	0.01	0.34	0.65
Portugal	0.29	0.37	0.34	0.10	0.64	0.26	0.01	0.28	0.71
Romania	0.56	0.29	0.15	0.13	0.55	0.32	0.01	0.49	0.50
Russia	0.48	0.34	0.18	0.08	0.61	0.31	0.02	0.40	0.58
Slovenia	0.43	0.30	0.27	0.04	0.71	0.25	0.02	0.32	0.66
Slovakia	0.47	0.28	0.25	0.04	0.72	0.24	0.01	0.27	0.72
South Africa	0.08	0.59	0.33	0.10	0.62	0.28	0.00	0.34	0.66
Spain	0.18	0.56	0.26	0.08	0.67	0.25	0.02	0.33	0.65
Sweden	0.14	0.51	0.35	0.05	0.58	0.37	0.02	0.26	0.72
Thailand*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68
Turkey	0.50	0.27	0.23	0.11	0.64	0.25	0.02	0.45	0.53
UK	0.17	0.34	0.49	0.03	0.58	0.39	0.00	0.21	0.79
USA	0.37	0.31	0.32	0.05	0.59	0.36	0.02	0.23	0.75
Uruguay*	0.33	0.37	0.30	0.08	0.62	0.30	0.01	0.31	0.68

H.2 Utility Function Parameters

Table H.3: Consumption Shares

Country	λ^A	λ^M	λ^S
Argentina*	0.05	0.30	0.65
Australia	0.01	0.22	0.77
Austria	0.02	0.25	0.73

Continued on next page

Table H.3 – continued from previous page

Country	λ^A	λ^M	λ^S
Brazil	0.06	0.33	0.61
Canada	0.01	0.25	0.74
Chile*	0.05	0.30	0.65
Colombia*	0.05	0.30	0.65
Costa Rica*	0.05	0.30	0.65
Denmark	0.01	0.21	0.78
Ecuador*	0.05	0.30	0.65
Estonia	0.04	0.34	0.62
Finland	0.02	0.19	0.79
France	0.03	0.29	0.68
Germany	0.02	0.31	0.67
Hungary	0.05	0.31	0.64
India	0.30	0.27	0.43
Indonesia	0.13	0.44	0.43
Iran*	0.05	0.30	0.65
Ireland	0.03	0.31	0.66
Israel*	0.05	0.30	0.65
Italy	0.02	0.27	0.71
Japan	0.02	0.23	0.75
Kenya*	0.05	0.30	0.65
Malaysia*	0.05	0.30	0.65
Mexico*	0.05	0.30	0.65
Netherlands	0.01	0.23	0.76
New Zealand	0.02	0.27	0.71
Czech Republic	0.04	0.38	0.58
Poland	0.05	0.34	0.61
Portugal	0.04	0.39	0.57
Romania	0.14	0.37	0.49
Russia	0.12	0.37	0.51

Continued on next page

Table H.3 – continued from previous page

Country	λ^A	λ^M	λ^S
Slovenia	0.05	0.33	0.62
Slovakia	0.08	0.39	0.53
South Africa	0.03	0.41	0.56
Spain	0.03	0.24	0.73
Sweden	0.01	0.26	0.73
Thailand*	0.05	0.30	0.65
Turkey	0.19	0.36	0.45
UK	0.02	0.30	0.68
USA	0.01	0.20	0.79
Uruguay*	0.05	0.30	0.65

Appendix I

Base Solutions

I.1 Wages

Table I.1: Wages (Relative to the United States)

Country	Modified	EK Model	Country	Modified	EK Model
Japan	5.36	5.42	Portugal	0.35	0.36
Iran	3.07	3.19	Estonia	0.35	0.39
Ireland	2.33	2.45	Australia	0.29	0.32
Finland	1.78	1.92	Slovakia	0.25	0.27
Sweden	1.47	1.60	Chile	0.21	0.21
Austria	1.21	1.34	Poland	0.21	0.22
Denmark	1.18	1.19	South Africa	0.21	0.21
Italy	1.10	1.24	Mexico	0.16	0.18
Netherlands	1.09	1.10	Argentina	0.15	0.17
Germany	1.02	1.19	Costa Rica	0.14	0.14
USA	1.00	1.00	Turkey	0.14	0.14
Canada	0.96	1.13	Thailand	0.13	0.16
Israel	0.93	0.94	Uruguay	0.13	0.13
France	0.92	1.11	Brazil	0.12	0.14
UK	0.82	0.87	Romania	0.09	0.09
Slovenia	0.76	0.75	Russia	0.06	0.06
Malaysia	0.60	0.61	Indonesia	0.04	0.05
New Zealand	0.59	0.66	Colombia	0.03	0.03
Spain	0.55	0.65	Ecuador	0.03	0.03
Czech Republic	0.44	0.49	India	0.03	0.03
Hungary	0.36	0.42	Kenya	0.00	0.00

I.2 Price Indices

Table I.2: Tradable Sector Price Indices (Relative to the United States)

	Agriculture (p_n^A)		Manufacturing (p_n^M)	
Country	Modified	EK Model	Modified	EK Model
Canada	112.84	2.82	0.95	0.94
Thailand	68.12	3.71	1.25	1.24
Germany	49.34	2.65	1.09	1.08
Indonesia	33.60	2.27	1.26	1.24
Russia	26.86	0.86	1.09	1.07
France	18.38	1.34	1.05	1.03
Sweden	16.94	4.66	1.16	1.15
Spain	16.02	1.49	1.08	1.06
Argentina	13.63	0.81	1.10	1.08
Austria	13.48	2.03	0.97	0.95
UK	12.80	3.09	1.07	1.07
New Zealand	11.18	1.69	1.17	1.15
Italy	9.81	1.78	1.07	1.06
Iran	9.30	5.50	0.37	0.36
Australia	8.95	1.01	1.31	1.30
Brazil	8.22	1.46	1.09	1.08
Finland	7.66	2.91	1.12	1.11
Colombia	6.62	3.10	0.98	0.98
Mexico	6.28	1.85	1.09	1.08
Japan	6.09	7.68	0.81	0.81
India	5.93	1.52	0.92	0.91
Slovenia	4.96	1.52	0.98	0.98
Kenya	4.39	2.61	0.90	0.89
Estonia	4.25	2.05	1.08	1.07

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Table I.2 – continued from previous page

	Agriculture (p_n^A)		Manufacturing (p_n^M)	
Country	Modified	EK Model	Modified	EK Model
Romania	4.04	1.13	0.95	0.94
Ireland	3.75	2.09	1.10	1.09
Uruguay	3.65	1.32	1.18	1.17
Costa Rica	3.25	5.35	1.16	1.16
Hungary	3.24	1.21	1.07	1.05
Slovakia	3.14	1.65	1.03	1.02
Israel	3.07	3.21	0.87	0.87
Poland	2.99	1.08	0.92	0.91
Denmark	2.97	2.25	1.07	1.06
Czech Republic	2.85	1.42	0.94	0.93
Ecuador	2.81	2.86	1.00	1.00
Malaysia	2.79	2.52	1.30	1.29
Portugal	2.16	2.61	1.07	1.07
South Africa	2.09	1.10	1.12	1.12
Turkey	1.89	0.81	1.01	1.01
Netherlands	1.83	3.71	1.15	1.14
USA	1.00	1.00	1.00	1.00
Chile	0.87	1.61	1.15	1.15

I.3 Labor Allocations

Table I.3: Sector Share of Labor Force*

	Agriculture %		Manufacturing %		Services %	
Country	Models	Data	Models	Data	Models	Data
Argentina	2.12	0.70	51.61	22.7	46.28	76.20
Australia	1.97	5.00	53.87	21.70	44.16	73.30
Austria	2.08	5.80	53.95	30.30	43.96	64.00

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Table I.3 – continued from previous page

	Agriculture %		Manufacturing %		Services %	
Country	Models	Data	Models	Data	Models	Data
Brazil	2.00	NA	50.78	NA	47.23	NA
Canada	2.29	3.30	54.95	22.50	42.76	74.20
Chile	2.12	14.40	51.61	23.40	46.28	62.20
Colombia	2.12	1.10	51.61	25.50	46.28	73.30
Costa Rica	2.12	20.40	51.61	22.30	46.28	56.70
Denmark	2.13	3.30	57.51	25.20	40.36	71.40
Ecuador	2.12	29.30	51.61	19.90	46.28	50.80
Estonia	3.01	7.10	46.19	33.30	50.80	59.60
Finland	1.95	6.00	50.02	27.20	48.02	66.40
France	2.36	4.10	48.26	26.30	49.37	69.60
Germany	2.12	2.60	52.38	33.50	45.51	63.80
Hungary	3.57	6.50	45.39	33.70	51.05	59.70
India	1.27	59.90	48.16	16.00	50.57	24.00
Indonesia	2.12	45.30	51.61	17.40	46.28	37.30
Iran	2.08	NA	52.35	NA	45.57	NA
Ireland	2.12	6.50	51.61	27.70	46.28	65.40
Israel	2.12	2.20	51.61	23.70	46.28	73.00
Italy	1.70	5.20	49.14	31.80	49.16	63.00
Japan	1.95	5.10	50.02	31.20	48.02	63.10
Kenya	2.12	NA	51.61	NA	46.28	NA
Malaysia	2.12	18.40	51.61	32.20	46.28	49.50
Mexico	2.12	18.00	51.61	26.80	46.28	55.20
Netherlands	2.41	3.00	50.35	20.20	47.23	70.40
New Zealand	2.51	8.70	51.90	23.20	45.60	67.70
Czech Republic	2.72	5.10	47.22	39.50	50.07	55.40
Poland	2.81	18.80	52.12	30.80	45.07	50.40
Portugal	2.10	12.50	48.08	34.40	49.82	53.00
Romania	1.93	42.80	53.02	26.20	45.04	31.00

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Table I.3 – continued from previous page

	Agriculture %		Manufacturing %		Services %	
Country	Models	Data	Models	Data	Models	Data
Russia	1.74	14.50	56.28	28.40	41.98	57.10
Slovenia	1.69	9.50	69.69	37.40	28.62	52.30
Slovakia	2.94	6.70	47.37	37.30	49.69	56.10
South Africa	2.04	15.60	53.11	24.20	44.85	59.4
Spain	1.80	6.70	48.53	30.80	49.67	62.50
Sweden	2.12	2.40	51.61	24.50	46.28	73.00
Thailand	2.12	48.80	51.61	19.00	46.28	32.20
Turkey	1.42	36.00	56.94	24.00	41.64	40.00
UK	2.17	1.50	56.62	25.10	41.21	73.10
USA	2.37	2.60	55.02	23.20	42.61	74.30
Uruguay	2.12	4.10	51.61	24.70	46.28	71.30

*Both models predict an identical allocation of labor across sectors

Appendix J

Results of Agricultural Liberalization Counterfactual

J.1 Increase in Agricultural Imports

Table J.1: Increase in Ag Imports over Base Solution

Country	Full Liberalization $\frac{1-\pi_{nn}^{A\ F}}{1-\pi_{nn}^{A\ *}}$	Partial / Full Liberalization $\frac{1-\pi_{nn}^{A\ P}}{1-\pi_{nn}^{A\ F}}$
Argentina	1.07	1.00
Australia	3.37	1.00
Austria	27.50	1.00
Brazil	6.96	0.98
Canada	1.03	1.00
Chile	15.30	0.79
Colombia	13.76	0.92
Costa Rica	2.23	1.00
Denmark	22.35	1.00
Ecuador	50.29	0.65
Estonia	85.36	0.98

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Table J.1 – continued from previous page

Country	Full Liberalization $\frac{1-\pi_{nn}^{A\ F}}{1-\pi_{nn}^{A\ *}}$	Partial / Full Liberalization $\frac{1-\pi_{nn}^{A\ P}}{1-\pi_{nn}^{A\ F}}$
Finland	39.84	1.00
France	2.18	1.00
Germany	2.58	0.99
Hungary	5.27	0.99
India	1.69	0.98
Indonesia	32.01	0.54
Iran	1.00	1.00
Ireland	93.89	0.99
Israel	29.30	1.00
Italy	7.49	1.00
Japan	2.05	0.98
Kenya	265.28	0.95
Malaysia	4.68	1.00
Mexico	1.87	1.00
Netherlands	35.19	0.99
New Zealand	2526.35	1.00
Czech Republic	4.61	1.00
Poland	1.25	1.00
Portugal	42.46	0.98
Romania	3.29	1.00
Russia	1.07	1.00
Slovenia	6.83	1.00
Slovakia	9.32	0.99
South Africa	96.79	0.93
Spain	4.62	0.99
Sweden	6.18	0.99
Thailand	6.15	0.66

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Table J.1 – continued from previous page

Country	Full Liberalization $\frac{1-\pi_{nn}^{A\ F}}{1-\pi_{nn}^{A\ *}}$	Partial / Full Liberalization $\frac{1-\pi_{nn}^{A\ P}}{1-\pi_{nn}^{A\ F}}$
Turkey	1.90	0.89
UK	3.75	1.00
USA	1.08	1.00
Uruguay	25.61	0.95

J.2 Increase in Average Foreign Market Share

Table J.2: Increase in Average Foreign Market Share –Full vs. Partial Liberalization

	Ave. % Change in π_{ni}^{A} from Base Solution, $(i \neq n)$	
Exporter	Full Liberalization	Partial/Full Liberalization
Argentina	116%	1.00
Australia	252%	1.00
Austria	528%	1.00
Brazil	302%	1.00
Canada	-72%	1.02
Chile	73%	1.00
Colombia	246%	1.02
Costa Rica	384%	0.95
Denmark	730%	1.00
Ecuador	124%	1.00
Estonia	192%	1.02
Finland	770%	1.00
France	930%	0.99
Germany	213%	1.00
Hungary	178%	1.00

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Table J.2 – continued from previous page

	Ave. % Change in π_{ni}^{A} from Base Solution, $(i \neq n)$	
Exporter	Full Liberalization	Partial/Full Liberalization
India	513%	1.00
Indonesia	269%	1.00
Iran	318%	1.00
Ireland	41%	1.06
Israel	815%	1.00
Italy	227%	1.00
Japan	513%	1.00
Kenya	68%	0.97
Malaysia	903%	1.00
Mexico	603%	1.00
Netherlands	165%	1.01
New Zealand	213%	1.00
Czech Republic	785%	1.00
Poland	179%	1.00
Portugal	528%	1.00
Romania	939%	1.00
Russia	1089%	1.00
Slovenia	932%	1.00
Slovakia	329%	1.00
South Africa	116%	1.00
Spain	473%	1.00
Sweden	414%	0.98
Thailand	283%	1.00
Turkey	166%	1.00
UK	450%	1.00
USA	69%	1.00
Uruguay	903%	1.00

J.3 Size of Shifts in Bilateral Agricultural Trade Patterns

Table J.3: Rank Correlation between Base and Liberalized Market Shares

Import Market	Rank Correlation π_{ni}^{A*}, π_{ni}^{AF}	Import Market	Rank Correlation π_{ni}^{A*}, π_{ni}^{AF}
Argentina	0.73	Japan	0.66
Australia	0.70	Kenya	0.61
Austria	0.79	Malaysia	0.53
Brazil	0.76	Mexico	0.77
Canada	0.57	Netherlands	0.56
Chile	0.69	New Zealand	0.59
Colombia	0.70	Poland	0.77
Costa Rica	0.74	Portugal	0.53
Czech Republic	0.75	Romania	0.74
Denmark	0.56	Russia	0.57
Ecuador	0.73	Slovakia	0.77
Estonia	0.62	Slovenia	0.70
Finland	0.67	South Africa	0.64
France	0.75	Spain	0.68
Germany	0.75	Sweden	0.64
Hungary	0.75	Thailand	0.61
India	0.66	Turkey	0.75
Indonesia	0.69	UK	0.71
Iran	0.50	Uruguay	0.69
Ireland	0.62	USA	0.62
Israel	0.59	Japan	0.66

J.4 Increase in Real Income from Ag Liberalization

Table J.4: Percent Change in Real Income over Base Solution

Country	Full Liberalization	Partial/Full Liberalization
Argentina	2.84%	0.99
Australia	0.75%	1.00

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Table J.4 – continued from previous page

Country	Full Liberalization	Partial/Full Liberalization
Austria	3.14%	1.00
Brazil	3.08%	0.99
Canada	6.67%	1.00
Chile	0.62%	0.99
Colombia	1.18%	0.96
Costa Rica	0.39%	1.00
Denmark	1.72%	1.00
Ecuador	0.51%	0.96
Estonia	0.86%	1.00
Finland	2.44%	1.00
France	4.99%	1.00
Germany	5.30%	1.00
Hungary	1.99%	1.00
India	10.88%	0.97
Indonesia	16.16%	0.78
Iran	8.96%	1.00
Ireland	1.40%	1.00
Israel	0.70%	1.00
Italy	2.63%	1.00
Japan	2.57%	1.00
Kenya	0.80%	0.99
Malaysia	3.41%	0.99
Mexico	11.09%	1.00
Netherlands	4.22%	1.00
New Zealand	0.37%	1.00
Czech Republic	3.17%	1.00
Poland	2.65%	1.00
Portugal	6.57%	1.00
Romania	6.70%	1.00

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Table J.4 – continued from previous page

Country	Full Liberalization	Partial/Full Liberalization
Russia	16.59%	1.00
Slovenia	1.26%	1.00
Slovakia	6.03%	1.00
South Africa	0.26%	0.97
Spain	2.37%	0.99
Sweden	3.86%	1.00
Thailand	10.14%	0.85
Turkey	1.58%	0.83
UK	3.08%	1.00
USA	0.37%	1.00
Uruguay	1.52%	0.99