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Understanding China's Soybean Boom from a Global Perspective

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UNDERSTANDING CHINA'S SOYBEAN BOOM FROM A GLOBAL PERSPECTIVE

by

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To my family

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ABSTRACT

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China's soybean demand boom in the past two decades has been very dramatic. It involves socioeconomic and environmental interactions of multi-coupled systems. Over this period, China doubled its GDP, and the ensuing income growth generated strong growth in the demand for livestock products -- a major consumer of soybean meals. In addition, the goal of producing more meat and milk boosted protein content requirements in feed formulations and intensified China's soybean meal demands. Brazil and Argentina stepped in to satisfy this increased demand. In the case of Brazil, rapid technical change, coupled with the expansion of cultivated area, played a key role in meeting the increased soybean demand in China's global soybean boom. In 2011, Brazil became the largest soybean supplier for China, and soon in 2013, it overtook the US as the leading global soybean exporter.

Soybean trade offers a notable instance of the emerging "telecoupling" concept – China, Brazil and the US closely interact with each other across distances. Chapter 2 aims to bridge agricultural trade with this telecoupling concept. The goal of Chapter 2 is to understand the historical soybean boom by focusing on the supply-demand-trade nexus of these three countries with a modified version of the GTAP-BIO model. We decompose historical changes into five groups of socio-economic drivers – macroeconomic growth, soybean productivity, other crop productivity, government policies, and pasture and forestry changes – quantifying each driver's contributions to soybean trade, production, and land use changes over 2004-2011.We find that China's macroeconomic growth boosted soybean production and exports from Brazil and the US, whereas macroeconomic growth in the latter two regions actually dampened soybean exports over the 2004-2011 period under examination. Brazil's strong soybean productivity growth over this period, allowed that country to become dominant in the global soybean market. It also had strong spillover effects, displacing the US in the Chinese market and reducing overall growth in soybean

output in the US. This strong soybean productivity growth also contributed to cropland expansion in Brazil.

We introduce Genetically Modified (GM) and non-GM soybeans into our modified version of the GTAP-BIO model, which requires new trade elasticity estimates, especially the elasticity between GM and non-GM soybeans. However, such estimates are missing from the existing literature, and current trade data does not distinguish GM and non-GM varieties. In this dissertation, we treat soybeans from countries that predominantly export GM and non-GM varieties as GM and non-GM soybean bundles. In Chapter 3, we apply a structural gravity model to estimate three parameters: elasticities of substitution across GM and non-GM soybean bundles, respectively, and substitution between nested constant elasticity of substitution (CES) bundles of GM and non-GM soybeans. Following the Armington assumption, we employ a single nest CES structure for the elasticities of substitutions among each soybean bundle and a nested CES structure for the elasticity of substitution between GM and non-GM soybean bundles by using Poisson Pseudo Maximum Likelihood (PPML) estimators. Our estimates show that the elasticity among GM soybean bundles is as high as 29, indicating GM soybeans are homogeneous productions. The elasticity among non-GM soybean bundles is lower at 12. Although varieties of non-GM soybean bundles are substitutable, their qualities are differentiated by its origins. Low substitutability between GM and non-GM soybeans at 0.4 implies that GM and non-GM soybean bundles are viewed as poor substitutes by countries.

By applying the historically-validated and well-tuned GTAP-BIO model from Chapter 2 and the trade elasticities estimated from Chapter 3, we aim to understand soybean boom from the supply side and investigate how the US lost its lead in the global soybean trade. We decompose changes of two main indices – the US/Brazil soybean production ratio and the US/Brazil soybean exports to China ratio – into a more detailed specification of socio-economic drivers. By pinpointing negative and positive drivers, we shed light on the factors driving to the US "losses" and "gains" in soybean exporting to China over 2004-2011 and provide insights on future soybean trade patterns.

CHAPTER 1. INTRODUCTION

Soybeans are one of the most heavily traded agricultural commodities worldwide. Processed soybeans are the global largest protein source for animal feed and second largest source of vegetable oils (USDA 2017). Over 2000-2014, China's soybean imports have increased by 6 times, at an annual growth rate of 15%. In 2000, China's soybean imports were only 50% higher than its soybean production. This number grew to 600% in 2014 (UN Comtrade 2016). China's fast-growing demands for soybeans is fueled by increased demands for meats driven by its income growth. The Chinese government even lowered its soybean tariffs to encourage raw soybean imports and incentivized domestic soybean processing industries. Driven by China's soybean boom, global soybean production has doubled by about 200 million metric tons, and the global soybean exports has increased by 10 folds in the past two decades (FAO 2015; UN Comtrade 2016). In 2014, the US and Brazil produced over 63% of global soybeans. They are also the largest global soybean exporters. 42% of the US soybeans and 39% of the Brazilian soybeans were exported in 2014. China, the largest soybean consumer, purchased over 60% and 70% from the US and Brazilian soybean exports in 2014 (FAO 2015). Although these three countries are distantly located, they are closely connected through global soybean trade. A strong dependence on global markets makes the US and Brazilian farmers sensitive to each other's competition signals and China's demand signals.

Accompanying by China's soybean boom, Brazil's aggressive soybean production expansion and increasing market shares concerned the US soybean farmers. In 2011, Brazil overtook the US and became the largest China's soybean supplier. In 2013, Brazil took the lead in the global soybean market. This rapid expansion came from Brazilian cropland expansion and deforestation (Fehlenberg et al. 2017; Hecht and Mann 2008; Walker et al. 2009; Richards, Walker and Arima 2014). A 70+% growth in genetically-modified (GM) soybean penetration significantly lowered Brazil's soybean production costs and increased Brazil's soybean production. China's GM-friendly import policies give opportunities for Brazilian soybeans.

This new Brazil-China soybean trade relationship has attracted a great deal of attention. Some efforts have contributed to qualitatively explaining historical increasing Brazil-China soybean partnership and future projections of this relationship (Torres, Moran and Silva 2017; Silva et al. 2017; Brown-Lima, Cooney and Cleary 2009a). Some other efforts have focused on comparing the US-Brazil comparative advantages and disadvantages on a one-by-one basis. Many studies concentrate on one factor's roles in soybean trade (e.g. exchange rates, supply chains) (Godar et al. 2015; Garrett, Rueda and Lambin 2013; Richards et al. 2012) or one country's soybean production revolution and consequences (e.g. deforestation) (Fehlenberg et al. 2017; Hecht and Mann 2008; Walker et al. 2009; Richards et al. 2014). However, these factors interact with each other, and these three countries' consumers and farmers also interactively respond to each other. A global study focusing on the supply-demand-trade nexus of these three countries that incorporate all potential factors are missing from the current literature.

This dissertation aims to fill this gap and provides a comprehensive analysis of these historical changes in soybean production and trade. A modified version of the GTAP-BIO model is developed in this dissertation for market-mediated analyses of soybean trade. Historical soybean revolution cannot progress without the participation of GM technology. To better replicate this change, we introduce GM and non-GM soybeans into this version of the model. This dissertation also provides an innovated estimation of trade elasticities for GM and non-GM soybeans to back up the introduction of GM-non-GM nexus.

This dissertation comprises three essays. Chapter 2 focuses on the soybean supply-demand-trade nexus of three major countries: China, Brazil, and the US. It applies the modified version of the GTAP-BIO model to analyze the economic and consequences of historical Brazil-China soybean boom. It connects agricultural trade studies with the new emerging "telecoupling" concepts. In this chapter, we propose five groups of socio-economic drivers – macroeconomic growth, soybean productivity, other crop productivity, government policies, and pasture and forestry changes – to replicate historical changes of soybean production, trade, and land use changes. Applying the decomposition technique developed by Harrison, Horridge, and Pearson (2000), we quantify each socio-economic driver's local and distant contributions to these historical changes in human and natural systems. Understanding historical contributions of these drivers offer valuable insights and tools for future soybean trade analyses.

One of the major modifications of the GTAP-BIO model is the introduction of GM and non-GM soybean nexus. It requires new trade elasticity estimates, especially the elasticity between GM and non-GM soybeans. These new elasticity estimates are essential for computable general equilibrium (CGE) and computable general partial equilibrium (CPE) studies. Past literature only estimates one elasticity with the mixture of the two varieties of soybeans by applying a single nest demand structure. However, current bilateral trade flows do not track GM and non-GM soybean varieties. Therefore, as a workable alternative, we treat soybeans from countries that predominantly export GM and non-GM varieties as GM and non-GM soybean bundles. Following the Armington assumption in the GTAP-BIO model, Chapter 3 applies a structural estimation method to estimate these elasticities. The estimation has two steps. The first step employs a single nest CES utility function for the elasticities of substitutions among each soybean bundle. The second step utilizes a nested CES structure for the elasticity of substitutions between GM and non-GM soybean bundles. Both steps apply Poisson Pseudo Maximum Likelihood (PPML) estimator. These elasticity estimates provide valuable insights about the relationships between soybean variety preferences and substitutability from the demand side, as well as farmers' producing behaviors from the supply side. We apply these elasticity estimates into the modified version of the GTAP-BIO model to motivate further analyses.

In Chapter 4, we apply the fully-validated and well-tuned GTAP-BIO from Chapter 2 and elasticities estimated from Chapter 3 to motivate an important question: "How did the US lose its lead in the global soybean trade?" Two indices – the US/Brazil soybean production ratio and the US/Brazil soybean exports to China ratio – are decomposed into a more detailed specification of the five groups of drivers proposed in Chapter 2. The decomposition procedure allows us to pinpoint positive and negative drivers of the historical changes. By pinpointing negative and positive drivers, we shed light on the factors driving the US "losses" and "gains" in soybean exporting to China over 2004-2011. An exploration of the US/Brazil relative competitiveness provides guidance for the US and Brazil future global soybean market strategy.

CHAPTER 2. ECONOMIC DRIVERS OF TELECOUPLING AND TERRESTRIAL CARBON FLUXES IN THE GLOBAL SOYBEAN COMPLEX

2.1 Introduction

"Telecoupling" is a relatively new approach to conceptualizing simultaneous interactions between both micro- and macro-level drivers of economic and environmental change across long distances (Liu et al. 2013). International trade is one important element of "telecoupling" and has featured importantly in a number of recent studies of telecoupling. Pioneering work from Yu et al. (2013) used a global multiregional input-output (MRIO) model to investigate the relationships between local consumption and global land use change. However, their MRIO model neglects market-mediating factors associated with economic responses to scarcity and ignores the role of technological progress. In this paper, we use a modified version of the Global Trade Analysis Project model (GTAP-BIO), which can be viewed as an economic extension of MRIO analysis that captures interactive supply-demand relationships both locally and globally, traces market-mediated responses to resource constraints, and takes into account technological progress. It emphasizes the role that international trade plays in mediating between different land use and environmental outcomes across the globe – hence the relevance to telecoupling. A particularly attractive feature of this framework is that it allows for the quantification of the relative contribution of each socio-economic driver to observed telecoupling between different regions.

The telecoupling concept has evolved from the literature on Coupled Human and Natural Systems (CHANS) (Wang and Liu 2016). Previously, each CHANS was treated as a closed system (Carpenter et al. 2009; Monticino et al. 2007; Moran 2011; Ostrom and Nagendra 2006; Shaver et al. 2015). For example, Gasparri et al. (2013) investigate the linkages between the soybean economy, cattle ranching, and deforestation in Argentina. Telecoupling further connects each CHANS through inter-regional flows and expands them into a globally-interacting framework. In a telecoupled framework, each CHANS is treated as an open system, in which the agents interact with agents in other CHANS (Wang and Liu 2016). Current telecoupling studies have been mainly theoretical in nature with few empirical applications (Eakin et al. 2014; Liu, Hull, et al. 2015; Liu, Mooney, et al. 2015; Liu et al. 2013) and many have called for more empirically based, global-level human-nature research (Liu et al., 2007, 2013).

The international soybean economy provides a good example of a telecoupled system with significant global environmental change implications. A stylized description of this system is shown in Figure 2.1. It involves three major players: China, Brazil, and the US. China is the world's largest soybean importer; Brazil and the US are the two largest soybean producers and exporters. They are connected through trade flows. In this research, we primarily investigate Brazil-China soybean trade relationship and its major spillover impact on the US. In this context, Christofoletti, Silva and Mattos (2012) find that China developed strong price linkages with the US, Brazil, and Argentina after 2006, and that the US prices adjusted more rapidly than other countries. By analyzing the evolution of China-Brazil soybean trade and its implications for land use in these two countries, Torres et al. (2017) conclude that international soybean trade enabled China to conserve its forests and biodiversity while transferring these pressures to Brazil's natural ecosystems. Silva et al. (2017) also focus on the China-Brazil telecoupled system. They conclude that soybean production in Brazil incentivized maize-soybean rotation and increased maize production, which subsequently brought local pressures on Brazil's domestic stocks and supplies. They emphasize the need for further investigations of the socio-economic drivers of telecoupling. Sun et al. (2017) mapped the finer-scale spatial distribution of soybean land use changes in China, Brazil and the US. They aim to motivate further studies of international trade relationships and the ensuing land use changes. Our paper takes up this challenge and provides an empirical analysis of the trade linkages between these three countries. More specifically, our analysis of the telecoupled soybean system brings to bear not only the drivers of change within the soybean industry itself, but also key changes in related sectors – including the feedstuffs industry and livestock production in China, biofuels produced across the world, changes in agricultural and trade policies, exogenous and endogenous price induced technological progress, as well as macroeconomic growth.

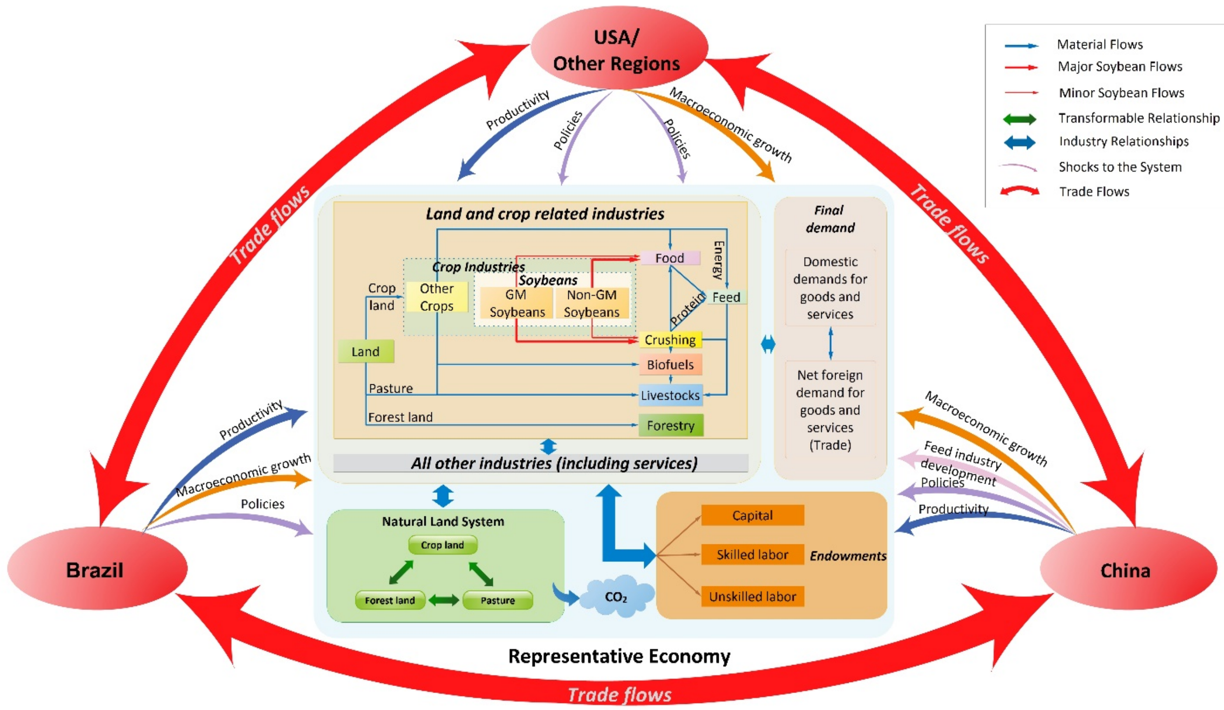

Figure 2.1 Telecoupling conceptual framework for analyses of the soybean trading system. Brazil, China, and the US are connected through trade flows. China's economic growth generates strong demand for soybean production. Meanwhile, Brazil's agricultural productivity has further facilitated soybean growth. Domestic and trade policies mediate these supply and demand relationships. The graphic in the middle shows the soybean production and marketing system in a representative national economy in our model. Arrows refer to input flows. Thick arrows represent primary flows while thin arrow lines represent secondary (lower volume) flows. Red arrows highlight soybean flows, and blue arrows are other general flows. Colored curved arrows originate from each system and denote socio-economic drivers that incentivize soybean production.

Studying soybean production and trade using a comprehensive telecoupling framework advances the previous soybean system literature that has typically focused on either the supply or the demand side of the system while neglecting their interconnections at regional and global scales – the spillover impacts. Research focusing on the supply side frequently compares soybean production and marketing in the US, Brazil, and Argentina. US variable production costs are typically lower, and farms are better connected to the international transportation system than in Brazil and Argentina (Sutton, Klein and Taylor 2005a). However, abundant land – and the ensuing low prices for land – is the factor which ultimately favors Argentina and Brazil (Sutton et al. 2005a; Leibold and Osaki 2009a). In addition, the US corn ethanol program led some US farmers to reduce soybean plantings in favor of corn production (Hauser 2002). Meanwhile, Political reforms, more engagement in international business, improvements in transportation systems, farm management improvements, the government supports, and favorable climate conditions have helped Brazil to rapidly expand soybean production during the past two decades (Schnepf, Dohlman and Bolling 2001a; Sutton et al. 2005a). As a result, in 2013, Brazil surpassed the US as the largest soybean exporter in the world and this rapid growth in soybean area has, in turn, given rise to concerns about the environmental consequences, including potential loss of biodiversity and release of terrestrial carbon through increased rates of deforestation (Brown et al. 2005; Fehlenberg et al. 2017; Hecht and Mann 2008; Morton et al. 2006; Richards et al. 2014; Richards et al. 2012; Walker et al. 2009). Recent analyses suggest much of this environmental degradation has been fueled by China's growing demand for soybean imports (Beckman et al. 2017; Garcia and Ballester 2016; Grecchi et al. 2014; Richards et al. 2012). Despite the gradual decoupling relationship between soybean production and deforestation, soybean production may continue to result in deforestation though indirect linkages, such as livestock displacements as well as capital and skill movements in agricultural and livestock sectors (Arima et al. 2011; Barona et al. 2010; Gasparri et al. 2013; Richards 2012; Richards et al. 2014). However, an explicit decomposition of the factors driving this growth in international soybean trade is thus far missing from the literature.

There is also substantial literature focusing largely on the demand side of the soybean boom. China has been the fastest growing economy in the world over the past two decades, leading to very strong growth in the demand for livestock products (Hansen and Gale 2014). In order to produce more meat and milk, the protein content in feed formulations was raised, and this intensified China's use of soybean meal (a key protein source in feed formulations) demands (Gale

2015). Meanwhile, China's prohibition of genetically-modified (GM) soybean cultivation and corn stockpiling policies motivated Chinese farmers to switch from soybean to corn production, leading to a 15% cumulative soybean production decline between 2004 and 2011. This added to the growing demand for imported soybeans. Moreover, China lowered soybean tariffs, even while increasing its soybean meal tariff to protect the domestic soybean crushing industry, thereby further fueling soybean imports. USDA anticipates that China will continue to be the dominant soybean importer for the foreseeable future, and China's soybean imports could reach up to 70% of global soybean imports by 2023/2024 (Hansen and Gale 2014).

In recent work using the telecoupling framework to examine soybean trade, Oliveira and Schneider (2016) describe the shifting political geography of soybean trade from the perspective of soybean processing industries, soybean legacies and trajectories in China and Brazil, food and feed demands in China, and diverse soybean consuming industries in Brazil including livestock, vegetable oils, and biodiesel. These authors call for a better understanding of the mechanisms behind this shifting economic geography. Our study aims to fill this gap, offering a more complete perspective of the individual drivers of international soybean trade as well as the consequences for natural systems – particularly in Brazil.

We begin our analysis by identifying key socio-economic drivers of the telecoupled system and incorporate these into the GTAP-BIO model to permit quantitative evaluation of their relative importance within the soybean complex during the 2004-2011 "boom." This is the period during which Brazil overtook the US as the primary supplier of soybeans to China. We are able to quantify the contribution of each individual driver to land use and terrestrial CO2 emissions. In so doing, we provide new insights into this telecoupled system, strengthening the basis for future projections, and providing insights for decision makers focusing on the mitigation of adverse environmental consequences within this evolving system.

2.2 Material and Methods

2.2.1 Model

We bring to the telecoupling challenge a modified version of the global, general equilibrium model, GTAP (Hertel 1997). It is underpinned by economic theories of demand, supply, trade, as well as macroeconomic equilibrium. Firms respond to consumers' demands by adjusting their input purchases, invested capital, labor force and production levels. Income generated from these sales accrues to households, which, in turn, spend it on private consumption, public goods and services and savings. The latter are re-invested into the economy. Each national economy is linked with other economies through household and firms' demands for imports. And each national economy is underpinned by a full set of intermediate input demands. Therefore, this framework allows for both multiregional and inter-sectoral analyses. GTAP is widely used to investigate the economic and environmental impacts of sector- and region-specific policies as well as global trade and environmental policies. Unlike the MRIO approach previously employed in the telecoupling literature (Yu et al. 2013), this model captures consumers' and producers' responses to changes in relative prices, also taking into account fundamental macroeconomic constraints such as the balance of payments and factor market equilibrium. Hence, it provides a necessary advance in the literature used to study interactions among the components of a telecoupled system.

There are many variants of the GTAP model in use today. Given our interest in the soybean complex, we employ a recently modified version of GTAP, dubbed GTAP-BIO. This version disaggregates the oilseed and related sectors in GTAP into soybeans, palm fruit, rapeseeds, and other oilseeds; takes into account production and consumption of biofuels and their by-products; and traces changes in crop production, harvested area, and land cover items including forest, pasture, and cropland at the global scale by region at an Agro-Ecological Zone (AEZ) level. This model has been refined over time for the study of economic and environmental consequences of agriculture-energy-environmental-trade policies (Hertel, Golub, et al. 2010; Liu et al. 2014; Taheripour et al. 2010). The latest version of this model is reported in Taheripour et al. (2017a). Unlike its predecessors, this version of GTAP-BIO takes into account land intensification in agriculture due to improvements in harvest frequency (e.g., double-cropping of soybean and corn). Taheripour et al. (2017) provide additional background on this model and the associated database.

For the present work, we further modify GTAP-BIO by splitting the soybean sector into GM (genetically modified) and non-GM soybean sectors (Figure 2.1). GM soybeans are mainly sold to the crushing industries, which produce soybean meal and oil. Soybean meal is the major protein source for the livestock industries, and soybean oil is an important ingredient for processed food. In China, non-GM soybeans are mainly used by the food industries due to consumers' safety concerns, although some non-GM soybeans also find their way into the livestock, feed and crushing sectors. The model also focuses on other crops, especially coarse grains which serve as a key source of energy in feed formulations. Corn, sugarcane, wheat, and sorghum are also major bio-ethanol feedstocks, while oilseeds can be used to produce bio-diesel. Their by-products can also serve as protein sources in feed industries, and GTAP-BIO fleshes out these inter-sectoral linkages. The biofuel industries are important sources of crop demand in the US, the European Union, and Brazil and therefore play a role in the telecoupled soybean system.

Land, capital, and labor (both skilled and unskilled) are primary factors of production in crop, livestock and forestry sectors in GTAP-BIO. Importantly for the present study, land use within each of the countries is disaggregated by Agro-Ecological Zone (AEZ). Within each AEZ, three uses of land are distinguished: cropland, pastureland, and forests. Each land use/AEZ combination exhibits a unique terrestrial carbon intensity (Gibbs, Yui and Plevin 2014). Soybeans and other commodities may be used to meet domestic demands within the local system, or they may be exported to other systems (Figure 2.1). The model determines bilateral trade flows endogenously as a function of relative prices and international transport costs. See APPENDIX A for more details on extended GTAP-BIO model structures.

In this paper, we consider the global economy as a fully coupled system. We examine changes in this system and its components, using the GTAP-BIO model to simulate the transition of the global economy from 2004 (base year) to 2011, given the observed changes in the key socio-economic drivers summarized in Table 2.1 and discussed in the next section.

2.2.2 Historical Validation and Decomposition

For discussion purposes, we have grouped the key historical socio-economic drivers into five groups: macroeconomic drivers, soybean productivity, other crop productivity (land intensification and land, labor, capital, and fertilizer productivity), government policies, pasture and forestry changes (pasture and forestry land use changes driven by land, capital, and labor productivity). A complete listing of these drivers is provided in Table 2.1. As shown in this table, we draw on a variety of primary and secondary data sources to compute their dynamic development over the 2004-2011 period. We infer unobserved productivity changes based on observed soybean output and harvested area, asking the model to then predict bilateral soybean trade within the telecoupled system.

A key feature of our analysis involves the use of the so-called "subtotal function" in GEMPACK (Harrison et al. 2000; Harrison and Pearson 1996). This utilizes numerical integration techniques to partition the impacts of various groupings of exogenous telecoupling drivers. In so doing, this novel numerical technique solves the problem faced by modelers seeking to attribute changes in key endogenous variables such as soybean trade to exogenous drivers of change. Normally, one might shock each driver one-at-a-time in order to identify their relative importance. However, this has the obvious drawback that the sum of these individual outcomes will not equal the outcome generated when all drivers are shocked together – due to interactions among the various telecoupling drivers. By employing the method of Harrison et al.(2000), we are able to obtain individual subtotals for each driver which, when summed, are precisely equal to the overall simulation result. This is accomplished by assuming a linear path from pre-simulation to post-simulation values. Under this assumption, the rate of change in any exogenous variable is constant along the path. This decomposition technique will be used throughout this paper in order to evaluate the contributions of the five groups of socio-economic drivers to the changes in the human and natural systems related to the telecoupled soybean complex over the period 2004-2011.

2.2.3 Data and Historical Drivers

The main database used in this study is the 2004 GTAP v7 database (Narayanan and Walmsley 2008) as extended in GTAP-BIO (Taheripour and Tyner 2013). The database is aggregated into 6 regions: US, Brazil, China, European Union (EU27), other South America (S_o_Amer), and Rest of the World (RoW). Further modifications were undertaken to bring the China component more closely into line with China's official input-output table for 2002 (NBSC 2006). Tariff rates for all types of oilseeds, vegetable oil, and oilseed meals are adjusted to match tariffs as reported in TASTE (Horridge and Laborde 2008a). Income elasticities are modified to match Muhammad et al. (2011)'s estimates of consumer demand behavior.

Table 2.1 groups the socio-economic drivers into five categories. Macroeconomic drivers include demand-side factors (population and GDP), as well as supply-side changes (labor force and capital accumulation – as well as accompanying demand for investment goods). Over the 2004-2011 period, China's real GDP grew by more than 100%, investment flows increased by 131%, and capital accumulation rose by 121%. This rapid income growth triggered strong increases in meat consumption, with attendant growth in demand for soybean meal. This derived demand for soybeans was further strengthened by the sharp increase in targeted protein intensity in the Chinese feed industry which was adopting US livestock production technologies over this period (last item in the first grouping in Table 2.1).

Table 2.1 Historical socio-economic drivers in the model

Categories of drivers	Sub-categories of drivers	Explanation	Data sources
Macroeconomic	GDP growth	Driven by labor productivity growth in non-agricultural industries	World Development Indicators, World Bank (2016)
	Population growth	Total population growth	World Development Indicators, World Bank (2016)
	Labor accumulation	Includes skilled and unskilled labor	Global Bilateral Migration Data Base (GMig2 database), (Walmsley et al. 2013)
	Capital accumulation	Capital stock	Penn World Table (PWT), (Feenstra, Inklaar and Marcel 2013)
	Investment growth	Investment flow	World Development Indicators, World Bank (2016)
	Feed industry restructure in China	Protein intensity, feed production expansion	USDA (2016a), Gale (2015)
Soybean Productivity	GM soybean productivity growth	Labor, capital, and fertilizer productivity Hicks neutral productivity adjustments Land productivity to target land use changes	GMO Compass (2015), FAO (2015)
	Non-GM soybean productivity growth	Labor, capital, and fertilizer productivity Hicks neutral productivity adjustments Land productivity to target land use changes	GMO Compass (2015), FAO (2015)
Other Crop Productivity	Non-soybean labor, capital and fertilizer productivity	National average labor, capital, and fertilizer productivity in agricultural and crop production	Fuglie and Rada (2013a)
	Other cropland use productivity (including multiple cropping)	Land productivity improvement and intensification due to multiple cropping	FAO (2015)
Policy	Domestic agricultural policies	Output payments, intermediate input payments, endowment-based payments, all factor payments	Producer Support Estimates (PSEs), OECD (2016a)
	Trade border policies	Bilateral tariff changes	Tariff Analytical and Simulation Tool for Economists (TASTE), Horridge and Laborde (2008a)
	Biofuel policies	Ethanol and biodiesel	Taheripour et al. (2007)
Pasture and Forestry Changes	Land, capital and labor productivity, and other factors in forestry, pasture, and cropland-pasture	Pasture, cropland-pasture, and forestry land use changes driven by pasture, cropland-pasture, and forestry productivity changes and other factors	FAO (2015)

The ability of producers around the world to meet this growing demand depended on the availability of additional land, as well as associated productivity growth (the second and third groupings in Table 2.1). In China, productivity growth for soybeans was constrained by the ban on domestic production using GM-soybeans. In contrast, Brazilian GM soybean harvested area climbed by 60% over this period (GMO Compass 2015; OECD 2015). Pasture and forestry land changes are driven by productivity changes in these sectors as well as other factors, such as environmental regulations (de Waroux et al. 2017).

Government policies (the fourth group in Table 2.1) also played a role in shaping land use and agricultural trade over this period. This included changes in domestic producer support, trade border policies, and biofuel policies. Nowhere was this more evident than in China. With off-farm work opportunities rising, China faced the challenge of maintaining its agricultural outputs (Gale 2013). As a result, China has provided increasing support to its agricultural production (OECD 2016b). However, China's domestic agricultural supports put soybean production at a relative disadvantage, since China increased price supports for wheat, rice, and corn by 45%, 88%, and 54%, respectively, versus an increase for soybeans of just 41% over the 2008-2011 period (Lee et al. 2016). In addition, the nation-wide corn stockpiling policies starting from 2007 onwards incentivized Chinese farmers to turn soybean cropland, grassland, deserts, and marshes into corn cropland (Wu and Zhang 2016). These area shifts were also influenced by China's trade policies. China maintained a low soybean import tariff rate, but a relatively high soybean meal and oil import tariff to encourage soybean imports and protect domestic crushing industries (Brown-Lima, Cooney and Cleary 2009b).

In Brazil, the US and the European Union, one of the most important policy developments over this period involved the sharp increase in biofuel output. These biofuels mainly included corn-based ethanol (US), sugarcane-based ethanol (Brazil), and soybean-based and rapeseed-based biodiesel (EU27) (Table B.3 in APPENDIX B). This provided an important competing demand for crop use – and hence cropland – over this period.

2.3 Results

2.3.1 Soybean Trade

Over the period 2004-2011, China's total soybean imports have increased dramatically. The GTAP-BIO framework employed here permits us to identify the role of each of the five groups of drivers identified in Table 2.1 on this remarkable growth in soybean trade.

Given the changes in productivity and other drivers over this period, our model is able to explain more than 80% of bilateral soybean trade changes among our focal regions: Brazil, China, and the US (See APPENDIX C Figure C.1 for more details). Figure 2.2 presents a decomposition of the model's predicted change in China's soybean imports from Brazil (middle panel) and the US (lower panel), as well as China's total soybean imports (from all regions combined – including from all other regions: upper panel). Each panel decomposes the grand total change in the relevant trade variable (left-most bar) into contributions from the five groups of drivers identified in Table 2.1: macroeconomic forces, soybean productivity, other crop productivity, policies, as well as pasture and forestry changes. By way of illustration, it can be seen from Figure 2.2 that macroeconomic developments were the most important source of growth in total soybean imports into China, while productivity growth from other land uses in crops, pasture, and forestry dampened this growth in imports.

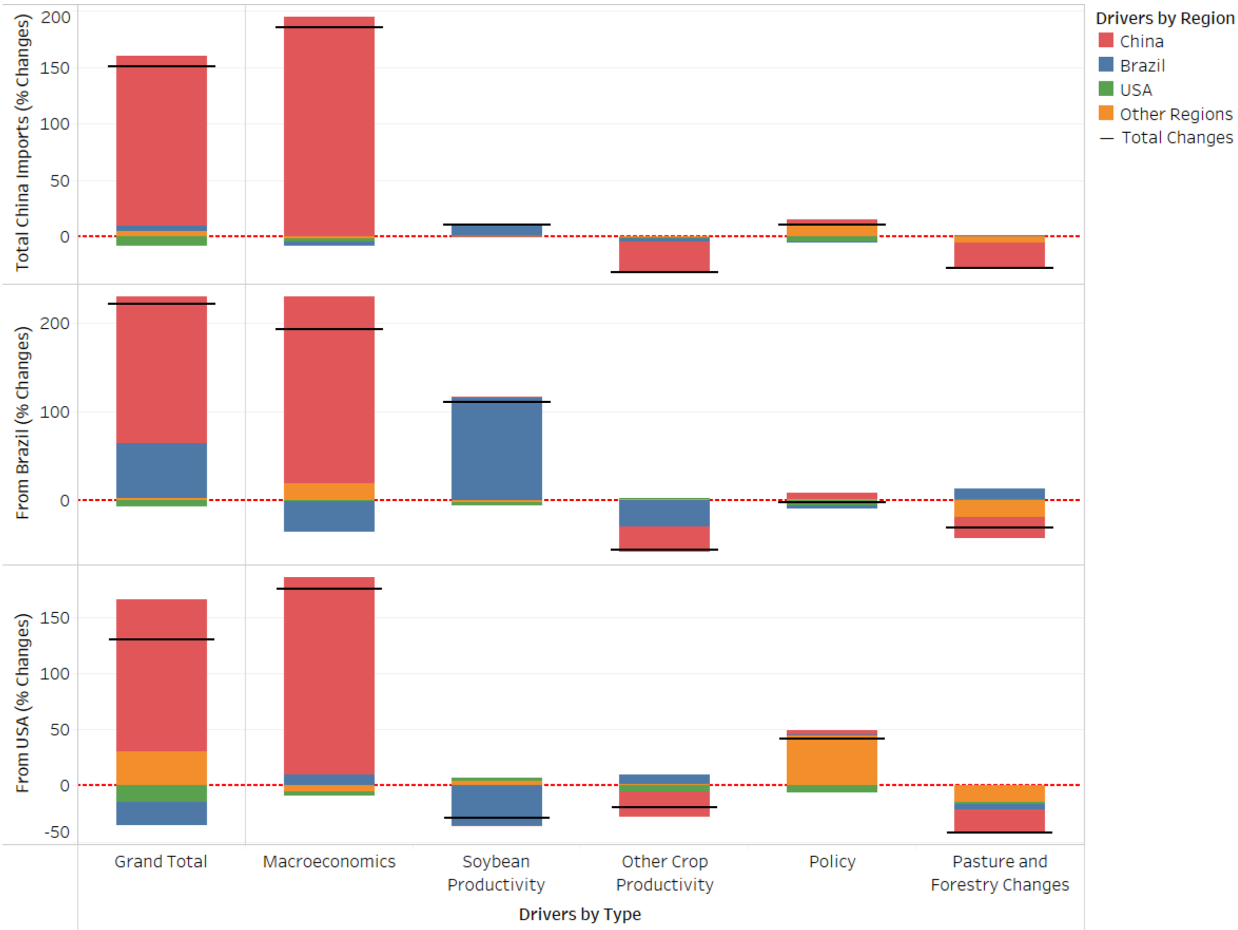

Figure 2.2 China's predicted soybean trade decomposition in percentage changes (2004-2011) Total estimated soybean trade percentage changes are shown as "grand total." This is decomposed into contributions from macroeconomics, soybean productivity, other crop productivity, pasture and forestry changes, and policy. Each group of drivers identifies effects driven by 4 regions: China (red), Brazil (blue), USA (green), and other countries (orange). The black horizontal line on top of the stacked bars indicates each driver's net contributions to the "grand total." From this figure, it is clear that China's macroeconomic development drove up its total soybean imports, including its soybean imports from Brazil and the US. Other agricultural productivity limited China's soybean imports. Pasture and forestry changes in China released land for China's soybean production and thus declined its soybean demands.

Each of the five drivers of telecoupling can be further decomposed into impacts emanating from Brazil, the US, and from China, as well as from other countries. Referring to the “grand total” bar in Figure 2.2 for soybean exports from Brazil to China, we see that socio-economic drivers in China (red segment) and Brazil (blue segment) were the dominant factors driving the 200+% increase in Brazilian exports to China over the 2004-2011 period. On the other hand, US drivers (green segment) and those of other spillover regions (orange segment) slightly dampened the rise in bilateral exports from Brazil to China. Absent drivers from other regions , Brazilian exports to China would have risen by an additional 6%. To aid in further understanding this decomposition, Table C.1 in APPENDIX C provides a numerical representation of Figure 2.2 where the row of “grand total for each driver” sums up each driver type’s total contributions to China’s soybean imports (the net height of each stacked bar in horizontal axis), and the column of “grand total” represents contribution of each region driver (the size of each color in “grand total” bar). China’s total soybean imports are the net height of the grand total bar, corresponding to the top left intersection of “grand total for each driver type” row and “grand total” column.

It is evident from Figure 2.2 that China’s macroeconomic growth dominated China’s growth in soybean imports. Taken alone, productivity improvement from other agricultural products reduced China’s demands for soybeans, while changes in China’s forest and pasture released land for domestic soybean production, thereby dampening soybean imports. China’s land subsidies for soybean production did little to impede its soybean imports, while its corn stock-piling policies accelerated its soybean imports, leaving a positive overall net policy effect on China’s soybean imports. China’s trade and domestic agricultural policies had a stronger impact on China’s soybean imports from the US, but a negligible impact on Brazilian soybean imports (See Figure C.4 in APPENDIX C for more details in policy impact decomposition in China’s soybean imports).

The decomposition in the second panel of Figure 2.2 clearly highlights the importance of Brazilian soybean productivity growth in driving China’s bilateral imports from Brazil (blue segment in the “soybean productivity” bars). Faster than average productivity growth in Brazil contributed to a very significant increase in its soybean exports to China. It also contributed to an erosion of the US soybean market share in China – suggesting a strong spillover effect (negative blue bar under soybean productivity in the third panel). Indeed, while US productivity growth in soybeans contributed slightly positively to bilateral exports to China (green bar), this was more than offset by the effect of Brazilian soybean productivity growth on US exports. In contrast, the dampening effect of US productivity on Brazil's soybean exports to China was much weaker.

2.3.2 Soybean Production

We turn next to the decomposition of drivers behind the expansion in soybean production in each of the key regions, as shown in Figure 2.3. With all other regions in the telecoupled system playing a role in influencing soybean producers' decision-making process, China's influence is weaker in Figure 2.3, compared to the decomposition of China's soybean imports in Figure 2.2. Beginning with China's soybean output (top panel, grand total), we see that China's soybean output shrank significantly over this period. Despite some improvements in domestic productivity and a boost from soybean supporting policies in China (red segment of the policy bar in the first panel of Figure 2.3), overall output fell by 13%. Our decomposition points to the restructuring of China's economy over this period as a key driver. While population and income growth boosted demand for livestock, soybean meal and other soybean products, the overwhelming macroeconomic impact during the 2004-2011 period was that of rapid economic growth and the associated surge in manufacturing exports. As previously noted, the capital stock in China rose by more than 120%, thereby stimulating the expansion of the capital-intensive manufacturing and capital goods sectors. This had the effect of drawing labor and other resources away from the labor-intensive farm sector – an economic phenomenon known as the Rybczynski effect (Rybczynski 1955). Indeed, in 2011, an estimated 250 million rural workers migrated to the cities in search of higher wages (CLB 2016). In addition, the surge in manufacturing exports stimulated imports, which grew by 267% over this period (exports grew even more rapidly, resulting in a growing trade surplus) (FAO 2015). This strong growth in imports hurt import-competing sectors such as soybeans. China's domestic agricultural support, especially its land subsidies in soybean production, effectively offset these negative macroeconomic impacts (See Figure C.5 in APPENDIX C for more details on policy impact decomposition in soybean production). However, the strong competition from Brazil's soybean productivity growth ultimately led to a decline in China's soybean production over this period.

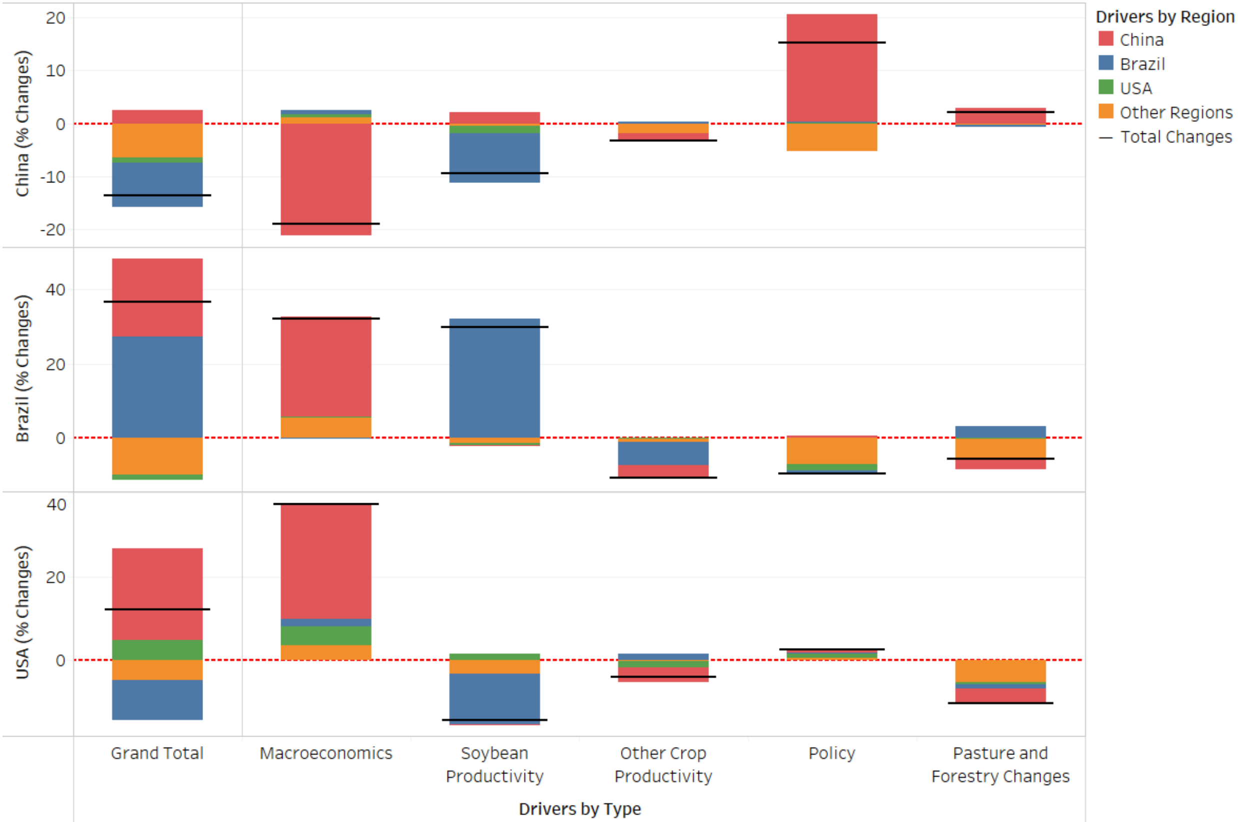

Figure 2.3 Soybean production decompositions in percentage changes (2004-2011)

Total soybean production percentage changes in China, Brazil, and the US are shown as "grand total." It is decomposed into contributions from macroeconomics, soybean productivity, other crop productivity, policy, and pasture and forestry changes. Each group of drivers contains impacts from 4 regions: China (red), Brazil (blue), USA (green), and other countries (orange). The black horizontal bar crossing the stacked bars indicate each driver's *net* contributions to "grand total" changes. As can be seen here, it was the strong soybean productivity growth in Brazil that drives the remarkable soybean output growth in that country over this period.

Over this same period, Brazilian soybean output grew by over 35%. It is hardly surprising that the most important drivers behind this strong expansion emanated from Brazil itself (blue segment of the grand total bar). And of these, the most important was the improvement in Brazil's soybean productivity, largely due to the adoption of GM technology. We find that Brazil's soybean total factor productivity growth itself contributed about 30% to its soybean production growth, mostly through cropland expansion induced by the ensuing cost reductions. We find that soybean yields (production per unit of land) remain little changed over this period. China's macroeconomic growth, while constraining its own soybean production, boosted Brazilian soybean output and served as the second most important driver of Brazilian soybean output. Changes in border policies from other regions sought to protect their own soybean production and served as constraints on the growth in Brazilian soybean production (orange bar in Figure 2.3) . Pasture and forestry land use changes in other regions also had an indirect bearing on Brazil's soybean production. By increasing agricultural production in other crops in Brazil and China, this non-soybean crop productivity growth in these two countries dampened the overall rise in Brazilian soybean output, reducing it by 6% and 3.5%, respectively, relative to it would otherwise have been.

US soybean production grew more slowly over the 2004-2011 period . As with Brazil, this was fueled by economic growth in China. Unlike Brazil, productivity growth was not a net contributor to output expansion, as the positive impact of US productivity (green segment of the soybean productivity bar) was offset by improvements in the rest of the world – particularly Brazil (blue segment). As with Brazil, other crop productivity in China was also a drag on output growth of soybeans of a similar magnitude (3.5%).

Next, we investigate these socio-economic drivers development impacts on land use and terrestrial carbon.

2.3.3 Land Use Changes and Carbon Dioxide Emissions

Agricultural activities impact land use changes, which are responsible for a significant share of the world's CO_2 emissions (Edenhofer et al. 2014). Three types of land cover are modeled in GTAP-BIO: forest land, pasture land (for livestock, including cropland pasture), and active cropland (cropland includes converted cropland pasture currently under cultivation). The distinction between cropland and cropland pasture is an important one, as the latter category, representing pasture land that has been in crops in the recent past, can move readily between the two uses and is expected to have an intermediate level of terrestrial carbon intensity. To calculate land use emissions induced by changes in land cover items we use the emissions factors developed by Gibbs et al. (2014) and used by the California Air Resources Board (2016) for regulatory analysis.

Over the 2004-2011 period, Brazil expanded its active cropland and its agricultural activities induced terrestrial carbon emissions. China and the US, on the other hand, experienced negligible cropland expansion. For this reason, we focus our attention on Brazil where cropland expansion was largely driven by domestic agricultural productivity improvements as well as growing demands in China (Figure 2.4). As a large agricultural exporter to other regions, Brazil is sensitive to macroeconomic growth across the globe. Domestic agricultural productivity led to an expansion in active cropland due to rebound effects (see the soybean and other crop productivity blue bars in Figure 2.4). Agricultural productivity growth in other countries had a very small downward impact on active cropland change in Brazil. Domestic macroeconomic growth in Brazil motivated the non-agricultural development and offset the cropland expansion spurred by China's growing demands (see the negative blue bar for macroeconomics in Figure 2.4). Pasture and forestry changes released land for Brazil's cropland expansion over this period. Finally, more restrictive border policies in other regions dampened cropland expansion in Brazil (orange bar in Policy column of Figure 2.4).

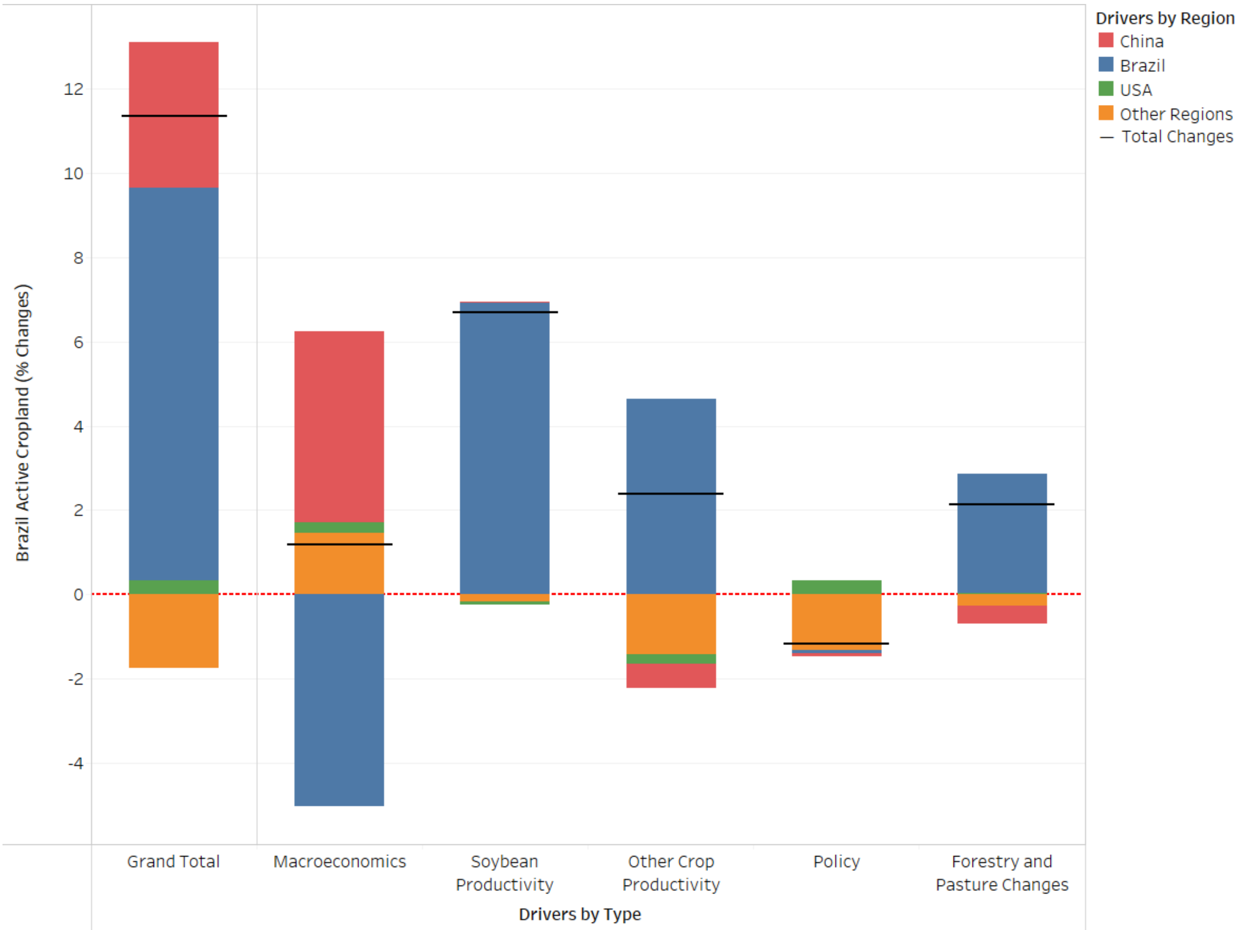

Figure 2.4 Active cropland decomposition, in percentage changes in Brazil (2004-2011) Total active cropland percentage changes in Brazil are shown as "grand total." It is decomposed of contributions from macroeconomics, soybean productivity, other crop productivity, policy, and pasture and forestry changes. Each group of drivers contains impacts from 4 regions: China (red), Brazil (blue), USA (green), and other countries (orange). The black horizontal bar crossing the stacked bars indicate each driver's *net* contributions to "grand total" changes. Brazil's active cropland expansion mainly results from its strong agricultural productivity improvements over this period.

Based on these cropland changes, we can proceed to investigate the implications for total land cover changes and the subsequent terrestrial carbon emissions. These emissions depend critically on the type of land cover that is converted to crops. Cropland pasture is relatively low in terrestrial carbon, while native tropical forests are high. In our framework, terrestrial carbon emissions are the net result of changes in land cover between active cropland, cropland-pasture, permanent pastureland, and forest land. Here, we present total land cover changes and the subsequent terrestrial carbon emissions by land cover type ("total changes" in Figure 2.5), associated with socio-economic drivers identified in this study. China and the US show slight carbon emission reductions over this period, as their macroeconomic forces drive a reallocation of labor and capital to non-agricultural sectors, thereby constraining agricultural activities and releasing land for other uses (in particular, forests). However, globally, active cropland expanded strongly, and largely at the expense of forestry. Brazil follows a similar pattern of cropland expansion and deforestation, where the rebound effects from agricultural productivity improvement were the most important factor.

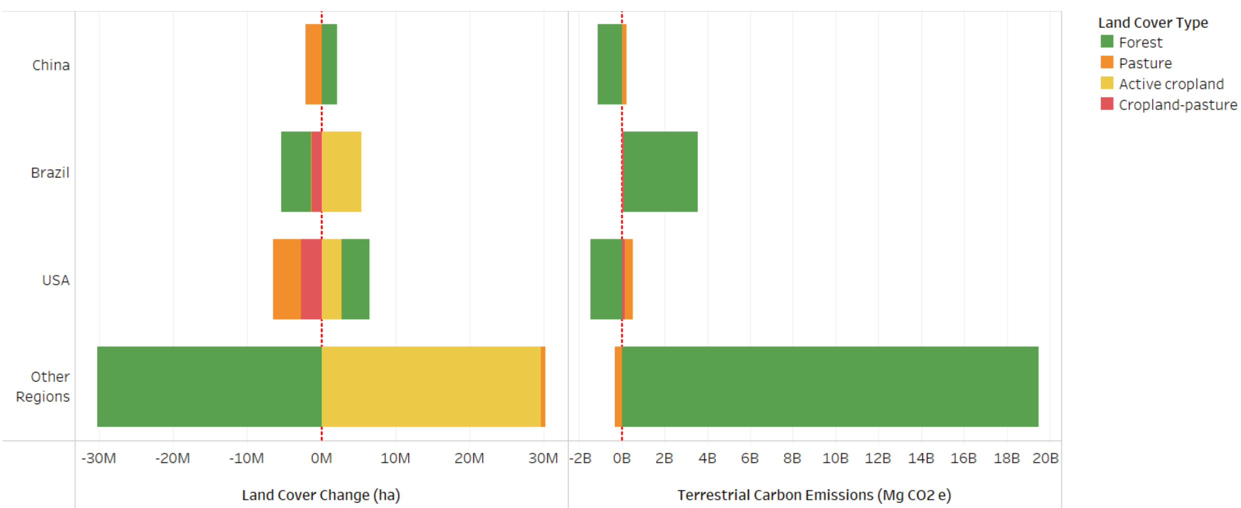

Figure 2.5 Total land cover changes and terrestrial carbon emissions by land cover type and region Land cover changes (left panel) are measured in hectares, and terrestrial carbon emissions (right panel) are evaluated in Mg CO2 e (Megagram CO2 equivalent). The land cover changes and total terrestrial carbon emissions shown here are only due to the socio-economic drivers identified in this research: macroeconomic development, soybean productivity, other crop productivity, policy, and pasture and forestry changes. Both Brazil and the global economy display a pattern of cropland expansion and deforestation. In contrast, China and the US had little cropland expansion, limited terrestrial carbon emission changes, and a carbon saving effect overall.

Brazilian soybean productivity, according to Figure 2.4, increases Brazil's soybean production and results in cropland expansion. It is a subject of some controversy whether Brazilian soybean productivity growth has contributed to land sparing or clearing. Hertel et al. (2014) find that productivity growth results in cropland area expansion when the absolute value of the price elasticity of excess demand facing local producers is greater than 1. Our model has an absolute value for the Brazilian price elasticity of excess demand for soybeans which is roughly equal to 4, therefore indicating cropland expansion is to be expected. The extent of cropland expansion, in our model, derives from three considerations: 1) land intensification, 2) changes in crop mix, 3) changes in the area of cropland-pasture and its productivity. Ignoring these factors, Brazilian productivity alone results in deforestation. However, in the presence of changes in land intensification, crop mix, and changes in cropland-pasture and its productivity, we find that this effect is greatly diluted.

2.4 Discussion

2.4.1 Implications for the Future

While this analysis has focused on the past, it also offers important insights into the future of telecoupling within the global soybean complex. As shown in Figure 2.2, China's rapid economic growth coupled with Brazil's strong total factor productivity improvements in soybeans were key drivers of the changing trade patterns over the 2004-2011 period. As we look to the future, these drivers are changing. China's annual GDP growth fell from 9.5% in 2011 to 6.7% in 2016 (World Bank 2016). In addition, China's feed formulations – now much more protein intensive – have largely caught up with the international industry standards (Gale 2015; USDA 2016a). As a consequence, China's soybean import growth has slowed dramatically, although China is projected continue to remain the world's largest soybean importer for the foreseeable future (USDA 2016b). On the productivity growth side, Brazil has benefitted greatly from the rapid adoption of GM soybeans which grew from 20% to 80% of the total soybean harvested area in that country (GMO Compass 2015). The ensuing cost reductions helped fuel area expansion and contributed to Brazil's overtaking the US as the world's dominant soybean exporter by the end of this period. Future production growth in Brazil will likely depend more on reducing the high domestic transport costs (Friend and da Silva Lima 2011; Haddad et al. 2011) which have hitherto frustrated global market access by producers in the interior of the country where most of the production growth is occurring (e.g., Mato Grosso). Preferences for non-GM and deforestation-free soybeans are leading to a greater reliance on integrated supply chains which allow producers to segregate their premium soybeans, thereby catering to these more profitable markets. This could, in turn, contribute to reduced deforestation (Garrett et al. 2013). Brazilian exports have also benefited from China's ban on domestic GMO production. If that ban were relaxed, it would likely change the relative balance of soybean productivity growth going forward, and there might dampen the demand for imported soybean.

Over time, the most dynamic demand systems in the telecoupled soybean complex are expected to shift away from China. Many soybean exporters are now looking to India, where rapid economic growth combined with continuing population growth create strong soybean consumption potential – although the composition of diets is quite different from China (Masuda and Goldsmith 2009). Additionally, anticipated economic growth in Africa, the Middle East, and other countries in Asia may make cause them to emerging as soybean markets as well as potential suppliers for China (Gasparri et al. 2016; USDA 2016b). How, and where, the global production system responds to this future demand growth will determine the consequences for the natural systems with which agriculture competes for land.

2.4.2 Limitations

Telecoupling impacts are not limited to agriculture-induced land use changes and terrestrial carbon emissions. They also result in biodiversity loss (Chaudhary and Kastner 2016; Lenzen et al. 2012). Food security, poverty, and water scarcity issues are also closely related to agricultural trade and could be explored in future applications of this framework (Hertel and Rosch 2010; Liu et al. 2014; Liu et al. 2013).

A key limitation of this study is the emphasis on market-mediated, economic drivers of telecoupling. However, land use changes and terrestrial carbon emissions are often driven by other factors such as the construction of highways and rail lines (Pfaff and Robalino 2011),changing environmental regulations (de Souza Cunha et al. 2016; de Waroux et al. 2017), indirect effects of agriculture driven by changing land rents (le Polain de Waroux et al. 2018; Richards 2015; Richards et al. 2014), as well as speculative motives for land clearing (Bowman et al. 2012). Additionally, we neglect the role of subnational trade patterns and private sector supply chains as drivers of the pattern and extent of international soybean trade (Godar et al. 2016). Finally, we have largely abstracted from local processes which can influence individual farmers' decision-making and the responses in this telecoupled system (Godar et al. 2015; Meyfroidt et al. 2013).

2.5 Conclusions

This paper introduces a new approach to the analysis of telecoupling, extending prior work based on MRIO models to incorporate market-mediated responses to economic scarcity using the Global Trade Analysis Project (GTAP) framework. It allows for a better understanding of how supply-demand-trade relationships connect different socio-economic drivers of telecoupled national systems, enabling the evaluation of spillover impacts – a topic which has hitherto received less attention in the literature. This framework allows us to explain over 80% of the growth in bilateral soybean trade between Brazil and China over the 2004-2011 period. It also explains most of the growth in trade with the US which was eclipsed by Brazil over this same period. Indeed, Brazil and the US are found to be strong competitors in the soybean market, with Brazilian productivity growth over this period having a greater influence on the US than US productivity had on Brazil.

Our methodology allows us to decompose the main drivers of changes in production, land use and terrestrial carbon over this soybean boom period. We find that macroeconomic growth in China was the dominant factor driver of global soybean production, even as soybean production in China declined over this period. This decline is shown to be due to relatively slow soybean productivity growth, in the absence of GMO adoption, along with surging soybean imports. We also show that, in the absence of land subsidies on soybean cultivation, China's soybean output would have fallen even more. Changes in other agricultural support and border policies did little to impede China's soybean imports. Rapid capital accumulation in China stimulated growth in the manufacturing sector, which drew resources away from agriculture and further stimulated imports.

The strong productivity growth and surging soybean exports from Brazil during this period resulted in large spillover effects on the US, as the main competitor in the global soybean market. It also played an important role in cropland expansion in Brazil. Taken together, these new insights demonstrate the value of this novel telecoupling framework which offers an economy-wide perspective on the evolution of trade, land cover and terrestrial carbon during the soybean boom.

CHAPTER 3. STRUCTURAL GRAVITY MODEL ESTIMATES OF NESTED CONSTANT ELASTICITY OF SUBSTITUTION IMPORT DEMANDS FOR SOYBEANS

3.1 Introduction

The past two decades have seen dramatic changes in the global soybean market. On the supply side, genetically modified (GM) soybeans have largely displaced their non-genetically modified (non-GM) counterparts in world trade. This development is related to the rapid growth of Brazil and other Latin American countries in global export markets. GM soybean penetration in Brazil grew from 20% in 2004 to 93% in 2014 (GMO Compass 2015; Meade et al. 2016). In 2015, 90% of globally traded soybeans were GM soybeans (Lucht 2015).

On the demand side, the growth of Chinese import demand has also shaped the global market in important ways. Since 2000, China's soybean imports have had an average annual growth rate of 15%. In 2014, China's soybean imports were 6 times higher than its soybean production. The nexus of this supply-demand-trade relationship has important implications for welfare, prices, and land use decisions. Much of the quantitative analysis of these relationships has been accomplished with Computable General Equilibrium (CGE) or Computable Partial Equilibrium (CPE) models. Quantitative inferences of CGE and CPE models will largely depend upon parameter estimates that are not yet available in the literature. Most recent GMO studies in the CGE and CPE literature have simply applied exogenously determined productivity improvements to aggregate soybean production to replicate GMO adoption; they have not actually disaggregated these two commodities (Mahaffey, Taheripour and Tyner 2016; Yang 2015; Chatterjee, Pohit and Ghose 2016; Nielsen and Anderson 2000). Those with GM and non-GM crop disaggregation do not report the elasticity parameters used (Hsu, Chang and Wu 2004; Jensen, Jensen and Gylling 2010).Sobolevsky, Moschini, and Lapan (2005) assume both undifferentiated and differentiated preferences for these two varieties of soybeans in their 4-region CPE model. They find that consumers do have differentiated preferences for GM and non-GM varieties: GM soybeans are inferior substitutes for non-GM soybeans.[1] Therefore, the estimation of trade

[1] Sobolevsky, Moschini, and Lapan (2005)'s study is based on 1998-1999 database. Much has changed in the global soybean market since that time.

elasticities for GM and non-GM soybean varieties are needed for future GM and non-GM soybean studies.

In this paper, we seek to inform the literature by undertaking a structural estimation of key import demand parameters related to GM and non-GM soybeans. Unfortunately, current existing bilateral trade data sources do not track GM and non-GM soybean varieties. However, there is little doubt that the export bundles of the GM producing countries contain sizable shares of GM soybeans. We, therefore, proceed by estimating Armington trade elasticities among major GM soybean exporters and among major non-GM soybean exporters, and an elasticity between exports from the two types of countries.[2] We call soybeans exported by major GM and non-GM soybean exporters as GM and non-GM bundles for simplicity in this paper thereafter. Our estimating strategy is as follows. We define a modified gravity model based on an Armington specification; soybeans are distinguished by their country of production. Our modification is that we define a nested Constant-Elasticity-of-Substitution (CES) demand system. Soybeans from the 9 major GM soybean producers (the US, Argentina, Brazil, Canada, Mexico, Paraguay, South Africa, Uruguay, and Bolivia) are also major GM soybean exporters, and they enter into the GMO nest (GMO Compass 2015); all other exporters enter into the non-GMO nest.[3] We apply a standard approach from the gravity literature to estimate substitution elasticities within each nest, and incidentally, the distance elasticity of trade costs. The entire strategy follows Caron, Fally, and Markusen (2014), except that we estimate the substitution elasticity across the GMO and non-GMO nests rather than a non-homothetic demand structure across broad categories of goods. Parameters within each nest are identified in a fixed effect regression that identifies structural parameters in a manner similar to Hummels (2001). We use bootstrapping to estimate the uncertainty of the parameter estimates.

Our results for the parameters within each sub-nest are quite plausible. We find quite high elasticities of substitution among major GM soybean exporters; our central estimate is 29.37. GM soybeans are overwhelmingly used inputs into industrial processes that produce soybean meals and oils, so a high estimated elasticity is plausible (Lucht 2015). Among major non-GM soybean

[2] GM and non-GM soybeans are also produced in different countries with different industrial organizations. GM soybeans are usually grown in North and South America where large-scale farming is predominant, while non-GM soybeans are mainly produced in Asia and Europe with small family farming. Our estimates are also influenced by these differences in industrial organizations.

[3] 7 countries fully ban GMO imports: Algeria, Bhutan, Kyrgyzstan, Madagascar, Peru, Russian Federation, and Venezuela (GMO Compass 2015). There is considerable uncertainty about how to treat trade flows from GM exporters to the 7 countries that ban GM imports. We will undertake robustness checks with different treatments of these trade flows to judge the robustness of our results.

exporters, our estimate of the substation elasticity is somewhat lower; our preferred estimate is 11.7. Non-GM soybeans are typically premium products used for human consumption, and products might be less substitutable because of place-based variation in demands for specific varieties (Brown-Lima et al. 2009a). Another reason for lower elasticities of substitution within non-GM varieties is that the credibility of the non-GM credence varies across countries of origin.

A central contribution of the paper is an estimate of the elasticity of substitution between GM and non-GM soybean bundles.[4] At first glance, one might assume the two varieties of soybeans are close substitutes. However, the very different uses (GM for industrial uses and for feed, non-GM for human consumption) also allow a high degree of market segmentation. After 2004, a premium market for non-GM soybean emerged. In 2015, non-GM soybeans were $1-4/bushel higher than GM soybeans (Preiner 2016). GM soybeans are mainly imported in bulk, while non-GM soybeans are generally purchased by food companies targeted for "premium markets" through contracts (Zheng et al. 2012; Garrett et al. 2013; The Organic & Non-GMO Report 2009). Many countries implemented GM labeling policies to help consumers distinguish products containing these two varieties of soybeans. All these facts suggest less than perfect substitutability between GM and non-GM soybeans. Our central point estimate suggests that there is indeed a high level of segmentation, although the uncertainty around this parameter is large. Our central estimate of elasticity between GM and non-GM soybean nests is 0.4, which suggests that the two varieties of soybeans are poor substitutes in world trade.[5] In order to bolster this claim, we provide supplementary evidence that soybeans from major GM and non-GM sources are often imported jointly.

Section 3.2 will review the past literature on oilseed elasticity estimation, followed by a methodology and a data section. Results and empirical implications will be discussed following the data section. The paper concludes with a summary of contributions.

3.2 Previous Estimates of Soybean Elasticities

Many previous studies have attempted to estimate trade elasticities in order to support CGE analyses, but there are relatively few estimates of trade elasticities for oilseeds or soybeans.

[4] GM and non-GM soybean bundles refer to soybeans exported by major GM and non-GM soybean exporters, respectively.

[5] 95% confidence interval around this estimate ranges widely from 0 to 6.83, substantially lower than elasticities across each soybean variety's sources.

Using cross-sectional import data from 6 countries, Hummels (2001) applies an empirical gravity model and direct measures of trade costs to estimate elasticities of substitution for 57 commodities. Among these estimates is an estimate of the elasticity of substitution for oilseeds of 4.83 at 10% significance level. Hertel et al. (2007) use the same method and datasets and derived a trade elasticity of oilseeds at 4.9, also at 10% significance level.

Hillberry et al. (2005) apply a structural estimation method to GTAP data to estimate trade elasticities in a single CES demand system. These authors minimize differences between national and global import shares.[6] Their estimates for the oilseed sector is 8.92 using GTAP data from 1995.

Broda and Weinstein (2006) estimate trade elasticities for 171 commodities and 73 countries by applying the Feenstra (1994) method to 1994-2003 UN Comtrade data. Their estimates show that 90% of countries have soybean elasticities under 11.60, and the minimum soybean elasticity is 1.37. Soderbery (2015) re-estimate Feenstra (1994) and Broda and Weinstein (2006)'s (F/BW) estimation and improved their methodology by correcting small sample biases with a hybrid estimator. This hybrid estimator combines limited information maximum likelihood (LIML) with a constrained non-linear LIML routine. His re-estimates on the US soybean trade elasticity using F/BW methods is 4.04, and his improved estimator yields a soybean trade elasticity of 1.52. Table 3.1 summarizes all these trade elasticities shown in past literature.

[6] National and global import shares represent the taste parameters in CES function.

Table 3.1 Summary estimation of trade elasticity in past literature

Source	Commodity	Time	Country	Trade Elasticity
GTAP Version 5 (Dimaranan, McDougall and Hertel 2002)	Oilseeds	1997	Global	4.4
Hummels (2001)	Oilseeds	1992	US, New Zealand, Argentina, Brazil, Chile and Paraguay	4.83
Hertel et al. (2007)	Oilseeds	1992	Same with Hummels (2001)	4.9
Hillberry et al. (2005)	Oilseeds	1992	Global	8.92
Broda and Weinstein (2006)	Soybeans	1994-2003	73 Countries (Regional)	1.37 -107.14
Soderbery (2015) F/BW	Soybeans	1993-2007	US	4.04
Soderbery (2015) Hybrid Estimator	Soybeans	1993-2007	US	1.52

The existing literature on trade elasticities mainly focuses on imports of a given commodity (soybeans or oilseeds) from different sources (Hertel et al. 2007; Hummels 2001). These estimates assume a single elasticity of substitution across all origin countries.[7] It has been far less common to estimate a nested CES utility structure and calculate elasticities between two different commodities as well as elasticities of one commodity from different sources.

A two-level nested CES utility function makes econometric estimation and identification more challenging. In this study, we use a structural gravity model to first estimate elasticities of substitution across national varieties of GM and non-GM soybeans bundles, respectively. In a second step, we estimate substitution between CES bundles of the two sets of soybeans. The nested structure is important for analyzing the interaction between rising soybean demands in China and land use decisions in the countries that supply soybeans.

[7] Another group of literature has only focused on a single home-foreign nest of a particular commodity (Alaouze, Marsden and Zeitsch 1977; Reinert and Roland-Holst 1992; Gallaway, McDaniel and Rivera 2003).

3.3 Methodology

The model is primarily based on a single nest CES utility function for GM and non-GM soybean bundles for the elasticity of substitutions among each soybean variety. A nested CES structure is applied for the elasticity of substitutions between GM and non-GM soybean bundles. We follow the Armington assumption that each commodity is differentiated by its origin. We assume further that demanders differentiate soybeans from countries that mainly do and do not primarily export GM soybeans. Major GM soybean exporters are also main GM soybean producers.[8]

We then define a nested CES gravity model over imports of GM and non-GM soybean bundles and structurally estimate the parameters of interest. We estimate substitution elasticities over sources of GM and non-GM soybean bundles respectively using Poisson Pseudo Maximum Likelihood (PPML) regressions with origin- and destination- fixed effects (Hummels 2001). The PPML procedure is standard in the literature with appropriate treatment of zero trade flows and heterogeneity (Silva and Tenreyro 2006). In this study, we extend the standard framework, illustrating a structural method for estimating a parameter that defines substitution between GM and non-GM soybean bundles. We separate trade in soybeans into "GM" and "non-GM" bundles based on country policies toward GM soybeans.[9] We use the standard approach to estimate structural parameters within each CES nest. We then use the first stage estimates to calculate implied CES price indices of GM and non-GM import bundles and apply these estimates in a structural estimator of the elasticity of substitution between GM and non-GM nests. A bootstrapping method is applied to derive the distributions of these three elasticities of interest. All the estimations are implemented in GAMS.

[8] We have defined earlier that soybeans exported by major GM and non-GM soybean exporters are classified GM and non-GM soybean bundles.

[9] This is an imperfect assumption. In reality, many countries produce both varieties of soybeans, export and import both. Existing trade database (e.g. UN Comtrade) does not track trade flows based on variety of soybeans. To simplify our assumption, we assume GM soybean producers export GM soybeans to GM-import friendly countries (e.g. China) as GM trade flows. We presume that non-GM soybean producers all export non-GM soybeans. This is our main assumption. We also propose two alternative assumptions by assuming trade flows from GM soybean exporter to strict non-GM soybean importer as the GMO trade flows and the non-GM trade flows respectively. In the result section, we provide estimates for all three assumptions.

3.3.1 Elasticity among Genetically-Modified and Non-Genetically-Modified Importers

3.3.1.1 Single Nest Constant Elasticity of Substitution and Structural Gravity Model

With the single nest CES framework for each GM/non-GM soybean bundle importer *j* from different origins *i*, we assume that a representative agent in importer *j* maximizes her utility as specified in Equation (3.1), subject to her budget constraints:

$$\max_{q_{ij}} U_j = \left[\sum_i \left(\frac{q_{ij}}{\alpha_i} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{3.1}$$

$$s.t. \ \sum_i q_{ij} p_{ij} \leq E_j$$

where q_{ij} are traded GM/non-GM soybean quantity from origin *i* to destination *j*, and p_{ij} is the corresponding bilateral price. α_i denotes how each origin *i*'s GM/non-GM soybean bundles is preferred by each importer. σ is the elasticity of substitution of each GM/non-GM soybean bundle. The total expenditures on GM/non-GM soybean bundle is denoted by E_j. With price transmission theory, $p_{ij} = p_i \tau_{ij}$, where p_i is GM/non-GM bundle price in origin country *i*, and τ_{ij} is the bilateral trade cost, a function of distance (with distance elasticity) and bilateral tariffs: $\tau_{ij} = (DIST_{ij})^{\rho}(1 + tariff_{ij})$ (Hummels 2001).

The solution to this maximization problem in Equation (3.1) yield the demand system from origin *i* to destination *j*:

$$q_{ij} = \left(\frac{\alpha_i}{P_j} \right)^{1-\sigma} p_{ij}^{-\sigma} E_j \tag{3.2}$$

where P_j is a price index and specified as $P_j = [\sum_i (\alpha_i p_i \tau_{ij})^{1-\sigma}]^{\frac{1}{1-\sigma}}$. Multiplying both sides in Equation (3.2) by p_{ij} yields the function of the bilateral traded value X_{ij}:

$$X_{ij} = \left(\frac{\alpha_i p_i \tau_{ij}}{P_j} \right)^{1-\sigma} E_j \tag{3.3}$$

A log-linearized version of Equation (3.3) yields the estimating equation:

$$\ln X_{ij} = \underbrace{(1-\sigma)\ln\alpha_i + (1-\sigma)\ln p_i}_{\text{Origin Fixed Effects}} \underbrace{-(1-\sigma)\ln P_j + \ln E_j}_{\text{Destination Fixed Effects}} + (1-\sigma)\ln(1+tariff_{ij}) + \rho(1-\sigma)\ln DIST_{ij} + \varepsilon_{ij} \tag{3.4}$$

By treating $(1-\sigma)\ln\alpha_i + (1-\sigma)\ln p_i$ as origin fixed effects γ_i and $-(1-\sigma)\ln P_j + \ln E_j$ as destination fixed effects γ_j, the final log-linearized version of the estimation equation is:

$$\ln X_{ij} = \gamma_i + \gamma_j + (1-\sigma)\ln(1+tariff_{ij}) + \rho(1-\sigma)\ln DIST_{ij} + \varepsilon_{ij} \tag{3.5}$$

In Equation (3.5), variations in tariffs are sufficient to identify the elasticity of substitution σ.[10] Once σ is estimated, an estimate of ρ can be generated as well.

3.3.1.2 Poisson Pseudo Maximum Likelihood Estimator with Fixed Effects

Zero trade flows are always a controversial issue in trade economics. Poisson Pseudo Maximum likelihood (PPML) estimator is proposed by Silva and Tenreyro (2006) by treating each bilateral trade flow as a pseudo "count" variable. PPML is widely used in gravity model estimation due to its many advantages. First, it allows the inclusion of zero trade flows in the sample, and takes information from them. Second, its multiplicative form allows for heteroscedasticity in its error terms. Third, it avoids the underestimation of large trade flows caused by logarithmic transformation (Yotov et al. 2016; Arvis and Shepherd 2013). Finally, it has the adding-up property that gravity fixed effects are identical to their counterparts in structural terms (Fally 2015).

With PPML estimator, Equation (3.5) is written as:

$$X_{ij} = \exp(\gamma_i + \gamma_j + (1-\sigma)\ln(1+tariff_{ij}) + \rho(1-\sigma)\ln DIST_{ij}) + \eta_{ij} \tag{3.6}$$

The coefficient in front of the variable $tariff_{ij}$ is the main parameter we aim to estimate. It allows us to uncover the elasticity of substitution among each type of soybeans. Following Gourieroux, Monfort, and Trognon (1984)'s approach, we maximize the log-likelihood function for the Poisson model:

$$L(b) = constant - \sum_{i=1}^{n}\exp(x_i b) + \sum_{i=1}^{n} y_i x_i b \tag{3.7}$$

[10] High and unchanging tariffs on all soybean exporters is not helpful in determining σ. Only variations in tariffs for different soybean sources can help to identify σ estimation. For example, in 2011, Mexico had no tariffs on the US soybeans and low tariffs on Canadian soybeans at 1%. However, its tariffs on other soybean sources were higher at 5%. This gives rise to useful price variation for the imported products.

with $\exp(x_i b) = \exp(\sum_{i=1}^{K} x_{ik} b_{ik})$. x_{ik} represents the *k*th variable in Equation (3.6) and b_k is the corresponding coefficients. Combining Equation (3.6) and (3.7), the final objective function to maximize is:

$$\begin{aligned} L = & -\sum_i \sum_j \exp\left(\gamma_i + \gamma_j + (1-\sigma)\ln(1+tariff_{ij}) + \rho(1-\sigma)\ln DIST_{ij}\right) \\ & + \sum_i \sum_j X_{ij}\left(\gamma_i + \gamma_j + (1-\sigma)\ln(1+tariff_{ij}) + \rho(1-\sigma)\ln DIST_{ij}\right) \end{aligned} \tag{3.8}$$

Since both origin and destination fixed effects are greater than zero, Equation (3.8) is subject to $\gamma_i > 0$ and $\gamma_j > 0$.

Maximizing Equation (3.8) for either GM or non-GM soybean trade flows yields estimates of the elasticity of substitution among GM/non-GM soybean suppliers σ from $\ln(1 + tariff_{ij})$ coefficient, distance elasticity ρ from $\ln DIST_{ij}$ coefficient, $\alpha_i p_i$ from origin fixed effects γ_i, and price index P_j for either GM or non-GM soybean bundles from destination fixed effects γ_j.

The maximization specified in Equation (3.8) is solved through General Algebraic Modeling System (GAMS) Programming. We apply a PPML package in STATA to verify our estimation results in this first stage. Our GAMS central estimates are the same with the STATA PPML estimates, inferring the credibility of our GAMS estimates.

3.3.2 Estimating the Elasticity of Substitution between Genetically-Modified and Non-Genetically-Modified Soybeans

3.3.2.1 Nested Constant Elasticity of Substitution

To estimate the elasticity of substitution between composite imported GM soybeans and non-GM soybeans θ, we expand a single nest CES structure to a double-nest CES structure by introducing importer's preference weights for GM and non-GM soybeans $\beta^m (m = GM, non-GM)$[11]:

$$\max_{q_{ij}^m (m=GM,non-GM)} U_j = \left\{ \sum_{m=GM,non-GM} \beta^m \left[\sum_i \left(\frac{q_{ij}^m}{\alpha_i^m} \right)^{\frac{\sigma^m - 1}{\sigma^m}} \right]^{\frac{\sigma^m}{\sigma^m - 1}\frac{\theta-1}{\theta}} \right\}^{\frac{\theta}{\theta-1}} \tag{3.9}$$

[11] GM and non-GM denotes GM and non-GM varieties of soybeans, respectively.

$$s.t. \sum_{m=GM,non-GM} \beta^m = 1; \quad \sum_i q_{ij}^m p_{ij}^m \le E_j^m; \quad \sum_{m=GM,non-GM} E_j^m = E_j.$$

Demand equation from origin *i* to destination *j* with respect to soybean variety *m* derived from solving the constrained maximization problem specified in Equation (3.9) is:

$$q_{ij}^m = \left(\beta^m\right)^\theta \left(p_i^m \tau_{ij}^m\right)^{-\sigma^m} \left(\frac{\alpha_i^m}{P_j^m}\right)^{1-\sigma^m} \left(\frac{P_j^m}{P_j}\right)^{1-\theta} E_j \tag{3.10}$$

The bilateral traded value from origin *i* to destination *j* with respect to soybean variety *m* is obtained by multiplying both sides the bilateral price p_{ij}^m:

$$X_{ij}^m = \left(\beta^m\right)^\theta \left(\frac{\alpha_i^m p_i^m \tau_{ij}^m}{P_j^m}\right)^{1-\sigma^m} \left(\frac{P_j^m}{P_j}\right)^{1-\theta} E_j \tag{3.11}$$

P_j^m is GM or non-GM soybean price index in each importer defined in Equation (3.2) and (3.3), and P_j is aggregate soybean price index in each importer defined as $P_j = [\sum_m (\beta^m)^\theta (P_j^m)^{1-\theta}]^{\frac{1}{1-\theta}}$. The final log-linearized model of Equation (3.11) is:

$$\begin{aligned} \ln X_{ij}^m = {} & \theta \ln \beta^m + \left(1-\sigma^m\right)\left(\ln \alpha_i^m + \ln p_i^m + \ln(1+tariff_{ij}) + \rho^m \ln DIST_{ij}\right) + \left(\sigma^m - \theta\right) \ln P_j^m \\ & -\left(1-\theta\right) \ln P_j + \ln E_j + \varepsilon_{ij}^m \end{aligned} \tag{3.12}$$

3.3.2.2 Poisson Pseudo Maximum Likelihood Estimator

At the first stage, the single nest CES structure gives us estimates of σ^m, P_j^m, and $\ln\alpha_i^m + \ln p_i^m$. At the second stage, we apply these estimated parameters and $tariff_{ij}$, $DIST_{ij}$, and E_j from outside data sources to our nested CES structure to get the estimates of θ, β^m, and P_j. We use PPML model derived from Equation (3.12) to estimate these three parameters:

$$\begin{aligned} X_{ij}^m = {} & \exp(\theta \ln \beta^m + \left(1-\sigma^m\right)\left(\ln \alpha_i^m + \ln p_i^m + \ln(1+tariff_{ij}) + \rho^m \ln DIST_{ij}\right) + \left(\sigma^m - \theta\right) \ln P_j^m \\ & -\left(1-\theta\right) \ln P_j + \ln E_j) + \eta_{ij}^m \end{aligned} \tag{3.13}$$

The log-likelihood function based on the model in Equation (3.7) and (3.13) is maximized subject to GM/non-GM soybean preference weight constraints $\sum_{m=GM,non-GM} \beta^m = 1$ and definition constraints on soybean price index P_j ($P_j = [\sum_m (\beta^m)^\theta (P_j^m)^{1-\theta}]^{\frac{1}{1-\theta}}$):

$$
\begin{aligned}
L = & -\sum_i \sum_j \exp(\theta \ln \beta^m + \left(1-\sigma^m\right)\left(\ln \alpha_i^m + \ln p_i^m + \ln(1+tariff_{ij}) + \rho^m \ln DIST_{ij}\right) \\
& \qquad + \left(\sigma^m - \theta\right) \ln P_j^m - \left(1-\theta\right) \ln P_j + \ln E_j) \\
& + \sum_i \sum_j X_{ij} (\theta \ln \beta^m + \left(1-\sigma^m\right)\left(\ln \alpha_i^m + \ln p_i^m + \ln(1+tariff_{ij}) + \rho^m \ln DIST_{ij}\right) \\
& \qquad + \left(\sigma^m - \theta\right) \ln P_j^m - \left(1-\theta\right) \ln P_j + \ln E_j)
\end{aligned}
\tag{3.14}
$$

PPML estimation in Equation distinguishes our estimates with past studies. It contributes to the current literature with estimates on the elasticity of substitution between GM and non-GM soybeans.

3.3.2.3 Heterogeneous Preference Weights for GM and Non-GM soybeans across Countries

Our initial estimates of the substitution assume preference weights for GM and non-GM soybean bundles. It assumes all countries have the same preference weights for GM and non-GM soybean bundles. However, in reality, countries show different expenditures on GM and non-GM soybean bundles. With the estimated elasticity of the two varieties of soybeans θ and composite soybean price index P_j , we apply PPML estimator in Equation (3.14) to obtain GM and non-GM bundle preference weights for each soybean importer. We introduce a new variable δ_j^m to β^m ($\hat{\beta}_j^m = \beta^m + \delta_j^m$) to estimate the heterogeneous differentiation around the common preference weights β^m. It follows the constraints of $\sum_m \delta_j^m = 0$, which ensures $\sum_m \hat{\beta}_j^m = 1$ for each importer j.

3.3.3 Bootstrapping

In order to construct confidence intervals for our estimates, we apply bootstrapping methods with resampled GM and non-GM soybean trade flows (Balistreri and Hillberry 2007; MacKinnon 2006).[12] With replacement, we draw the same number of GM soybean trade flows from original GM soybean trade flows, and the same number of non-GM soybean trade flows from original non-GM soybean trade flows. With each new GM and non-GM soybean sample pairs, we iterate the two estimation procedures 1000 times and obtain 1000 sets of estimates of unknown

[12] Trade flows for GM and non-GM soybean bundles and thereafter.

parameters. With these 1000 sets of estimated parameters, we derive distributions for σ^m, ρ^m, and θ, and thus obtain 95% confidence intervals for each parameter.[13]

3.4 Data and Assumptions

3.4.1 Data Sources

Our structural gravity model requires data on bilateral trade values of soybeans, bilateral soybean tariffs, bilateral geographic distances, and total soybean expenditures. We use data in 2011, the base year for GTAP data version 9. Countries with GM soybean adoption reached high GM technology penetration level in 2011.[14] Bilateral soybean trade values in 2011 are obtained from UN Comtrade (2016) and downloaded from World Integrated Trade Solutions (WITS).[15] Total soybean expenditures for each importer is calculated by summarizing its total soybean imports from bilateral trade data. Bilateral trade data is derived from the program of Tariff Analytical and Simulation Tool for Economist (TASTE), which reads from the MAcMapsHS6 data, produced by ITC-Geneva and CEPII, reconciled with GTAP 9 database (Horridge and Laborde 2008b). Weighted average applied tariffs are used. Bilateral distance data is from GeoDist database of CEPII (Mayer and Zignago 2011).[16] We use FAO (2015) soybean production data to filter exporters that actually produce soybeans in 2011.

3.4.2 Data Processing

UN Comtrade database provides both export and import trade flows by reporters. Here, we mainly focus on import trade flows. In cases where importers did not report their bilateral import flows, we use exporters' reports of their export trade flows. Country names and list are based on tariff data reported by TASTE. Countries that did not produce, did not export, or did not import soybeans at all in 2011 are excluded from the data. After combining trade, tariff, distance data,

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[13] We do not report confidence intervals for β. We later show that β is line with expenditure shares of each soybean variety (Figure E.4). In each bootstrapping sample, β represents an arbitrary resampling distribution for each soybean variety of that sample.

[14] In 2011, over 80% of soybeans produced by GM soybean producers were GM soybeans.

[15] Soybeans are specified under the HS4 code 1201. HS stands for Harmonized Commodity Description and Coding Systems. It is an international nomenclature for the classification products (UN Trade Statistics 2017). 1201 represents "Soya beans; whether or not broken". It includes 120100 (soya beans; whether or not broken), 120110 (Soya beans; seed, whether or not broken), and 120190 (Soya beans; other than seed, whether or not broken).

[16] 225 countries are included in the database. Capital city is used for distance calculation purpose for most countries. 13 out of 225 countries' capital cities are not populated enough. Both capital and economic centers are considered.

and production data, 13,651 trade flows including zero trade flows are reported with 73 exporters and 188 importers.[17]

3.4.3 Trade Flow Assumptions

Unfortunately, international trade data do not support this exercise directly because the trade statistics include both types of soybeans. Fortunately, national policies on the acceptability of GM production allow us a path forward. We assume that the soybeans produced in countries that do not allow GM production are non-GM soybeans. Trade flows from seven large producers of GM soybean are assumed, for our purposes, to be GM soybean bundles. The 7 large producers are Brazil, the US, Argentina, South Africa, Canada, Paraguay, and Uruguay.[18] We treat EU countries as well as China, Japan, and South Korea as non-GM soybean sources due to their traditions of non-GM soybean production and high data quality. Soybean flows originating from these non-GM soybean producers are treated as non-GM soybean trade flows.[19] Seven countries fully ban GMO imports: Algeria, Bhutan, Kyrgyzstan, Madagascar, Peru, Russian Federation, and Venezuela. Except for Bhutan, the other 6 countries actually import soybeans. It is not obvious how we should classify trade flows from GM soybean exporters, such as Brazil and the US, to strict non-GM soybean importers, like the Russian Federation. We thus propose three alternative treatments of the flows to tackle this issue:

Treatment 1 (Preferred): GMO exporters to strict non-GMO importers flow excluded from the sample

Treatment 2 (Robustness-Check): GMO exporters to strict non-GMO importers flow treated as the GMO sample

Treatment 3 (Robustness-Check): GMO exporters to strict non-GMO importers flow treated as the non-GMO sample.

The descriptive statistics with these three treatments are shown in Table 3.2. Treatment 1 is the preferred treatment. Categorizing trade flows from GMO exporter to strict non-GMO

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[17] We do not include domestic consumption (internal trade flows). It means each exporter has 187 importer (the exporter itself is excluded from the importer list).73 *187 = 13651 trade flows.

[18] Mexico and Bolivia are excluded from GM exporters because of their limited soybean exports. Treating these two countries as exporters generates excessive zero trade flows.

[19] GM and non-GM soybeans are also produced in countries with different industrial organizations. GM soybeans are usually grown in North and South America where large-scale farming is predominant, while non-GM soybeans are mainly produced in Asia and Europe with small family farming. Our estimates are influenced by these differences in industrial organizations.

importer as GMO trade flows is unclear. Since they are strict non-GMO importers, it is not fully appropriate to treat these trade flows as GMO trade flows. Due to the possible political corruption of border agents in these countries, it is not fully acceptable to treat these trade flows as non-GMO trade flows either. Instead, we use Treatment 2 and 3 as our alternative assumptions for robustness checks of our main results – the preferred treatment. All 3 treatments have 7 GMO exporters and 17 non-GMO exporters. [20] Treatment 1's 7 GMO exporters exported to 131 GM import-allowed countries, which were all treated as GMO trade flows. Treatment 1's 17 non-GMO exporters exported to 142 countries as non-GMO flows. Treatment 2 and 3 have 42 additional trade flows including GMO exporter to strict non-GM soybean flow. [21] Treatment 2 assumes these 42 additional trade flows are GMO flows, and Treatment 3 treats them as non-GMO flows. All three treatments have about 24% of non-zero trade flows out of which 41-43% are GMO flows. GM soybean flows account for 97-99% of total soybean traded values and quantities in the three treatments. Treatment 2 has 137 GMO importers, and Treatment 3 has 144 importers, compared to Treatment 1. For individual GMO and non-GMO sample in each treatment, importers that did not import from any exporters are excluded.[22]

Considering all exporters and importers in our sample, including GMO-exporter to non-GMO soybean importer trade flows, descriptive statistics for 24 exporters and top 10 importers ranked by their total soybean traded values are shown in Table 3.3 and Table 3.4. GMO soybean exporters are the major soybean exporter in the world. China and the US have the most GMO soybean exporting partners. The US-China partnership has the largest traded soybean flows (Table 3.2). Top 10 soybean importers from those 24 sources are mainly from Asia and Europe. Each importer only imports from a few sources.

Three trade elasticities for each treatment are estimated and presented in next section.

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[20] Non-GMO exporters in our sample include: Austria, Bulgaria, China, Czech Republic, Germany, Spain, France, Greece, Croatia, Hungary, Italy, Japan, Republic of Korea, Poland, Romania, Slovak Republic, and Slovenia.

[21] 7 GMO exporters with 6 strict non-GMO importers yields 42 total number of additional trade flows.

[22] Individual GMO and non-GMO samples for single-nest CES estimation are symmetric. Total sample for nested CES estimation is the combined GMO and non-GMO sample for each treatment. It doesn't necessarily mean "symmetric".

Table 3.2 Descriptive statistics of three treatments of GMO and non-GMO trade flow assumptions (2011)

	Treatment 1			**Treatment 2**			**Treatment 3**		
	Total	**GMO Trade Flows**	**Non-GMO Trade Flows**	**Total**	***GMO Trade Flows***	**Non-GMO Trade Flows**	**Total**	**GMO Trade Flows**	***Non-GMO Trade Flows***
No. of Trade Flows	3307	910	2397	3349	*952*	2397	3349	910	*2439*
No. of Non-Zero Trade Flows	802 (24.3%)	339 (37.3%)	463 (19.3%)	818 (24.4%)	*355 (37.3%)*	463 (19.3%)	818 (24.4%)	339 (37.3%)	*479 (19.6%)*
Max Trade Flow (Million US$)	12,579 (US-China)	12,579 (US-China)	153 (Slovenia - Italy)	12,579 (US-China)	*12,579 (US-China)*	153 (Slovenia - Italy)	12,579 (US-China)	12,579 (US-China)	*280 (Paraguay - Russia)*
Total Traded Values (Million US$)	49,404	48,672	732	50,011	*49,279*	732	50,011	48,672	*1,339*
Min Tariff	0	0	0	0	*0*	0	0	0	*0*
Max Tariff	4.870[23]	4.870	4.87	4.87	*4.87*	4.87	4.87	4.87	*4.87*
Tariff St. Dev.	0.407	0.427	0.399	0.404	*0.418*	0.399	0.404	0.427	*0.395*
Trade Value Weighted Tariff	0.092	0.085	0.521	0.091	*0.085*	0.521	0.091	0.085	*0.293*

Note: Percentage in parenthesis denotes portions of non-zero trade flows out of total trade flows. Treatment 2 treats GMO exporter to strict non-GMO importer trade flows as GMO trade flows, so Treatment 2's non-GMO trade flows are identical to Treatment 1's non-GMO trade flows. In contrast, Treatment 3 treats GMO exporter to strict non-GMO importer trade flows as non-GMO trade flows, so Treatment 3's GMO trade flows are identical to Treatment 1's non-GMO trade flows. Both Treatment 2 and 3 have 42 more observations than Treatment 1, and their total observations are identical. Source: UN Comtrade (2016).

[23] Maximum tariffs are from Republic of Korea (South Korea). Republic of Korea significantly raised their out-of-quota soybean import restrictions for many countries, including China, to protect their local agricultural industry (Choi, Francom and Ting 2012). 4.87 means the tariff rate is 487%.

Table 3.3. Soybean exporter statistics in the sample (2011)

Exporter Names	**Exporter Type**	**Total Export Values (Million US$)**	**No. of Non-Zero Trade Flows**
United States	GMO	20,286.518	93
Brazil	GMO	17,756.468	59
Argentina	GMO	5,594.526	54
Paraguay	GMO	2,815.401	36
Canada	GMO	1,749.062	71
Uruguay	GMO	1,049.034	18
China	Non-GMO	203.407	114
Slovenia	Non-GMO	153.744	8
Italy	Non-GMO	106.366	37
Germany	Non-GMO	65.571	46
Romania	Non-GMO	43.647	16
Austria	Non-GMO	39.189	38
France	Non-GMO	38.920	46
South Africa	GMO	28.025	24
Croatia	Non-GMO	27.845	11
Hungary	Non-GMO	24.740	13
Slovak Republic	Non-GMO	12.980	11
Spain	Non-GMO	6.891	21
Poland	Non-GMO	2.251	17
Czech Republic	Non-GMO	2.250	12
Bulgaria	Non-GMO	1.767	7
Japan	Non-GMO	1.052	33
Greece	Non-GMO	0.879	5
Korea, Rep.	Non-GMO	0.472	28

Note: All trade flows that appeared in the three treatments in our sample is presented here. It includes GMO exporters to strict non-GMO exporters trade flows. The Exporters are ranked based on its total export values, which is derived by summing all non-zero trade flows in our sample. Source: Bilateral soybean trade flows in 2011 from UN Comtrade (2016).

Table 3.4. Top ten soybean importer statistics in the sample (2011)

Importer Names	Total Import Values (Million US$)	GMO Importer?	GMO/Non-GMO Import Values (Million US$)	No. of Non-Zero Trade Flows
China	29,725	GMO	29,724.786	5
		Non-GMO	0.072	2
Germany	1,974	GMO	1,921.408	7
		Non-GMO	53.009	12
Japan	1,812	GMO	1,768.102	6
		Non-GMO	44.329	2
Spain	1,795	GMO	1,765.910	5
		Non-GMO	29.008	7
Netherlands	1,778	GMO	1,728.706	7
		Non-GMO	49.658	10
Mexico	1,762	GMO	1,762.055	3
		Non-GMO	0.028	1
Indonesia	1,130	GMO	1,128.466	6
		Non-GMO	1.659	1
Thailand	1,119	GMO	1,118.397	5
		Non-GMO	0.383	2
Egypt, Arab Rep.	862	GMO	862.142	4
		Non-GMO	0.031	1
Korea, Rep.	722	GMO	644.464	7
		Non-GMO	77.825	3

Note: Top ten soybean importers that import from the 24 exporters in our sample are selected. All importers are ranked based on their total soybean import values. Each importer's importing flows are divided into GMO, and non-GM trade flows based on our assumption. Source: Bilateral soybean trade flows in 2011 from UN Comtrade (2016).

3.5 Results and Discussions

In this section, we first present our trade elasticity estimates in our preferred treatment (Treatment 1). Trade elasticity estimates for our alternative treatments (Treatment 2 and 3) are presented next for robustness checks. Our main results for both single nest CES and nested CES are solved through GAMS. Two σ estimates (GM and non-GM soybeans) from the single nest CES demand structure are verified by STATA PPML package. We also find a negative non-linear relationship between trade preference weights for GM soybeans (β^{GM}) and elasticity between imported GM and non-GM soybeans (θ).

3.5.1 Trade Elasticities for GM and Non-GM Soybeans

Our estimation follows a two-step procedure. In our first procedure, two substitution elasticities: the Armington elasticities among imported GM or non-GM soybeans ($\sigma^{m}(m = GM, non-GM)$), as well as distance elasticities for GM or non-GM soybeans ($\rho^{m}(m = GM, non-GM)$). In the second step, nested CES estimation, we estimate the elasticity of substitution between imported GM and non-GM soybean bundles. Table 3.5 summarizes the seven parameters estimated from our GAMS model. Ranges shown in parentheses are 95% confidence interval of each estimate obtained from our bootstrapping procedure. Our estimate for GM soybeans are as high as 29.4, indicating that soybean bundles from major GM soybean exporters (GM soybean bundles) are treated as nearly homogeneous products. Soybeans bundles from major non-GM soybean exporters (non-GM soybean bundles) have a smaller estimated substitution elasticity of 11.7. Our bootstrapping methods allows us to derive a distribution for each σ estimates (please see Treatment 1 in Figure E.1 in APPENDIX E). Within our expectation, our central estimate summarized in Table 3.5 are at the center of their corresponding distributions. PPML estimates by STATA also yield the same trade elasticity estimates ("Implied σ" in Table 3.6) as those estimated by GAMS. The elasticity estimation for GM soybean bundles are at 10% significant level, and the elasticity for non-GM soybean bundles are at 5% significant level.

The corresponding distance elasticity estimated simultaneously with two trade elasticities are 0.039 for GM soybean bundles and 0.201 for non-GM soybean bundles. The GAMS estimates also match with the STATA estimates. Our estimates indicate that GM soybean bundles have relatively low distance elasticity. It implies that distance matters less in GM bundle trade. Most GM bundle trade occurs between the US or Brazil and China, with large quantities. Massive volume trading occurs despite long distances. Distance in non-GM bundle trade, in contrast, play an important role in influencing trade activities. This is mainly because 70% non-GM bundle trade values occur within Europe and Asia continent in our preferred treatment. Non-GM soybean bundles are more likely to happen in shorter distances.

We apply PPML estimation in GAMS to solve for nested CES structure, which cannot be achieved by STATA. In this second procedure, we estimate the elasticity between GM and non-

GM sub-nest (θ). Common preference weights for GM and non-GM soybean bundles ($\beta^m(m = GM, non - GM)$ by importers are also derived simultaneously. Table 3.5 present the estimates of these three parameters. A 95% confidence interval for θ are obtained from bootstrapping. A low central estimate θ at 0.4 implies that GM and non-GM soybean bundles are distinct varieties. Two varieties of soybean bundles have two distinct markets and supply chains: GM soybean bundles are imported in bulk, processed by crushing industries, served as protein sources for animal feeds; non-GM soybeans are generally purchased by food companies targeted for "premium markets" through contracts (Zheng et al. 2012; Garrett et al. 2013; The Organic & Non-GMO Report 2009). Changes in GM soybean prices are more likely to trigger substitutions among GM soybean bundles. Companies and consumers with strong preference weights for non-GM soybeans will be less likely to switch their sources due to price changes. Figure E.2 in appendices plot GM soybean expenditure shares out of total soybean expenditure shares with respect to relative GM/non-GM soybean price indices. It tells us that when GM soybean price increases, there is a weak substitution between GM and non-GM soybean bundles. But in general, countries still mainly consume GM soybean bundles. Elasticities less than 1 can be understood in the following way: many EU and East Asian countries, whose non-GM soybeans supply are not self-sufficient, are usually both large GM and non-GM soybean importers. Germany, Spain, France, Italy, Japan, South Korea, Malaysia, and the Netherlands are prominent examples. A distribution of θ estimates is presented in Figure E.3 APPENDIX E.

A close-to-1 preference weights for GM soybean bundles ($\beta^{GM} \approx 1$) suggest importers' strong preferences for soybeans from major GM soybean exporters in the global trade market. By allowing each importer has its own preference weights, we can derive their homogenous preference weights (Figure E.3 APPENDIX E). These preference weights are consistent with their expenditures shares on GM soybeans out of total soybean expenditures (Figure E.4 APPENDIX E).

Although our central estimate of θ is low with a high preference weight for GM soybeans (β^{GM}), we later find θ can vary from 0 to 6.83 based on its GM soybean expenditure shares (a proxy for β^{GM}). A θ of 6.83 is still lower than the substitution among each soybean variety. It further implies the differentiation of GM and non-GM soybeans. A detailed investigation on the θ-β relationship is discussed in Section 3.5.3.

Table 3.5. GAMS estimation of three trade elasticities, distance elasticities, and weight preferences for GM/non-GM soybeans

Treatment 1	**Single Nest CES**		**Nested CES**	
	$\boldsymbol{\sigma^{GM}}$	$\boldsymbol{\sigma^{Non-GM}}$	$\boldsymbol{\theta}$	
Elasticity Estimation	29.37	11.66	0.40	
	(2.74,55.82)	(-1.82, 23.98)	(0, 6.83)	
	$\boldsymbol{\rho^{GM}}$	$\boldsymbol{\rho^{Non-GM}}$	$\boldsymbol{\beta^{GM}}$	$\boldsymbol{\beta^{Non-GM}}$
Distance Elasticity and Preference Weights	0.039	0.201	9.991E-1	8.940E-5
	(0.012, 0.209)	(-0.739, 0.489)	--	--

Note: Numbers in parentheses represent each estimate's 95% confidence interval derived from 2.5~97.5 percentile of each estimate distribution using bootstrapping methods. It may vary slightly with different random seeds. Trade flows are randomly selected with replacements for θ and β distribution.

Table 3.6. STATA PPML estimation of the preferred treatment

	Treatment 1	
	GMO	**Non-GMO**
$\ln(1 + tariff_{ij})$	-28.37*	-10.66**
	(16.97)	(5.36)
$\ln DIST_{ij}$	-1.11*	-2.14***
	(0.59)	(0.25)
Intercept	65.51*	33.22***
	(30.49)	(9.83)
Implied σ	29.37	11.66
Implied ρ	0.039	0.201
R^2	0.97	0.87
No. of Observations	910	2397

Note: Exporter and importer fixed effects for each region are included in regression but not reported here. Implied σ and ρ are derived from coefficients for $\ln(1 + tariff_{ij})$ and $\ln DIST_{ij}$, respectively. Numbers in parentheses are robust standard errors. * represent significance at 0.9 confidence level; ** represent significance at 0.95 confidence level; *** represent significance at 0.99 confidence level.

The converging pattern that GM soybean producer prices displayed in 2011 also points towards a high degree of homogeneity among the GM soybeans. In contrast, non-GM soybean producers in our sample exhibit a more diverging pattern especially in Asian countries with traditional soybean diets (Table 3.7). It is consistent with the fact that GM soybean commodity market prices are primarily determined at the Chicago Board of Trade (CBOT) (CommodityBasis 2017). EU mainly trade their non-GM soybeans internally among EU countries. China, as one of the largest non-GM exporters, primarily exported soybeans to its Asian neighbors, EU countries, the US, and Canada.[24] South Korea, instead, the much smaller scale of soybeans to less developed countries, such as Algeria, Bangladesh, and Mongolia, besides its close Asian neighbors (China and Hong Kong (China)), the US and Canada. In contrast, consumers of Japanese soybeans are all in well-developed countries, such as Australia, Canada, UK, Italy, Singapore, Hong Kong (China), the US, Germany, New Zealand, etc. This evidence suggests that despite long distances, different groups of non-GM soybean consumers treat non-GM soybeans from different origins differently. Japan, as an accredited non-GM soybean exporter, its non-GM soybeans are welcome in more developed countries. Non-GM soybeans from China and South Korea are more preferred in less developed markets. Even though non-GM soybeans are still well substitutable, they are also differentiated based on its origins.

[24] Top 10 China's importers are South Korea, Japan, USA, North Korea, Malaysia, Canada, Belgium, Vietnam, Germany, Hong Kong (China).

Table 3.7. Producer prices (US$/Metric Ton) of soybeans in GM and non-GM soybean exporting countries (2011)

	Countries	**Prices (US$/Metric Ton)**
GMO Exporting Countries	Argentina	309
	Brazil	425
	Canada	447
	Paraguay	413
	South Africa	437
	Uruguay	484
	USA	459
Non-GMO Exporting Countries	China	803
	Japan	1,602
	South Korea	3,155
	Austria	481
	Bulgaria	438
	Croatia	456
	France	505
	Germany	534
	Greece	632
	Hungary	477
	Italy	378
	Latvia	514
	Poland	534
	Romania	426
	Slovakia	472
	Spain	467

Note: China, Japan, and South Korea had high producer prices due to their relatively high soybean production cost and limited domestic supply. South Korea also significantly raised their out-of-quota soybean import restrictions for many countries including China to protect their local agricultural industry (Choi, Francom and Ting 2012). Source: FAO (2015)

We also run a single nest PPML regression for aggregate soybeans and find that the elasticity for soybean composite is about 12 and insignificant. The single nest structure can be understood as restricting these three elasticities of interest equivalent to each other and imposing the same distance elasticities of two soybean bundles. Our structure would allow formal testing of the single nest restrictions on our more flexible model. A likelihood ratio test is one method that could be used to accomplish this test.

3.5.2 Robustness Analyses for GM and Non-GM Soybean Trade Flow Assumption

To check the robustness of our main results, we categorize trade flows from GMO exports to strict non-GMO importers as the GMO sample (Treatment 2) and the non-GMO sample (Treatment 3) and re-estimate the three trade elasticities, distance elasticities and weight preferences in Table 3.5. Table 3.8 summarizes these estimates of these two alternative treatments. Treatment 2 only changes the GMO sample, so its non-GMO estimates still remain the same. Similarly, Treatment 3 only changes the non-GMO sample, so its GMO estimates stay constant. Due to the resampling in bootstrapping, the 95% confidence interval for non-GMO estimates in Treatment 2 and the 95% confidence interval for GMO estimates in Treatment 3 in Table 3.8 are slightly different from those estimated for our main results in Table 3.5. STATA estimates for σs and ρs of these two alternative treatments in Table 3.9 again verify the correctness of estimates derived from GAMS. Taking trade flows from GMO exporter to strict non-GMO exporters as the GMO trade sample (Treatment 2) significantly lowers its σ^{GM} estimate to from 29.4 to 14.1. The estimate is insignificant. Taking trade flows from GMO exporters to strict non-GMO exporters as the non-GMO trade sample (Treatment 3) also significantly declines its σ^{non-GM} estimate to a negative value (-5.49). This strong distortion comes from soybean imports of Venezuela, which import a large volume of soybeans from US, Argentina, and Brazil but with high tariff rates[25]. The distribution for each σ are presented in Figure E.1 APPENDIX E .

By categorizing trade flows from GMO exporter to strict non-GMO exporter as the GMO trade sample (Treatment 2), each importer spends more on GM soybeans. They thus assign more preference weights to GMO soybeans. The elasticity between GM and non-GM soybeans is even lower at 0.14. Treating trade flows from GMO exporter to strict non-GMO exporter as the non-GMO trade sample (Treatment 3) means that each importer assigns more preference weights to non-GM soybeans. In this case, the elasticity between GM and non-GM soybeans increases to 2.0. Despite the variation of θ in our central estimates for three treatments, the 95% confidence intervals of θ in three treatments are close. This confirms the robustness of our θ estimates. See a distribution for θ in Figure E.3 APPENDIX E.

[25] Venezuela imports $25.5 million of soybeans from the US but its tariffs for the US soybeans are as high as 40%. Its tariffs for Argentina and Brazil are 1.4%.

Table 3.8. GAMS estimation of alternative treatments

Treatment 2	**Single Nest CES**		**Nested CES**	
Elasticity Estimation	$\boldsymbol{\sigma^{GM}}$	$\boldsymbol{\sigma^{Non-GM}}$	$\boldsymbol{\theta}$	
	14.14	11.66	0.14	
	(1.43,41.79)	(-1.66, 23.35)	(0, 5.24)	
Distance Elasticity and Preference Weights	$\boldsymbol{\rho^{GM}}$	$\boldsymbol{\rho^{Non-GM}}$	$\boldsymbol{\beta^{GM}}$	$\boldsymbol{\beta^{Non-GM}}$
	0.088	0.201	1.000	3.068E-13
	(0.004, 0.761)	(-0.678, 0.530)	--	--
Treatment 3	**Single Nest CES**		**Nested CES**	
Elasticity Estimation	$\boldsymbol{\sigma^{GM}}$	$\boldsymbol{\sigma^{Non-GM}}$	$\boldsymbol{\theta}$	
	29.37	-5.49	1.99	
	(0.78,54.69)	(-3.52, 11.72)	(0, 5.55)	
Distance Elasticity and Preference Weights	$\boldsymbol{\rho^{GM}}$	$\boldsymbol{\rho^{Non-GM}}$	$\boldsymbol{\beta^{GM}}$	$\boldsymbol{\beta^{Non-GM}}$
	0.039	-0.310	0.640	0.360
	(0.006, 0.250)	(-0.79, 0.563)	--	--

Note: Numbers in parentheses represent each estimate's 95% confidence interval derived from 2.5~97.5 percentile of each estimate distribution using bootstrapping methods. It may vary slightly with different random seeds. Treatment 2's non-GM estimates (σ and ρ) and Treatment 3's GM estimates (σ and ρ) coincide with the main results in Table 3.5. Their confidence intervals are slightly different from main results due to resampling. Trade flows are randomly selected with replacements for θ and β distribution.

Table 3.9. STATA PPML estimation of alternative treatments

	Treatment 2		Treatment 3	
	GMO	**Non-GMO**	**GMO**	***Non-GMO***
$\ln(1+tariff_{ij})$	*-13.14*	-10.66**	-28.37*	*6.49****
	(14.68)	(5.36)	(16.97)	*(2.48)*
$\ln DIST_{ij}$	*-1.16***	-2.14***	-1.11*	*-2.01****
	(0.58)	(0.25)	(0.59)	*(0.24)*
Intercept	*38.94*	33.22***	65.51*	*12.01***
	(26.29)	(9.83)	(30.49)	*(4.80)*
Implied σ	*14.14*	11.66	29.37	*-5.49*
Implied ρ	*0.088*	0.201	0.039	*-0.310*
R^2	*0.97*	0.87	0.97	*0.94*
No. of Observations	*952*	2397	910	*2433*[26]

Note: Exporter and importer fixed effects for each region are included in regression but not reported here. Numbers in parentheses are robust standard errors. * represent significance at 0.9 confidence level; ** represent significance at 0.95 confidence level; *** represent significance at 0.99 confidence level. Treatment 2's non-GMO estimates (σ and ρ) and Treatment 3's GMO estimates (σ and ρ) coincide with the main results in Table 3.6.

Summarizing the estimates of elasticity between GM and non-GM soybeans (θ) and importers' common preference weights to GM soybeans (β^{GM}), we find that a higher β^{GM} is associated with a lower θ. What does their relationship look like? We explore the relationships between β^{GM} and θ for three treatments in next section.

[26] 6 observations are omitted due to collinearity of due to Argentina exporter fixed effects and South Korea importer fixed effects.

3.5.3 Relationships between Preference Weights and Substitutions between GM and Non-GM Soybeans

To better understand the relationships between "preference weights" and "substitutions," we plot "preference weights for GM soybean bundles" (β^{GM}) versus "elasticity of substitution between imported GM and non-GM soybean bundles" (θ) for each treatment (Figure 3.1).

All three graphs in Figure 3.1 show a similar and intuitive pattern that the weaker the estimated preference for GM soybeans, the stronger is the estimated substitution between GM and non-GM soybean. This pattern also follows a clear negative non-linear relationship. It means that our θ estimate is primarily dependent on a country's relative preferences for GM and non-GM soybean bundles. Stacking three graphs of three treatments (Figure 3.2) shows us that the three treatments' β-θ relationships coincide with each other very well. It implies this β-θ relationship can be generalized to all GMO and non-GMO assumptions. Knowing the expenditure shares on GM soybean bundles (a proxy for β^{GM})[27] can generally tell us the approximate GM and non-GM substitutions without detailed calculations.

GM soybeans predominate historical observations in our sample, implying a low elasticity between GM and non-GM soybeans. In our main results (Treatment 1), 54% of bootstrapped samples have a θ estimation smaller than or equal to 1; 18% of θ estimates range from 1 to 2; another 23% are between 2 and 6, and only 5% of θ estimates are higher than 6. The most likely largest θ estimate is around 8-9.

Low substitutability between GM and non-GM soybean bundles suggests the inappropriateness of using the single nest estimates for elasticities of mixed GM and non-GM soybean bundles. Past literature obtains low elasticities for oilseeds/soybeans. The highest elasticity estimate is 8.92 estimated by Hillberry et al.'s (2005) for imported oilseeds substitution based on GTAP 4 database. This estimate is still much lower than either the GM or the non-GM Armington elasticities estimated here. It also indirectly reflects low substitutability between GM and non-GM soybean bundles.

[27] Figure E.4 shows preference weights for GM soybeans approximately equal expenditures on GM soybeans.

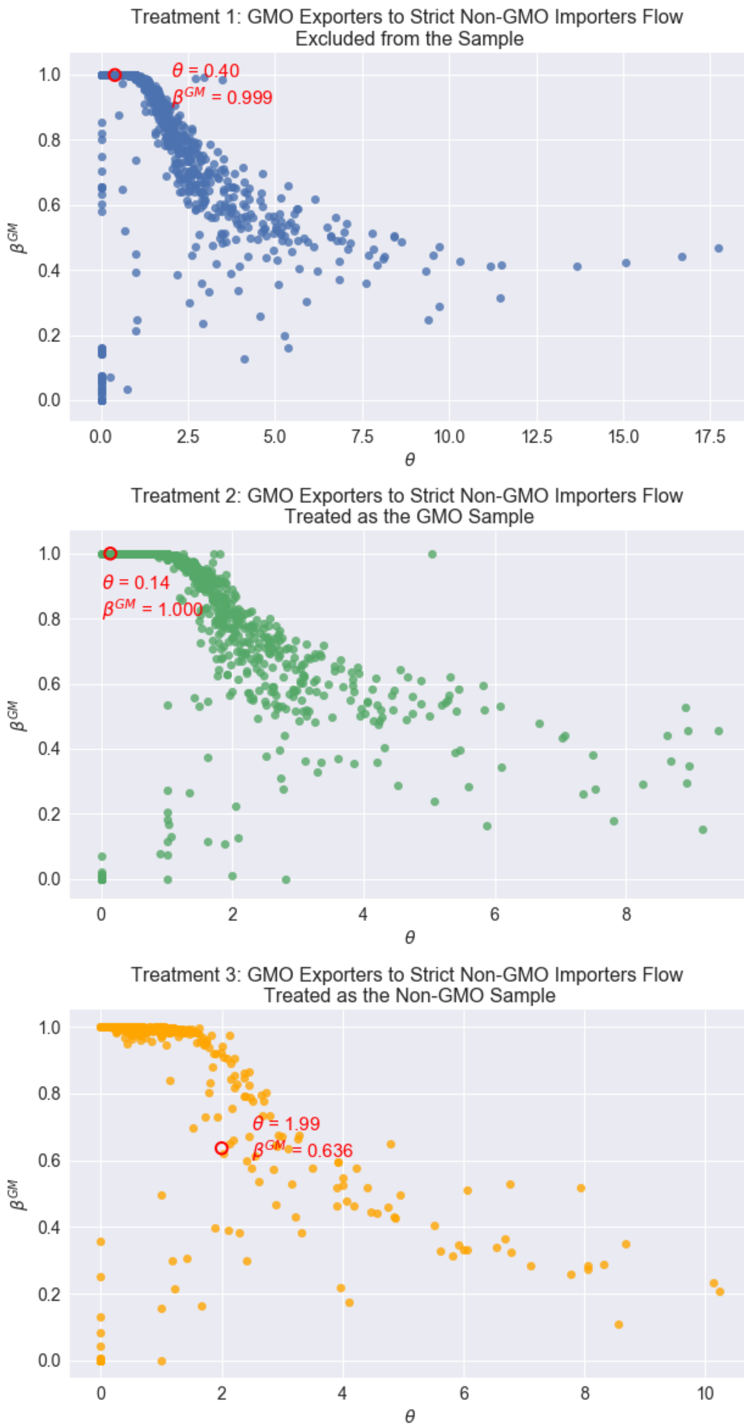

Figure 3.1. Relationships between "preference weights for GM soybean bundles" and "elasticity of substitution between imported GM and non-GM soybean bundles" of the three treatments.

The center estimates are labeled in red.

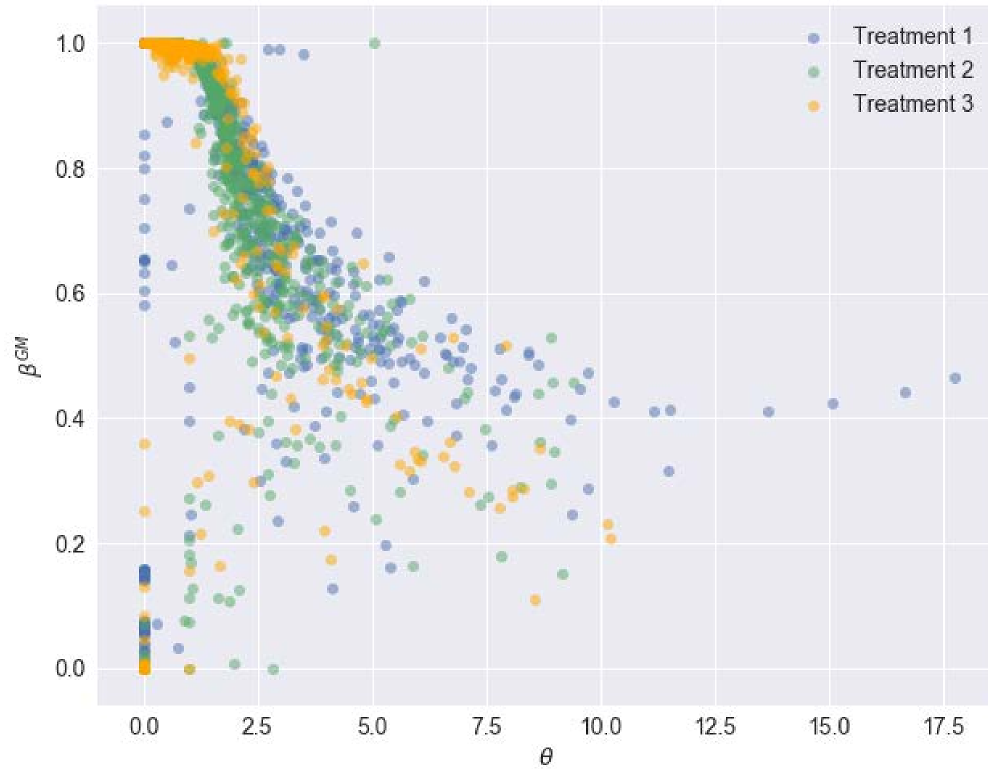

Figure 3.2. Stacked relationships between "preference weights for GM soybean bundles" and "elasticity of substitution between imported GM and non-GM soybeans bundles"

It stacks three graphs in Figure 3.1.

3.5.4 Implications and Discussions

Trade elasticities are essential for supply-demand analysis. An importer's preferences on GM soybeans from GM soybean suppliers, preferences on non-GM soybeans from non-GM soybean suppliers, and their preferences between GM and non-GM soybeans, would send signals to supply countries on their soybean production decisions and land use changes. High GM soybean substitutability indicates that land use changes in GM soybean exporters will most directly affect other producers of GM soybeans. Lower non-GM soybean substitutability implies a traditional pattern that countries tend to import non-GM soybeans from certain countries but can still be impacted by relative changes in non-GM supply prices. A low GM-non-GM soybean elasticity suggests a low substitution from a demand side and also low interactions among GM-non-GM suppliers. An emerging soybean supplier's land use changes will be largely determined by the variety of soybeans they will supply and the competitiveness of their soybeans.

Demand preferences for future GM and non-GM soybeans are subject to changes. On the demand side, stricter GMO labeling policies may be implemented in more countries. On the supply side, with increasing cost in GM soybean seeds and its increased resistance to weeds, farmers are less profitable in producing GM soybeans and may earn more from non-GM premium markets. Our estimates initiate the discussion of future substantiality-driven soybean supply-demand-trade interactions.

3.5.5 Limitations

The major constraint of this paper is the lack of availability of trade flows and tariffs for different soybean varieties. Each trade partnership is not limited to one variety of soybeans, and it may involve both GM and non-GM soybean trade. For example, China imports both GM and non-GM soybeans from the US. Unfortunately, there is no existing valid source to distinguish GM and non-GM varieties for each trade partnership. Additionally, trade tariffs based on soybean varieties is unattainable either. Better soybean elasticity estimates will be derived with the availability of reliable GM and non-GM soybean trade data sources in future.

3.6 Conclusions

This paper innovates structural elasticity estimation of two traded commodities – GM and non-GM soybeans. It relies on nested CES import demand system with an Armington-based modified gravity model. It allows for the estimation of three key trade elasticities: 1) the elasticity among GM soybean imports; 2) elasticity among non-GM soybean imports; 3) elasticity between GM and non-GM soybean imports. It follows two estimation steps: the first step involves the elasticity estimation for each soybean variety based on their corresponding single nest; the second step uses the price indices, elasticity estimates, and distance elasticities from the first step to get an estimate of nested elasticity and variety-preference weight parameters at the same time. Our estimate shows a high GM soybean substitution (29.37), implying its global homogeneous attribute while traded. Importers respond to GM soybeans primarily based on price signals. A lower non-GM soybean substitution (11.66) indicates specific preferences on soybean sources – soybean quality matters too. A low substitution between two varieties of soybeans at 0.4 implies that they are distinct products with segmented markets. Additionally, large non-GM soybean importers are usually large GM soybean importers. We also observe a negative non-linear relationship between "preference weights for GM soybeans" and "elasticity between GM and non-GM soybeans." This relationship enables direct estimates for "elasticity between GM and non-GM soybeans" with known GM soybean expenditure shares – a proxy for "preference weights for GM soybeans."

Estimation of these three parameters allows for the possibility to disaggregate GM and non-GM soybeans in CGE and CPE models when evaluating global soybean supply-demand-trade nexus and their land use impacts. It also enables evaluation of future uncertainty on GM soybean preferences, and potential soybean trade landscape with emerging soybean supplier, such as India and Africa (USDA 2016b; Gasparri et al. 2016). More importantly, parameter estimation and commodity disaggregation are not limited to soybeans. It can be generalized to any other two commodities or crops, adding flexibility for future GMO studies and CGE/CPE studies.

CHAPTER 4. HOW THE US LOST ITS LEAD IN GLOBAL SOYBEAN TRADE

4.1 Introduction

Globally, soybean trade has more than doubled since the year 2000, driven by a major boom in China's soybean imports and the subsequent soybean production boom in South America. As a major soybean consumer, China has a long tradition of soybean diets. Also, China's income growth boosted its livestock product consumption, resulting in a substantial increase in the indirect use of soybean meal which is now the primary protein source in the nation's animal feeds. Chinese consumers are resistant to consumption of genetically-modified (GM) soybeans, and the cultivation of GM soybeans is not permitted in China. However, their use in livestock production has not been an issue to date, thereby providing an opening for China to import GM soybeans from overseas to meet their increasing domestic demands. Historically, the US was the largest soybean exporter and a major supplier of China's imports. Most of these soybeans are genetically modified. However, during the past two decades production of soybeans in Brazil has increased massively – most of this involving production of GM soybeans – and that helped this country to closely compete with the US in the global soybean market. The share of GM soybeans in total production of soybeans in Brazil has increased from 20% in 2004 to 80% in 2011 at which point Brazil overtook the US, for the first time, as the largest soybean supplier to China. By 2013, Brazil had become the world's largest soybean exporter – a result which has been driven largely by its dominance of China's soybean markets (UN Comtrade 2016). This paper seeks to understand the key factors that contribute to this change in the global soybean market: Why did the US lose its lead as the world's dominant exporter of soybeans?

Several studies have examined the export competitiveness between the US and Brazil, as well as Argentina. For instance, in a recent paper, Meade et al. (2016) compared production and shipping costs in these countries using 5 year-average data from 2008 to 2012. According to these authors, Brazil achieved a significant reduction in seed cost with the development of new GM seed technology. Lower seed cost in combination with lower capital and land costs provided a comparative advantage in production costs for Brazil. Brazilian GM soybean adoption, accompanied by its low land and capital costs, are widely believed the major reasons for Brazilian rapid soybean production expansion (Brookes and Barfoot 2017). Before Meade et al. (2016), Leibold and Osaki (2009b) based on 2007-2009 data and Sutton, Klein, and Taylor (2005b) based on 2003 data made similar conclusions. In addition, political reforms, government support, and favorable climate conditions in Brazil and Argentina have further facilitated their soybean expansion (Schnepf, Dohlman and Bolling 2001b; Sutton et al. 2005b). Brazilian weather conditions give its GM soybeans higher protein content than its US counterparts, and these higher quality soybeans are more preferred by Chinese importers (Plume 2018). Changes in the exchange rates, especially the depreciation of Brazilian Real versus US Dollar over 1990-2003, is believed to have encouraged soybean exports (Richards et al. 2012).

The challenge for Brazil – as well as for Argentina – comes from high domestic transport costs and poorly developed domestic supply chains (Godar et al. 2015). Mato Grosso is now the major Brazilian soybean growing region, but it faces steep transport costs in delivering soybeans to the global market. This inland state is a long way from the coast, and Brazil's inefficient rail transportation and lack of commercial waterways make its soybean landed costs about 1.5% higher than that of the US. Meade et al. (2016) point out that Brazil's landed costs for soybeans delivered to China are 2% higher than that in the US. Argentina, despite low production and transportation costs, imposes export taxes which drastically weakens its soybean export competitiveness.

Another factor affecting the relative competitiveness of US soybeans has been the surge in biofuel production since 2000. Brazil, EU, and the US, combined, produced 84% of global biofuel production in 2014. The US, in particular, contributed approximately half of global biofuel production. The US was the main producer of corn-ethanol and soy-biodiesel. Regulated by Renewable Fuel Standards (RFS), the US motivated 14 billion gallons of ethanol output, which accounted for more than half of global production which totaled 25 billion gallons. In addition, US biodiesel production accounted for 16% of global biodiesel production in 2014 (Taheripour, Cui and Tyner 2018; Energy Information Administration 2017). The impacts of biofuel production on crop price, production, and land use changes are well documented in the literature. Biofuel production increased corn and soybean prices, spurred domestic corn and soybean demands, impacted their production, and resulted in some land use changes (Hertel, Golub, et al. 2010; Trostle 2010; Taheripour et al. 2010; Zilberman et al. 2012; Searchinger et al. 2008; Rathmann, Szklo and Schaeffer 2010; Ajanovic 2011). The biofuel policy can even impact livestock production through crop prices and biofuel by-product costs and availability. Changes in livestock sector will, in turn, impact producers' behaviors in crop production (Taheripour, Hertel and Tyner 2011; Popp et al. 2016).

The existing cost-comparison studies basically examine impacts of a few factors that affect the comparative advantage of each major player in the global market for soybeans on a one-by-one basis without a comprehensive assessment of their overall impacts and interactions. For example, while most of the preceding studies recognized production cost and exchange rates as two critical factors for Brazil and the US soybean competitiveness, they ignore the role of macroeconomic growth, structural change, and government policies. These factors also drive changes in exchange rates which are fundamentally endogenous factors in a global trading system. The existing cost comparison studies also ignore the role of biofuels and their impacts on soybean production and trade. The biofuel policies alter the relative magnitudes of domestic demands and supply, resulting in changes in relative export competitiveness. Domestic agricultural support and border policies can also influence supply-demand-trade relationships. In short, a more comprehensive approach to the problem is required.

Yao, Hertel, and Taheripour (2018) examine impacts of a wide range of important factors that altered production and trade of soybean across the world in recent years. They group drivers of soybean production, trade, and land use change into five groups: macroeconomic factors, soybean productivity, other crop productivity, policy changes, and changes in forest and pasture land and their productivities. Focusing on four regions including US, Brazil, China, and Rest of the World (RoW), these authors examine the contribution of each and all of these drivers to the observed changes in soybean production, trade, and land use of each individual region and their interactions. They find that Brazilian soybean productivity is the most important driver behind the growth in Brazil's soybean production over the period: 2004-2011.

In what follows we evaluate performances of US and Brazil in the soybean market with two indices: 1) the ratio of US soybean production relative to Brazilian soybean production, and 2) the ratio of US soybean exports to China over Brazil soybean exports to China. We refer to these two ratios as production index and export index, respectively. To evaluate contributions of important factors that altered these two ratios in the 2004-2011 period, we adopt the modeling framework and decomposition methods in Yao, Hertel, and Taheripour (2018). This method takes into account contributions of several important factors, individually and in combination, to the observed changes in the production and export indices. We first decompose these two indices into contributions of these five groups of drivers which compose distinct impacts from four regions: the US, Brazil, China and other regions[28]. By decomposing these two indices, we aim to investigate the interplay of all the components that contributed to Brazil surpassing the US as the world's leading soybean exporter. We then differentiate these regional drivers into positive drivers and negative drivers. Focusing on the export index, we further examine its positive drivers and negative drivers in greater detail. With the main contributors to the US "loss" identified (negative drivers), we aim to offer insights about the future, as well as possible policy interventions to alter the future course of global soybean trade.

4.2 Data and Methodology

This research builds on a new version of the GTAP-BIO model developed by (Yao et al. 2018).[29] This model is an extended version of the standard GTAP model with disaggregation of genetically-modified (GM) and non-GM soybeans to allow for analysis of bilateral trade, production and land use related to global soybeans. These authors have shown that this model is capable of reproducing changes in bilateral soybean trade between Brazil, US, and China over the period 2004-2011 (Yao et al. 2018). In this paper, we bring this model to bear on the question of how the US lost its lead in global soybean trade. Our objective is to fully decompose the key drivers of change using the numerical decomposition tool developed by Harrison, Horridge and Pearson (2000).[30]

As mentioned before, in this paper we use two indices, the US and Brazilian soy production and export ratios, to evaluate and understand the relative changes in US/Brazil soybean production and export competitiveness. By decomposing the changes in these two indices with respect to the full set of external shocks over the 2004-2011 period, we are able to pinpoint key changes.

The main drivers considered in this research are taken from Yao, Hertel, and Taheripour (2018) (see Table G.1), which include: macroeconomic variables, soybean productivity, other crop

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[28] The original model has six regions: The US, Brazil, China, the EU, other South American countries, and Rest of the World. For reporting purposes, we aggregate EU, South Other American Countries and Rest of the World as "other regions".
[29] CHAPTER 2 in this dissertation.
[30] This decomposition tool solves the problem that summing up the results from each partial simulation is unequal to their total changes. This is due to the interactions between the different drivers along the projection path. By assuming a linear path from pre-simulation to post-simulation values and a constant rate contribution of all exogenous variables, we are able to achieve the goal that the sum of contributions of each driver is exactly equivalent to its total changes (Yao, Hertel and Taheripour 2018; Harrison, Horridge and Pearson 2000).

productivity, agricultural and trade policies, and finally, forest and pasture land and their productivities. [31] Macroeconomic variables are GDP growth, population growth, labor accumulation, as well as investment and capital accumulation. Macroeconomic variables of each region not only could generate both domestic and import demands, but also could trigger endowment reallocation among different sectors. Soybean productivity is measured as the change in total factor productivity (TFP) over this period and distinguishes both GM and non-GM soybeans. From a policy perspective, domestic agricultural support, especially subsidies, as well as border policies (tariffs), could also effectively protect domestic soybean production. Biofuel policies in Brazil and the US could trigger increased domestic crop demands and rising crop competition for land. Finally, changes in forest and pasture land and their productivities, such as the conservation reserve program in the US, affect land transition among crop, forestry, livestock sectors. Table G.1 in APPENDIX G provides detailed explanation and data sources for each driver (Yao et al. 2018).

4.3 Results and Discussions

4.3.1 A Five-group Driver Decomposition

We first decompose the drivers behind the production index and export index into five groups: macroeconomic developments, soybean productivity, other crop productivity, policy changes, as well as forestry and pasture changes. Figure 4.1 presents the decomposition results of the two indices of interests. The “grand total” (first bar in Figure 4.1) presents the overall changes in each index over 2004-2011. The “grand total” for each index is equal to the sum of all changes induced by the five drives. Each group of drivers contains impacts from 4 regions: USA (green), Brazil (blue), China (red), and other countries (orange). The black horizontal lines crossing the stacked bars indicate each driver’s net contributions to “grand total” changes. Our model is able to replicate historical changes in each region’s changes in soybean production and trade. This net change in “grand total” also correspond to historical changes in these two indices.

In Figure 4.1, Brazilian soybean productivity (blue bar under “soybean productivity” driver) stands out as the most important driver in impeding the US soybean production and exports to China competitiveness. Improvement of Brazilian soybean productivity originated from its 80%

[31] External shocks chosen are arbitrary.

increase in GM soybean penetration, which significantly lowered its production cost, especially its herbicide costs and seed costs (Meade et al. 2016; Schmidt 2018). Strong GM soybean penetration had little effects on its yield (Xu et al. 2013; Gurian-Sherman 2009). Lower soybean production costs motivated Brazil's soybean production, resulting in a soybean harvested area expansion and cropland expansion. Our results show that soybean productivity was responsible for 32% of Brazilian soybean production. Percentage changes in soybean production compose percentage changes in harvested areas and percentage changes in yield. Out of 32% growth in Brazilian soybean production, 29% was transferred to Brazilian harvested area expansion with minimal impact on yield. This growth in harvested areas further contributed to a 7% cropland area expansion in Brazil.

Brazilian soybean productivity impacts the US production competitiveness (production index) to a lesser extent than its effects on the US export competitiveness (export index). Both the US and Brazil are two major soybean exporters to China. They are close competitors. Their interests in the global soybean markets are more closely related. However, the US soybean production is less impacted by the Brazilian soybean productivity than its exports due to the US trade partnership with other regions. The impacts on the US soybean production from Brazilian soybean productivity is mitigated by factors from other regions. This is consistent with the results in Yao, Hertel, and Taheripour (2018).

Alongside Brazilian soybean productivity, the impacts of other factors appear small in Figure 4.1. This is because the negative and positive driving forces frequently offset one another within each group of drivers. This hides the importance and magnitude of individual components of each group of drivers, resulting in a smaller net effect. For this reason, in the next figure, we will remove soybean productivity and focus on other drivers that contribute to the production and export indices.

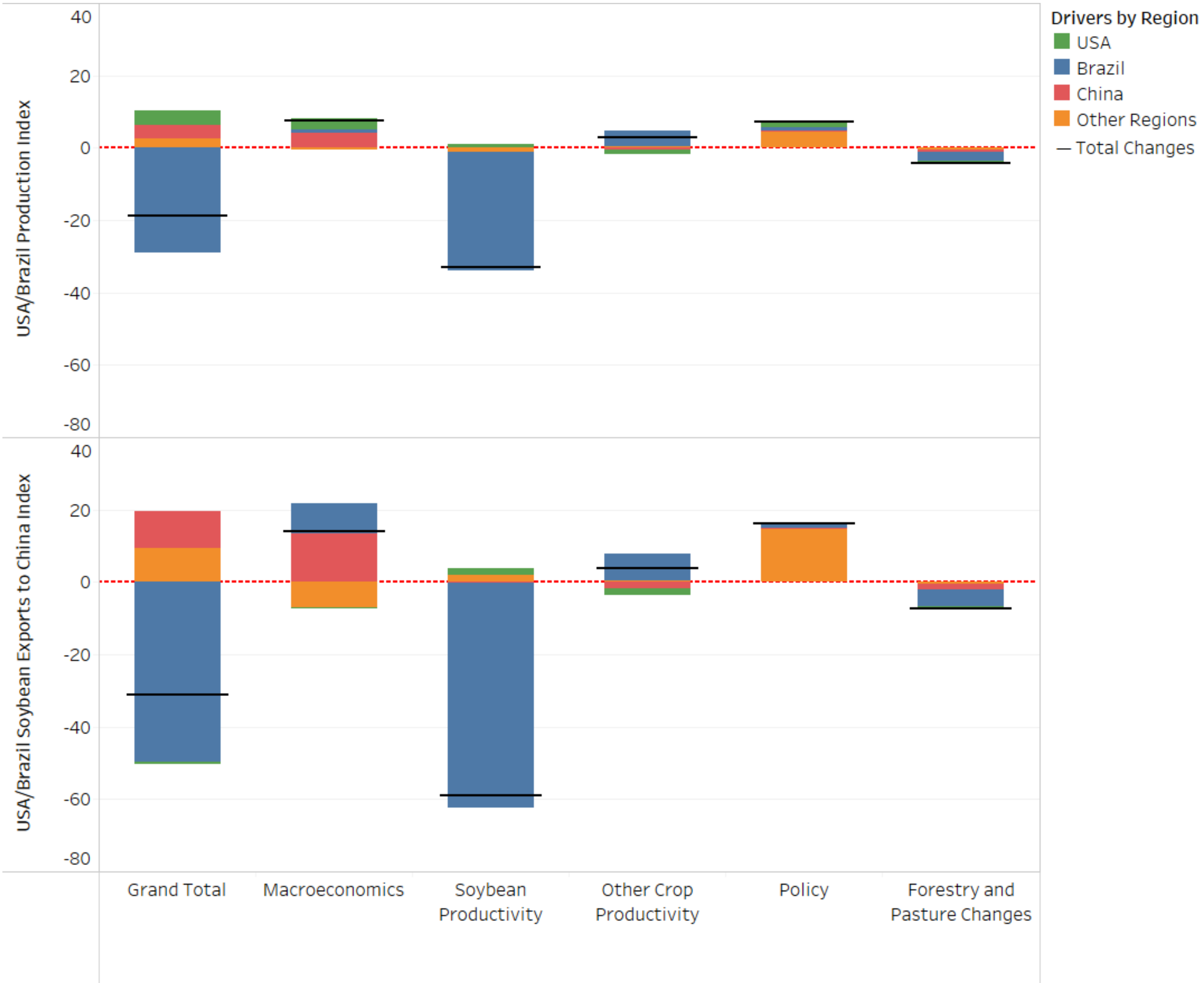

Figure 4.1 A comprehensive decomposition of the impacts of 5 main groups of drivers on the US/Brazil soybean production ratio and US/Brazil bilateral soybean export to China ratio.

Drivers are macroeconomics, soybean productivity, other crop productivity, policy, and forest and pasture land and their productivities. Total changes of these two indices are shown as "grand total." Each group of drivers contains impacts from 4 regions: USA (green), Brazil (blue). The black horizontal bar crossing the stacked bars indicate each driver's net contributions to "grand total" changes.

4.3.2 The US "Losses" and "Gains"

4.3.2.1 A Summary of "Losses" and "Gains"

Figure 4.2 breaks up the overall impacts of all other drivers except soybean productivity into positive and negative drivers by region. In this figure, the "grand total" shows net contributions of all non-soy-productivity drivers. Positive and negative drivers, each have their origins in four regions: the US, Brazil, China, and other regions. This figure clearly shows that a simple summation of these factors into a single "grand total" neglects nuances behind these changes.

From Figure 4.2 we see that, once the impacts of soybean productivity are removed, the net effect of all other drivers ("grand total") benefited the US production and exports competitiveness (production and exports indices). All regions contributed both positive and negative impacts on the production and export indices. The net effects of all regions assisted the US soybean production competitiveness ("grand total" in the upper panel of production index). Except for the US domestic factors, all other regions' net impacts helped the US relative soybean exports to China ("grand total" in the lower panel of the export index).

Within both positive and negative drivers, the US and Brazil had the most marked impacts on the US/Brazil relative production competitiveness (the green bars and the blue bars in positive and negative drivers in upper panel), implying a direct competition of these two countries in the global market.

Positive drivers of the export index show that the most beneficial factors are from other regions, Brazil, and the US (the blue and green bars in lower panel). Within the negative driving forces of the export index, the most lagging forces for the US exports to China is from the US itself and other regions. It tells us that the US domestic factors were mainly responsible for the US "loss" besides Brazilian soybean productivity. All these drivers impacted the export index more than the production index, indicating that soybean trade is more responsive than the domestic production when facing external interventions.

Figure 4.2 only presents the accumulative effects of positive and negative drivers from each region. What exactly happened behind these aggregate impacts that responsible for the US "gains" and "losses"? Understanding these is our next task, and for this, we will draw on another figure (Figure 4.3).

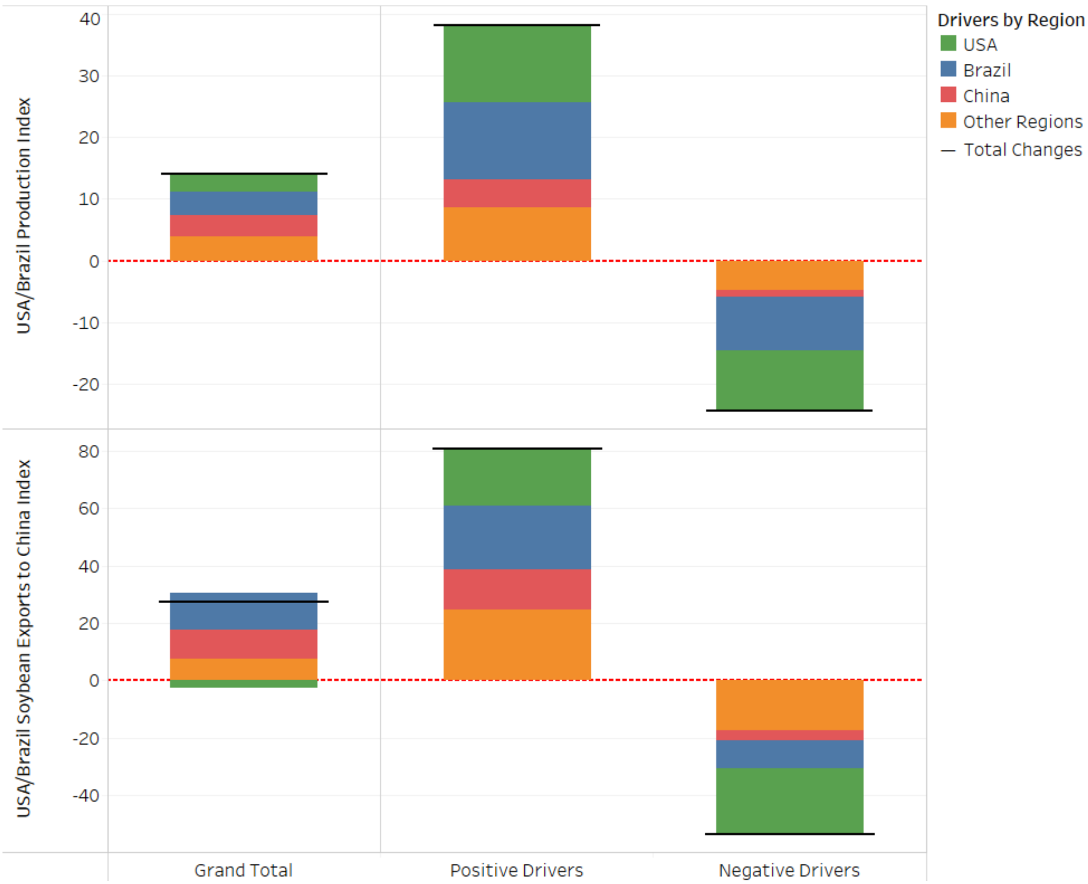

Figure 4.2 Regional decomposition of two key indices by positive and negative drivers
The total changes of each index are shown as "grand total." They are further decomposed into positive and negative drivers. Each driver contains impacts from 4 regions: the US (green), Brazil (blue), China (red), and other regions (orange). The black horizontal bar crossing the stacked bars indicate each driver's net contributions to "grand total" changes.

4.3.2.2 Factors driving the loss in US competitiveness

The US "loss" in the global soybean market mainly reflects on its shrinking share in China's market. Focusing on the US/Brazil relative export to China ratio (export index), we decompose accumulative effects of positive and negative drivers into more detailed components in Figure 4.3. Except for soybean productivity, each group of drivers is further broken down into its subcategory shown in Table G.1 APPENDIX G. Macroeconomics composes impacts from capital accumulation, investment, labor accumulation, labor productivity in non-agricultural sectors, population growth, and feed industry restructuring in China. Other crop productivity includes all non-soybean crop productivity and cropland intensification practices. Policy contains domestic agricultural support, biofuel policies, and border policies. Forest and pasture changes encompass external interventions in the forest and pasture land changes. Again, each detailed factor includes impacts from the US (green), Brazil (blue), China (red), and other regions (orange). The upper panel presents all positive drivers from each region within each subcategory of drivers. The lower panel shows all negative drivers.

We first focus on negative drivers – responsible for the US “loss” in export share over 2004-2011. Figure 4.2 tells us the US domestic drivers were the major lagging forces for the US export competitiveness. These negative drivers (green bars in lower panel in Figure 4.3) are the US biofuel policies, the US labor productivity and population growth in macroeconomics group, its non-soy productivity improvement, as well as its forest land and pasture land changes.

Over 2004-2011, The US biofuel policies mainly encouraged corn-ethanol and soy-biodiesel production. To better understand the impacts from the two types of biofuels, we focus on global biofuels’ contributions on soybean production and exports to China in the US and Brazil, as well as the production and export indices (See Figure H.1 in APPENDIX H for more details). The decomposition of the global biofuel policies suggests that the US corn-ethanol production encouraged corn production and depressed soybean production, while the US soy-biodiesel production benefited soybean production. By diverting potential exports to the biofuel industries, both types of biofuel policies contribute equivalently to the US loss in its relative competitiveness of exports to China (export index).

The US labor productivity in non-agricultural sectors (the green bar of lower productivity in the lower panel of Figure 4.3) lowered labor costs in non-agricultural sectors and drew labor from agricultural sectors to manufacturing and services. It thus slowed the agricultural development and exports, when taken on its own. Population growth in the US (the green bar of the population in the lower panel of Figure 4.3) increased its domestic demands, thereby reducing the amount available for exports. Productivity growth in non-soy crops (the green bar of non-soy crop productivity in the lower panel of Figure 4.3) led to more intense competition with soybean production, thereby also reducing soy exports. Moreover, historical reforestation efforts (the green bar of forest land in the lower panel of Figure 4.3) limited the US further cropland expansion. Productivity decline in cropland-pasture (the green bar of cropland-pasture in the lower panel of Figure 4.3) in the US released its land for cropland expansion.

Previous Figure 4.2 shows that the accumulative negative effects from other regions (orange bar) were the second largest contributor to the US “loss” in its exports (export index). Other regions comprise the EU, other South American countries, and rest of the world. It is a composite of three regions and a mixture of net soybean consumers (e.g., EU) and net suppliers (e.g., other South American countries). Impacts from other regions thus may appear in both negative and positive panels.[32] Other regions played a role in dragging the US relative exports through its macroeconomic growth, such as labor productivity in non-agricultural sectors, population, and its productivity in non-soy crops, as well as changes in pasture land.

The prominent negative driver of labor productivity in other regions in non-agricultural sector was mainly from the EU. EU’s labor productivity reduction in non-agricultural reduced their total demands for soybeans and livestock products. Also, EU’s labor productivity reduction in non-agricultural sectors reallocated labors to agricultural sectors and benefited its rapeseed production. Rapeseed meals gradually replaced soybean meals in EU’s pig and poultry feeds (Mavromichalis 2013). Therefore, EU’s total soybeans and livestock product imports declined. Brazil was the major livestock product suppliers for EU. EU’s declined demands for livestock products helped Brazil release more pasture land for its soybean production. Thus, Brazil’s total soybean production was harmed less than the US soybean production. With EU’s soybean imports reduction, Brazil actively sought vents for its soybeans. More Brazilian soybeans were exported to China, crowing out the US market shares in China. Other regions’ lagging forces due to other macroeconomic factors are from rest of the world. Rest of the world has both net soybean consumers and suppliers. Their economic growth might increase more relative soybean demands from Brazil than from the US.

Other regions’ non-soy crop productivity impeding power was from EU. EU’s non-soy crop productivity boosted other crop production and reduced soybean production. Domestic soybean supply decline in EU driven by EU’s non-soy crop productivity alone increased EU’s demands for soybeans. EU’s increased imports from the US hurt the US soybean exports to China. In other regions’ pasture land changes, it is the other South American’s livestock productivity improvement that released lands for their soybean production and hindered the US exports.

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[32] The US, Brazil, and China are single countries. Under each category, each country’s impacts appear either in the positive panel or negative panel. It cannot appear in both. We group EU, other South American countries and Rest of the World as “other regions”. The impacts of “other regions” may appear in both positive and negative panels.

Brazil contributed negatively to the US export competitiveness mainly through its capital accumulation, and more land released from forest and cropland-pasture. Brazilian agriculture is relatively more capital-intensive compared to other countries (Spolador and Roe 2013; Global Forest Atlas n.d.). High capital inputs in agriculture sector motivated its soybean production expansion. Also, Brazil's deforestation and slack deforestation policies allowed for further expansions in cropland and crop production. Its productivity growth in cropland-pasture also released land for crop production.

4.3.2.3 Factors driving gains in US competitiveness

Positive drivers in Figure 4.3 assist understanding for the stimuli of the US relative export competitiveness. The major accumulative major contributors were also from the US, Brazil, and other regions (Figure 4.2).

The US domestic positive drivers were capital and labor accumulation and investment growth in macroeconomics, domestic agricultural support and border policies, and its pasture productivity in livestock production. The growth of capital and labor inputs in agricultural sectors benefited the US agricultural production. The US soybean production and exports grew consequently. The US domestic agricultural support for soybeans was mainly its crop insurance for soybean production. Over 2004-2011, the US total subsidies for soybeans increased by 749 million dollars (OECD 2016a; EWG 2018).[33] Over this period, the US also declined its tariffs for manufacture imports, resulting in increases in its manufacture imports and agricultural exports. The US productivity in non-land inputs of livestock production released land for cropland expansion.

Brazilian macroeconomic growth, other crop productivity, and land intensification all assisted the US relative soybean production and export competitiveness. The Brazilian macroeconomic development increased its domestic demands and declined its exports. It indirectly helped the US produce and export more soybeans. Brazilian non-soy crop productivity and cropland efficiency improvement benefited other non-soy crops' production and exports. Brazilian non-soy crop production expansion crowded out its soybeans production, which also indirectly benefited the US soybean production and exports.

[33] The US soybean subsidies peaked in 2001 and declined significantly from 2001 to 2002. In 2004-2011, the US soybean subsidies had an increasing pattern. In 2004, the US total soybean subsidies were $1,376 million. This number increased to $2,126 million in 2011. Please see EWG (2018) for more details.

Other regions comprise a mix of net soybean consumers (e.g., EU, other Asian countries, etc.) and net soybean producers (e.g., other South American countries). From producer perspectives, soybean productivity in other crops in other South America competed with its own soybeans and benefited the US soybean production and exports. Its taxes on soybean production inputs indirectly assisted the US soybean production. Other regions mainly impacted the relative US/Brazil competitiveness from the consumer side – importing border policies. These border policies include their beneficial tariffs for Brazilian non-soy crops and meat products. Their preferences for Brazilian non-soy crops encouraged other non-soy crop production and impeded Brazilian soybean production. Other regions' desire for Brazilian meat products expanded Brazilian livestock production, and more pasture land was used in livestock sectors by crowding out cropland for soybeans.

China, as the major soybean consumer, mainly imports GM soybeans – a highly homogeneous product (Yao and Hillberry 2018).[34] China's macroeconomic growth significantly increased its GM soybean imports, from both Brazil and the US. It inserted very similar impacts on both the US and Brazil soybean production and exports. Together with Brazilian soybean productivity, China's economic growth boosted Brazilian GM soybean production and exports, especially its GM soybean exports to China. However, the US large GM soybean production share was as high as 80% in the base year 2004, while only 20% of soybeans produced in Brazil were GM soybeans. The US thus benefited more from China's increased demands for GM soybeans, driven by China's growing demands for livestock products.

[34] This reference corresponds to CHAPTER 3.

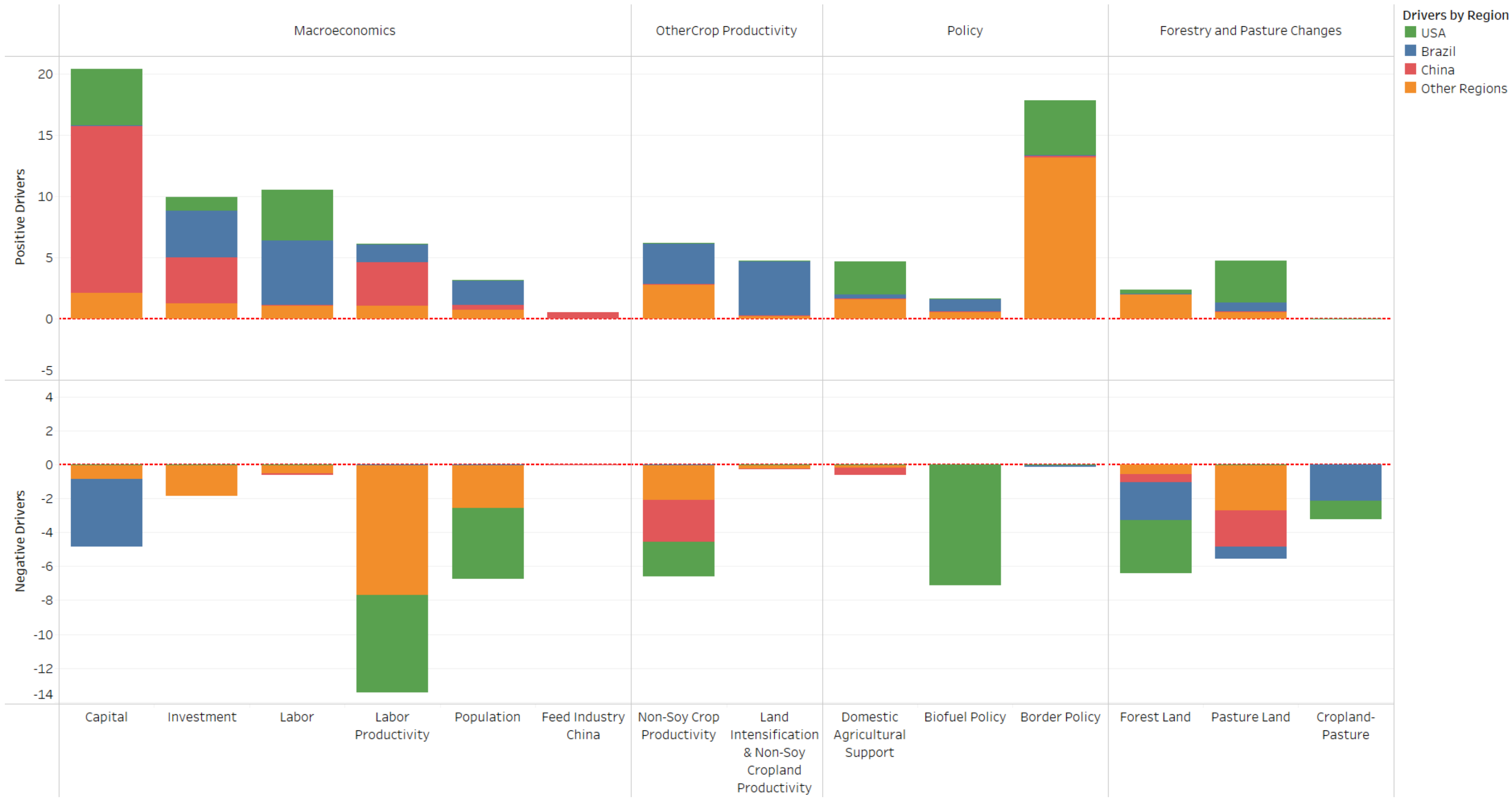

Figure 4.3 Decompositions of US/Brazil soybean exports to China ratio by a detailed specification of negative and positive drivers. US/Brazil soybean exports to ratio is first decomposed into positive (upper panel) and negative (lower panel) drivers. Positive and negative drivers are respectively further decomposed into contributions of each component within each group of the driver. Each component drivers contains impacts from 4 regions: the US (green), Brazil (blue), China (red), and other regions (orange).

4.4 Future Implications

Both export and production indices have historical positive and negative impacts on the US and all other regions. Future implications on the US/Brazil relative competitiveness in the global soybean market will be based on two aspects – whether the US strengths on its relative competitiveness (positive drivers) will maintain and whether the US weakness on its relative competitiveness (negative drivers) will diminish in future. For future analyses, a projection with a full set of drivers similar to the historical simulation decomposition can be applied. In this context, it will be of particular interest to focus on those drivers that may change in the future compared with the historical period analyzed here.

Among the factors driving the US "loss," Brazilian soybean productivity took the major responsibility. Brazilian GM penetration has already reached a 93% high-level penetration (Meade et al. 2016). Future potential productivity growth in Brazilian soybeans is less likely. Brazil, with low historical land intensification ratio, can still improve on its multiple cropping practices in agricultural production. Moreover, in history, landed costs of soybeans from Brazil's Motto Grosso is 1.5% higher than that of the US. Landed costs of soybeans from Brazil to China is even 2-3% higher than that of the US (Meade et al. 2016).[35] Further efficiency improvement in its domestic transportation will make Brazil more successful in the global soybean markets. Brazilian capital investment also dragged the US competitiveness in the past (Figure 3). Future capital investment in Brazilian agricultural sectors may continue to benefit Brazilian agricultural production and threaten the US exports. Especially, there is a recent tendency that Brazil is aggressive in winning larger China's soybean market shares (Thukral 2017). Brazilian historical soybean expansion largely benefited from cropland expansion and deforestation. However, severe environmental consequences associated with deforestation driven by cropland expansion warn Brazil for future sustainability. The Brazilian government may not allow the unlimited growth of soybeans by employing more land resources. Therefore, the lagging forces from Brazilian drivers will be weakened, and the US loss will slow down in future.

On the US side, the major domestic barriers for its soybean competitiveness were its labor productivity in non-agricultural sectors, population growth, other crop productivity, biofuel

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[35] Brazil soybeans from Parana has the lowest landed costs due to its lowest marketing and transportation costs (Meade et al. 2016) .

policies, and forest land restrictions. OECD (2014) projects the long-term US GDP growth at an annual average rate of 2% with a slower pattern up to 2060. U.S. Census Bureau (2017) projects a long-term US population growth rate at an annual average of 0.5% up to 2060. Slower GDP growth and population growth may insert limited impacts on the US domestic demands increase for soybeans. Biofuel production in the US may gradually switch to the second and third generation biofuels, reliving biofuel stresses on cropland. Environmental concerns and pursuits for sustainability will still actively protect the US forests and restrict cropland expansion. The US other crop productivity growth is very likely to slow down as well in future. All these evidence on potential changes in negative drivers suggests that the US weakness in soybean competitiveness may not reverse but will diminish.

Positive drivers responsible for the historical US “gains” in soybean competitiveness mainly came from the US and Brazilian impacts. The US drivers include its domestic capital and labor accumulation, investment, domestic agricultural supports and border policies. It suggests future capital and labor inputs in agricultural sectors will likely to continue to benefit the US soybean competitiveness. Beneficially agricultural supports and careful border policies on managing trade balances can be used as a useful tool for the US soybean competitiveness.

Positive Brazilian drivers that benefited the US were Brazilian macroeconomic growth and other crop productivity. OECD (2014) also projects that Brazilian GDP will continue to grow at 2.3% average annual rate up to 2060. It implies that Brazilian economic growth will increase its domestic demands and slightly improve the US future export competitiveness. Agricultural productivity from the other crops may continue to impact soybean production, and possible transportation infrastructure improvement may also benefit other crops. Beneficial impacts from Brazilian other crop productivity may not as large as it used to be.

China’s capital accumulation is also shown as an important individual contributor to the US “gains” in the past due to their long-term trade partnership. However, China’s economic growth has already slowed down. A potential tariff increase in China for the US soybeans, declining dependence on the US soybeans, and increasing reliance on Brazilian soybeans all challenge the US soybean future (Cang and Sedgman 2018; Craymer 2018; Taheripour and Tyner 2018). Our decomposition analyses indicate that border policies played important roles in shaping the global soybean trade pattern. A potential US-China trade war may also make Brazil a big winner in global soybean markets.

Besides factors discussed in this paper, there is a current trend that both the US and Brazilian farmers start to go back to traditional non-GM soybean production for its lower costs and higher returns driven by premium markets (United Soybean Board 2016; The Organic & Non-GMO Report 2009; Mano 2017). Previous GM soybean strength on herbicide resistance become weaker due to the increasing herbicide resistant capacity of weeds. China's attitude towards GM and non-GM soybeans are still unclear (Xia 2014; Wong and Chan 2016). Moreover, potential emerging suppliers and consumers from other regions, such as India, Africa, and the Middle East may reshape the global trade partnership (Gasparri et al. 2016; USDA 2016b). All these uncertainties in supply-demand relationship add complexities on future trade markets.

4.5 Conclusions

The US has been overtaken by Brazil and became the second largest soybean exporter since 2011. It is mainly achieved through increased Brazilian soybean's market share in China. It concerns the US farmers due to the US agriculture's high dependence on global soybean markets. Previous studies successfully compare production and shipping cost in the US and Brazil. Some other studies consider the importance of Brazilian soybean productivity and the US biofuel policies in shaping the global agricultural production and trade without considering other factors. These studies lack systematic assessment with considerations of interactions of all economic components.

This paper fills the literature gap and comprehensively assessing the factors underpinning the US soy sector's production and trade competitiveness, relative to Brazil. By employing a decomposition method with historically-validated GTAP-BIO model, we are able to pinpoint negative and positive drivers of two key indices – the US/Brazil soybean production ratio (production index), and the US/Brazil bilateral soybean export to China ratio (export index). Focusing on the export index, we find the largest negative accumulative regional impacts are from the US itself, followed by Brazil, other regions, and China. These negative drivers help us to better understand the US "loss" of competitiveness. The US and Brazil's drivers are the two largest positive accumulative regional contributors. Besides Brazilian soybean productivity and the US biofuel policy, other drivers, like labor productivity in non-agricultural sectors in the US and EU, the US population growth, Brazilian capital accumulation, etc. Neglecting these factors cannot fully explain the US "loss" in soybean exports.

With a high GM soybean penetration level in Brazil, the US soybean production and exports are less likely to lose due to Brazilian soybean productivity in future. The US, in reality, always face the land constraints that imposes future challenges for the US. Political uncertainty about potential trade wars makes the US future soybean exports riskier. Brazil, in contrast, can still work on its transportation improvement to increase its trade competitiveness. Its land intensification hasn't reached a high level, and its land can be more productive with multiple cropping practices. Any uncertain factors between the US and China on soybean trade can make Brazil a potential largest winner in future. Our analysis offers a tool to understand each uncertain factor's role in agricultural production and trade competitiveness within a complex system.

CHAPTER 5. CONCLUSIONS

5.1 Summary

This dissertation systematically analyses historical interactions of global soybean trade in three major countries: China, Brazil, and the US. Within the supply-demand-trade nexus, it explores the China-Brazil demand relationship and its spillover impacts on the US. It also investigates Brazil and the US competitive relationship from a global perspective. It also provides useful decompositions that quantify the contributions of each driver to the targeted historical changes. This approach has several desired attributes for future analyses: 1) the sum of each driver's contribution equal to the total changes; 2) it allows for the aggregation and disaggregation of different combinations of drivers for analyses purposes; 3) it successfully pinpoints the negative and positive drivers. This decomposition tool can be generalized to other global-scale economic analysis. It is not limited to historical analyses. It can also be applied to future analyses.

From a modeling perspective, this dissertation separates soybeans into GM and non-GM varieties. This GM and non-GM soybean nest is introduced to both the model and the database. More importantly, this dissertation offers a new approach to estimate the elasticity between GM and non-GM soybeans through a nested CES structure with the PPML estimator. Economy-wide GM crop studies are becoming more popular. Disaggregation of the soybeans is a starting point. Other GM crops can be further disaggregated and studied using the same approach. Similarly, this estimation approach can be extended to estimate elasticities between any two commodities.

5.2 Potential Extensions

This dissertation primarily focuses on historical analyses of international trade. Future extensions will concentrate on the following aspects: implications of additional infrastructure investment in Brazil, the role of GMO crops, drivers of the global expansion of the corn-soybean complex.

Many studies point out Brazil's potential advantage in global soybean markets if they lower the internal transportation costs from Mato Grosso to the ports (the major soybean production region in Brazil) to their southeastern ports (Meade et al. 2016; Sutton et al. 2005b). Future investments in transportation infrastructure may significantly improve Brazil's soybean competitiveness in the global market. Brazil's greater access to the global market may reshape the current global soybean supply-demand-trade equilibrium. This improvement may further change the US soybean export portion.

Additionally, the debate on GM technology, especially GM soybeans, has been fierce. No conclusion has been reached. As a result, the market for non-GM soybeans has grown rapidly since the 2000s (Zheng et al. 2012; Preiner 2016; CommodityBasis 2017). As a consequence, many US and Brazilian farmers start to focus on growing non-GM soybeans (United Soybean Board 2016; The Organic & Non-GMO Report 2009; Mano 2017). Due to the herbicide-resistant attribute that weeds have developed with GM soybean growing over the years, the advantages of GM soybeans compared to traditional non-GM soybeans have lessened (Schütte et al. 2017; The Organic & Non-GMO Report 2009). Moreover, non-GM soybeans are more seed cost-effective and may be more profitable. All these factors have motivated the US, and Brazilian soybean farmers switch back to non-GM soybean production. From China's perspective, on the one hand, private consumers hold a stong preference for non-GM soybeans; on the other hand, the government has invested in mastering GM technology (Xia 2014; Wong and Chan 2016). It is not clear where this conflict will end and what the ultimate impact will be on trade.

This dissertation mainly focuses on historical soybean production. Soybean production is accompanied by corn rotation in the US Corn Belt and in Mato Grosso Brazil. Soybean and corn production regions highly overlap, such as the US heartland (Meade et al. 2016). A corn production stimulus, in return, also potentially replace soybean production. Corn and soybean are substitutes from a production perspective in many cases. On demand side, corn and soybean become complements: corn is the major energy source for animal feed, and the soybean is the world's largest protein source for animal feed (USDA 2017; USDA 2018). Livestock production expansion boosted by economic growth demands more corns and soybeans all together. The drivers of the global expansion of the corn-soybean complex are worth further studies.

APPENDIX A. MODEL STRUCTURE AND MODIFICATIONS

A.1 GTAP and GTAP-BIO Model

Global Trade Analysis Project (GTAP) is a multi-regional and multi-sectoral computable general equilibrium model. The standard GTAP framework is detailly documented in *Global Trade Analysis: Modeling and Applications* by Hertel (1997) published by Cambridge University Press. A brief description of a standard GTAP model can be found in the appendices of Hertel et al. (2010). The standard GTAP model employs the simple, but robust, assumptions of constant returns to scale and perfect competition in all the markets with Walrasian adjustment to ensure a general equilibrium. As represented in the figure below (Brockmeier 2001), the regional household (e.g., the EU) collects all the income in its region and spends it over three expenditure types – private household (consumer), government, and savings, as governed by a Cobb-Douglas utility function. A representative firm maximizes profits subject to a nested Constant Elasticity of Substitution (CES) production function which combines primary factors and intermediates inputs to produce a final good. Firms pay wages/rental rates to the regional household in return for the employment of land, labor, capital, and natural resources. Firms sell their output to other firms (intermediate inputs), to private households, government, and investment. Since this is a global model, firms also export the tradable commodities and import the intermediate inputs from other regions. These goods are assumed to be differentiated by region, following the Armington assumption, and so the model can track bilateral trade flows. See Figure A.1 for a schematic of the GTAP approach.

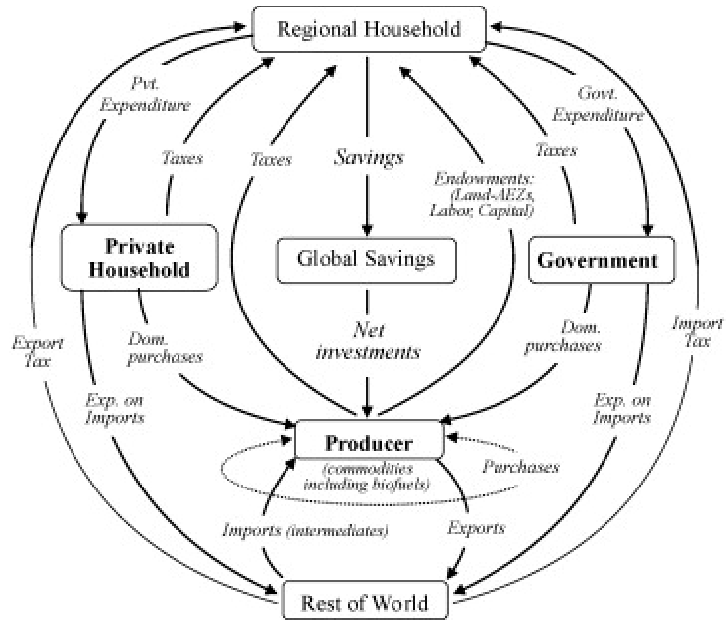

Figure A.1 Schematic of GTAP model

GTAP-BIO is an extension of a standard GTAP model evolved from GTAP-E which was originally developed by Burniaux and Truong (2002) to incorporate energy sectors. McDougall and Golub (2009) and Birur et al. (2008) further expanded GTAP-E with introductions of bioenergy. GTAP-BIO currently has 18 Agro-Ecological Zones (AEZ) in land supply, and we are able to trace land use changes and CO_2 emissions at AEZ level based on Hertel et al. (2008)'s modifications. The current version of GTAP-BIO that we use also fully considers biofuel and oilseed crushing by-products such as distiller's dried grains with solubles (DDGS) and oilseed meals (Taheripour et al. 2008). It also takes land intensification into account (Taheripour, Cui, et al. 2017).

We modified and extended the GTAP-BIO model by aggregating 19 regions into 6: USA, European Union (EU27), Brazil, China, other South American countries excluding Brazil (S_o_Amer), and rest of the world (RoW). Disaggregated individual oilseed sectors include soybeans, rapeseeds, palm fruit, and other oilseeds. Oilseed crushing industries produce both vegetable oil and oilseed meals for each oilseed. We further split soybeans into genetically-modified (GM) and non-GM soybean. Table A.1 shows the final industries (the second column), their descriptions (the third column), the by-products produced from each industry (the fourth column), and the commodity categories that they belong to (the fifth column).

Table A.1 Sectors and commodities in current GTAP-BIO model

No.	Industries	Explanations	By-products	Group
1	Paddy_Rice	Paddy Rice	None	Crops
2	Wheat	Wheat	None	
3	Sorghum	Sorghum	None	
4	Oth_CrGr	Other Coarse Grains	None	
5	GMSoy	Genetically Modified Soybeans	None	
6	NonGMSoy	Non-Genetically Modified Soybeans	None	
7	palmf	Palm Fruit	None	
8	Rapeseed	Rapeseed	None	
9	Oth_Oilseeds	Other Oilseeds	None	
10	Sugar_Crop	Sugar Crop	None	
11	OthAgri	Other Agricultural Sectors	None	
12	Forestry	Forestry	None	Forestry
13	Dairy_Farms	Dairy Farms	None	Livestock
14	Ruminant	Ruminant	None	
15	NonRuminant	NonRuminant	None	
16	Proc_Dairy	Processed Dairy Products	None	Processed Livestock
17	Proc_Rum	Processed Ruminant Products	None	
18	proc_NonRum	Processed Non-Ruminant Products	None	
19	Vol_Soy	Soybean Crushing Industry	Soybean Meal and Oil	Oilseed Crushing Industries
20	Vol_Palm	Palm Fruit Crushing Industry	Palm Fruit Meal and Oil	
21	Vol_Rape	Rapeseed Crushing Industry	Rapeseed Meal and Oil	
22	Vol_Oth	Other Oilseeds Crushing Industry	Other Oilseeds Meal and Oil	
23	Bev_Sug	Beverage and Sugar	None	Processed Food and Feed
24	Proc_Rice	Processed Rice	None	
25	Proc_Food	Processed Food	None	
26	Proc_Feed	Processed Feed	None	
27	OthPrimSect	Other Primary Sectors	None	Other Primary Sectors
28	EthanolC	Corn-based Ethanol	Corn-ethanol and DDGS	Biofuels
29	Ethanol2	Sugarcane-based Ethanol	None	
30	EthanolS	Sorghum-based Ethanol	Sorghum-ethanol and DDGSS	
31	Biod_Soy	Soybean-based Biodiesel	None	
32	Biod_Palm	Palm-based Biodiesel	None	
33	Biod_Rape	Rapeseed-based Biodiesel	None	
34	Biod_Oth	Other oilseed-based Biodiesel	None	
35	Coal	Coal	None	Fossil Fuels
36	Oil	Oil	None	
37	Gas	Gas	None	
38	Oil_Pcts	Oil Products	None	
39	Electricity	Electricity	None	Electricity
40	En_Int_Ind	Energy Intensive Industries	None	Other Industries
41	Oth_Ind_Se	Other Industries and Services	None	
42	NTrdServices	Non-tradeable Services	None	
43	Pasturecrop	Cropland Pasture	None	Cropland Pasture
44	CGDS	Capital Goods	None	Capital Goods

The original GTAP-BIO model assumes perfect labor and capital mobility between agricultural and non-agricultural sectors. However, the wages for farm and non-farm workers with comparable skills are unlikely to be equated in the near term, as would be the case if the perfect mobility of labor and capital mobility is assumed (Keeney and Hertel 2005). In countries like China, the rural-urban wage gap is very large (Zhao 1999). We adopt Keeney and Hertel (2005)'s imperfect mobility of labor and capital specification in GTAP-AGR model. Constant elasticity of transformation (CET) functions are introduced to "transform" labor and capital between agricultural and non-agricultural sectors (Keeney and Hertel 2005). Capital and labor are assumed perfectly mobile amongst agricultural sectors and amongst non-agricultural sectors, respectively. Figure A.2 presents the theoretical structure of this implementation.

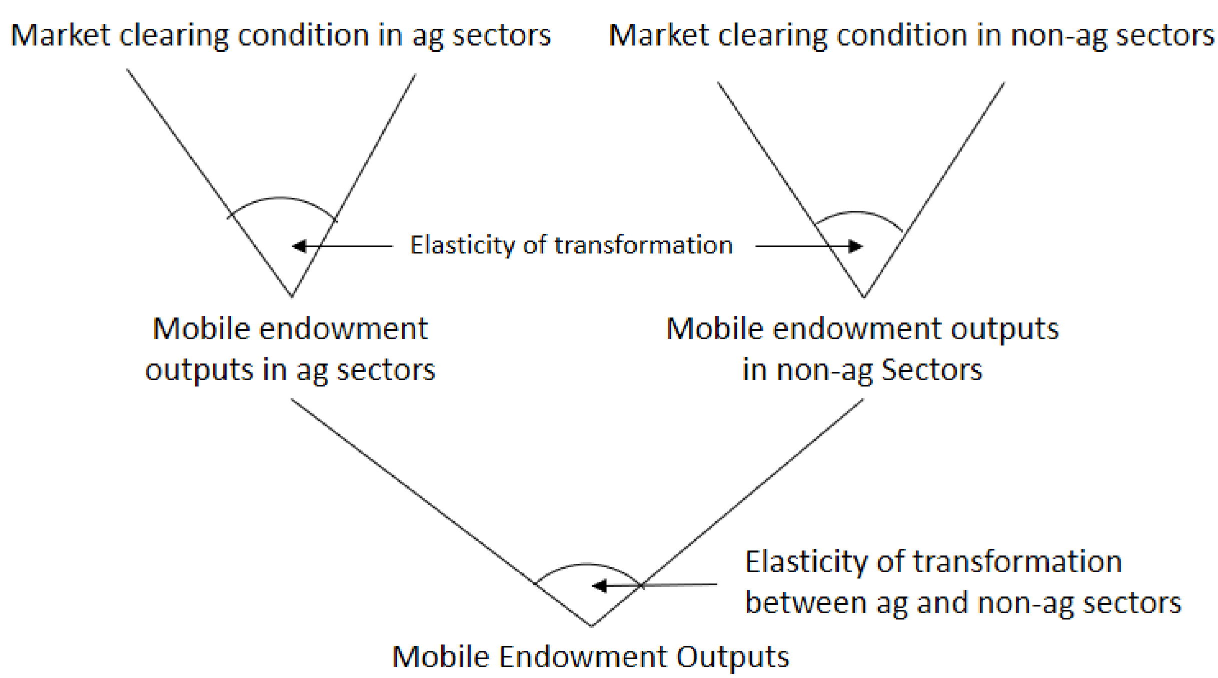

Figure A.2 Mobile endowment nests (land and labor transformation structure between agricultural and non-agricultural sectors)

A.2 GM and Non-GM Soybean Nest Structure

This section provides a schematic illustration of GM and non-GM soybean nests in our modified GTAP-BIO model. We assume that land is highly transferable between GM and non-GM soybean cultivation as is shown in Figure A.3 and Figure A.4 shows how GM and non-GM soybeans enter a feed composition. GM and non-GM soybeans are highly substitutable as feed ingredients. Figure A.5 presents household consumption of GM and non-GM soybeans. From the perspective of private consumption, GM and non-GM soybeans are partially substitutable.

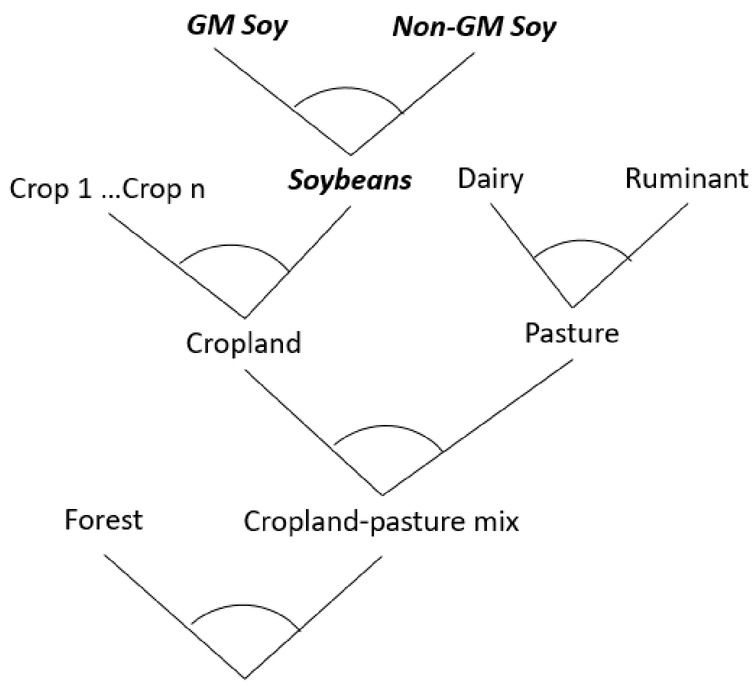

Figure A.3 Land supply nests (land transformation between different types of land cover)

In the first nest, the land is divided into forestland and cropland-pasture. Cropland-pasture, in the second nest, is composed of cropland and pasture. Cropland is a composite land supply for different crops, and pastureland provides land for livestock sectors. In the end, land for soybeans comprises GM soybeans and non-GM soybeans. Land is perfectly transformable between GM and non-GM soybeans.

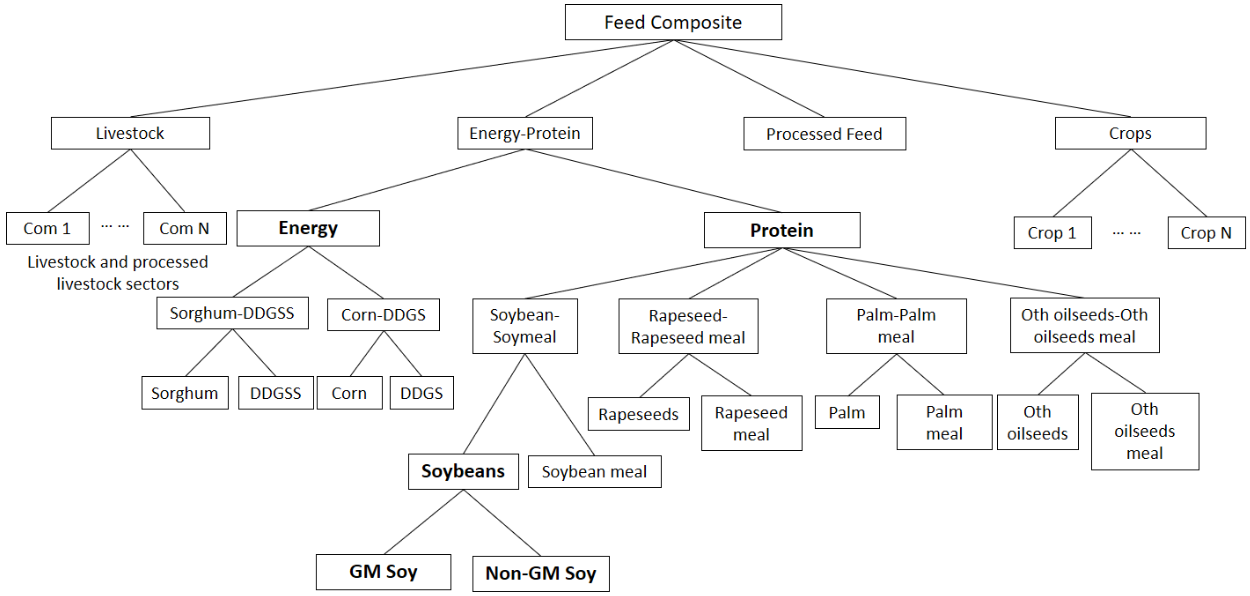

Figure A.4 Feed composite nested structure with soybean sub-nest

"Com" is short for commodities. In the top nest, feed composite is composed of livestock sectors, energy-protein composite, processed feed, and a crop composite. Energy-protein composite comprises energy and protein, where energy sources are sorghum-DDGSS composite and corn-DDGS composite, and protein sources are composed of composites of each oilseed and its meal. Soybean-soymeal composite is further decomposed into soybeans and soybean meal, and soybean is a nested structure of GM and non-GM soybeans.

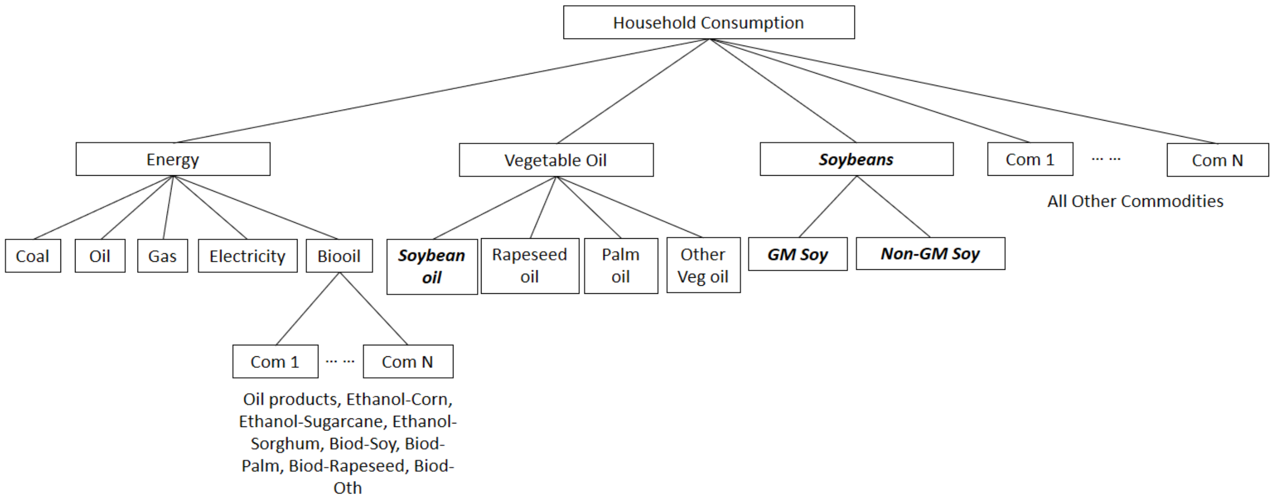

Figure A.5 Household consumption structure with soybean sub-nest

Household consumption is based on several composite commodities and all other original commodities. The composite commodities include energy, vegetable oil, and soybeans. Energy is a composite of coal, oil, gas, electricity, and biooil. Soybean oil, along with other vegetable oil is consumed as a vegetable oil composite. Soybean is a nest of GM and non-GM soybeans. Low substitutability between GM and non-GM soybeans is assumed at household consumption level.

APPENDIX B. HISTORICAL DRIVERS AND SHOCKS

Table B.1 Historical macroeconomic indicator growth for all six regions in percentage change (2004-2011)

	US	EU	Brazil	China	S_o_Amer	RoW
Population	6.46	2.32	7.74	3.71	9.24	11.69
Skilled labor	-9.35	14.87	21.25	6.23	20.22	12.48
Unskilled labor	14.83	0.07	10.33	6.05	14.68	12.21
Capital accumulation	11.85	16.47	23.76	121.47	35.68	32.89
Investments	-7.45	3.35	68.67	130.66	107.44	25.37
Agricultural capital productivity	13.28	2.73	20.05	-45.16	15.48	9.22
Agricultural labor productivity	19.10	23.62	43.38	48.66	16.02	13.64
Agricultural fertilizer productivity	6.36	10.96	12.47	6.37	-0.38	-5.07
Implied rate of growth in labor productivity	5.84	-33.87	2.50	17.07	5.13	-5.39
GDP	8.66	8.75	32.95	101.95	44.23	22.88

Data for population, investments, GDP, World Development Indicators (WDI), (World Bank 2016); skilled labor and unskilled labor quantity, Global Bilateral Migration Data Base (GMig2 database), (Walmsley et al. 2013); capital stock, Penn World Table (PWT), (Feenstra et al. 2013); agricultural productivity (Fuglie and Rada 2013b). Labor productivity growth is endogenously determined by the model to target the GDP growth.

Table B.2 Percentage growth in agricultural technology and targeted soybean outputs and harvested areas (2004-2011)

Region	TFP changes in GM soybean outputs	TFP changes in non-GM soybean outputs	Soybean output growth	Soybean harvested area growth
US	4.21	-11.58	12.31	8.18
EU	-4.99	6.24	-1.98	-6.39
Brazil	61.69	-7.17	36.89	20.68
China	8.15	1.96	-13.35	-19.00
S_o_Amer	1.06	-5.75	33.27	35.70

TFP changes in soybean outputs are inferred by the model composed of observed Hicks-neutral technical change and inferred weighted input-biased technical change. Multiple cropping effects due to land intensification are excluded. Land productivity for soybeans production only is included. Brazil has the highest soybean TFP growth, consistent with its output growth.

Data for productivity in the capital, labor, and fertilizer, (Fuglie and Rada 2013b); Soybean output growth and harvested area growth, (FAO 2015).

Table B.3 Biofuel production in billion gallons (2004-2011)

Biofuel	US	EU	Brazil
Ethanol-Corn	10.52	0.52	
Ethanol-Sugarcane		0.36	2.02
Biodiesel-Soybeans	0.47	0.21	0.41
Biodiesel-Rapeseeds		1.26	

APPENDIX C. SUPPLEMENTARY RESULTS FOR CHAPTER 2

C.1 Model Validation and Precision from China's Soybean Imports

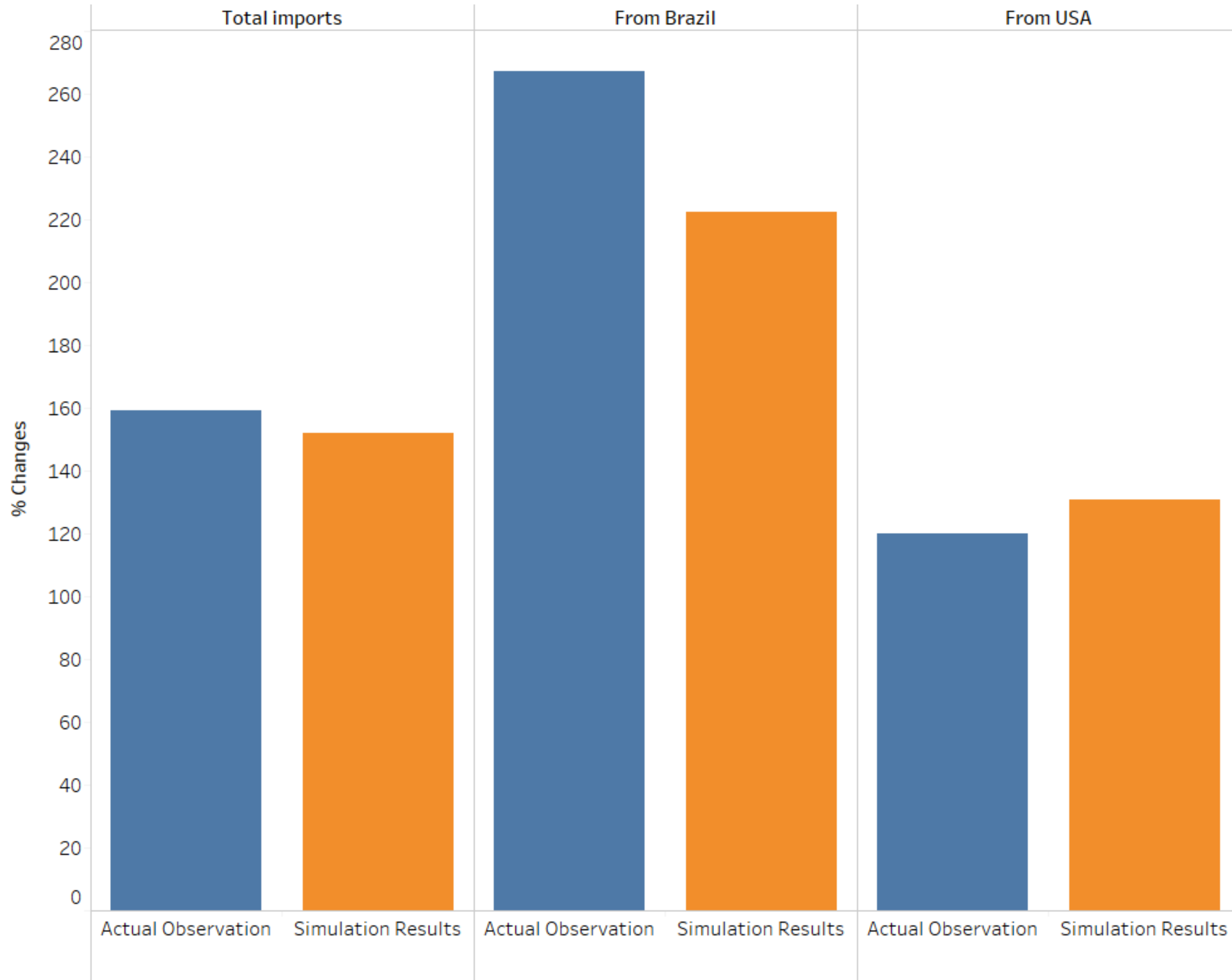

Figure C.1 The comparison of simulated results with actual historical observations in percentage changes in China's total soybean imports, China's soybean imports from Brazil, and its imports from the US

Our model is able to explain over 80% of China's historical soybean imports.

C.2 A Table Representation of Decomposition Results

Table C.1 China's major soybean trade decomposition in percentage changes by region driver and type driver (2004-2011)

		Drivers by Type					
	Drivers by Region	**Grand Total**	**Macroeconomics**	**Soybean Productivity**	**Other Crop Productivity**	**Pasture and Forestry Factors**	**Policy**
Total Imports	**Grand Total for Each Driver Type**	**152.0**	**186.3**	**11.6**	**-30.5**	**11.2**	**-26.6**
	China	**150.8**	194.6	-0.1	-26.1	4.8	-22.4
	Brazil	**4.3**	-4.1	10.7	-3.0	-0.5	1.3
	USA	**-8.4**	-2.8	0.1	-1.2	-3.9	-0.6
	Other Regions	**5.3**	-1.4	0.9	-0.1	10.8	-4.9
From Brazil	**Grand Total for Each Driver Type**	**222.3**	**193.7**	**111.6**	**-54.2**	**-0.1**	**-28.6**
	China	**164.5**	209.1	0.4	-28.3	7.3	-23.9
	Brazil	**61.8**	-34.3	116.3	-29.1	-3.8	12.8
	USA	**-6.6**	-1.1	-2.7	1.1	-5.1	1.2
	Other Regions	**2.5**	20.0	-2.4	2.1	1.5	-18.7
From USA	**Grand Total for Each Driver Type**	**130.7**	**176.2**	**-28.2**	**-18.9**	**42.6**	**-40.9**
	China	**135.8**	175.1	-0.3	-23.1	4.1	-20
	Brazil	**-20.1**	10.0	-35.0	8.1	1.1	-4.3
	USA	**-15.0**	-3.8	2.8	-5.1	-6.6	-2.3
	Other Regions	**30.0**	-5.2	4.3	1.2	44	-14.3

C.3 China's Macroeconomic Contributions to Soybean Trade and Production

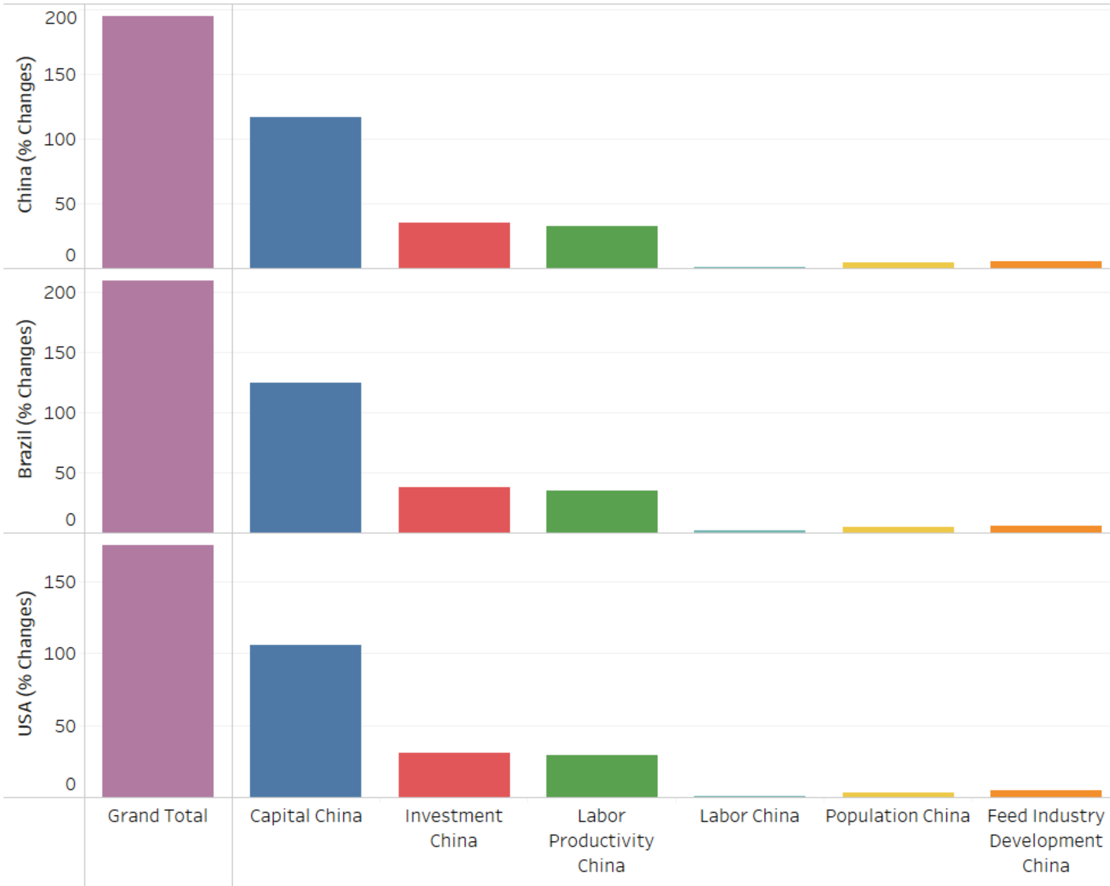

Figure C.2 Detailed China macroeconomic driver decompositions of China's soybean imports

The "grand total" bar indicates China's total macroeconomic contributions to China's total soybean imports, its imports from Brazil and from the US. The macroeconomic drivers comprise capital accumulation, investment growth, labor productivity in non-agricultural sectors, labor accumulation, population growth in China, and feed industry restructuring in China. The height of each individual driver shows their contribution share to aggregate macroeconomic influences from China. China's macroeconomic drivers have similar contributions to its total soybean imports, and bilateral imports from Brazil and the US. All macroeconomic drivers increased China's demands for imported soybeans. Capital and investment in China, in particular, facilitated its feed industry and boosted its demands for soybean imports.

Figure C.3 Detailed China macroeconomic driver decompositions of total soybean outputs

The "grand total" bar indicates China's total macroeconomic contributions to soybean output in China, Brazil, and the US. The macroeconomic drivers comprise capital accumulation, investment growth, labor productivity in non-agricultural sectors, labor accumulation, population growth in China, and feed industry restructuring in China. The height of each individual driver shows their contribution share to aggregate macroeconomic influences from China. China's macroeconomic drivers, again, contributed similarly to Brazil and the US soybean production with labor, population, and feed industry development increased China's soybean import demands. Labor productivity in China increased China's manufacturing exports, increasing agricultural imports. Capital and investment accumulation in China benefited capital-intensive industries, impeding labor-intensive industries. From China's perspective in the upper panel, labor, population, and feed industry development in China also increased domestic demands for soybeans. Development of feed industry benefited by productivity improvement increased China's demands for soybean imports and thus declined its domestic production.

C.4 Detailed Decomposition of Policy Drivers in Soybean Trade and Production

C.4.1 Soybean and non-soybean policy impacts on soybean trade

Soybean policies changed soybean's demands directly, but non-soybean agricultural policies also inserted greater aggregate impacts on soybean supply-demand-trade relationships among telecoupled regions (Figure C.4). We quantify aggregate soybean and non-soybean policy impacts to China's total soybean trade changes respectively. We further delve into each specific tax/subsidy effects within each soybean/non-soybean policy category. We aim to identify the relative magnitudes of interactions of detailed policies of Brazil, the US, and China. The "grand total" bar in Figure C.4 shows the contribution of net global policy impacts to China's soybean imports. The subtotal bars present proportions of China's soybean imports impacted by net global soybean/non-soybean policy impacts.

Figure C.4 Soybean and non-soybean policy decompositions of China’s soybean trade percentage changes

The leftmost bar shows China’s soybean trade changes that are driven by total policies. It is decomposed into soybean policy and non-soybean policy categories. The subtotals of trade changes due to soybean and non-soybean policies are shown in the left within each category. They are further decomposed into land-based input taxes/subsidies, output taxes/subsidies, other input-based taxes/subsidies, border policies and biofuel policies. Each driver composes effects from Brazil, the US, China, and other regions. Non-soybean policies from China inserted greater impacts on China’s imports in general. China’s corn stockpiling policies stimulated China’s soybean imports the most. Land subsidies on China’s soybean production prohibited China’s imports, but land subsidies on other crops increased other crop production and substituted away China’s demands for soybeans. China’s border policies of other crops towards other regions also spurred China’s soybean imports.

In general, China's soybean imports were more influenced by non-soybean policies rather than soybean policies. Within non-soybean policies, corn stockpiling policies included in output tax/subsidy was the major contributor to China's soybean imports by motivating farmers to switch from soybean production to corn production. Non-soybean border policies, such as soybean meal and oil imports, dampened soybean meal and oil imports and facilitated raw soybean imports with the goal of protecting domestic crushing industries. However, this border policies didn't impact China's soybean imports from Brazil and the US a lot. China subsidized its land for its soybean production and as well as other crops, triggering crop production competitions in land uses. China's soybean production benefited from this land subsidies, declining China's soybean imports.

Both Brazil and the US exports to China were facilitated by China's stockpiling policies but impeded by China's land subsidies on other agricultural products. Brazil itself didn't have many agricultural policies but influenced by the US policies. The US land subsidies on soybean production increased US exports to China but dampened Brazil exports to China. However, taxes collected on other inputs and output on soybean production declined the US soybean exports and facilitated Brazil exports. In contrast, the US land subsidies on other crops impeded the US soybean exports and facilitated Brazil soybean exports. Taxes collected on other inputs and output on other crop production benefited the US soybean exports and impeded Brazil's soybean exports. Restrictive border policies from other regions indirectly motivated Brazil and the US export more to China. In summary, China's soybean imports are mainly driven by its own policies and policies from other regions. Brazil's soybean exports to China benefited from China's policies but offset by the US subsidies. The US soybean exports to China were largely directed by border policies from other regions.

C.4.2 Soybean and non-soybean policy impacts on soybean production

China's soybean policy, in contrast, played a more important role in China's soybean production and a less important role in the US and Brazil soybean production (Figure C.5). China's land subsidies on soybean production successfully boosted its soybean production by about 20%. The weaker role that China's policy plays emphasizes the fact that China's supply behavior has less impact on Brazil and US production, and most of the impact power from China is on demand side. Non-soybean agricultural border policies relatively preferred Brazilian agricultural products to the US agricultural products. Brazilian soybean production was thus dampened, while the US soybean production was subsequently encouraged.

Figure C.5 Soybean and non-soybean policy decompositions of soybean production percentage changes

The leftmost bar shows soybean production changes in Brazil, the US, and China that are driven by total policies. It is decomposed into soybean policy and non-soybean policy categories. The subtotal of production changes due to soybean and non-soybean policies are shown at left within each category, which is further decomposed into land-based input taxes/subsidies, output taxes/subsidies, other input-based taxes/subsidies, border policies and biofuel policies. Each driver composes effects from Brazil, the US, China, and other countries. China's soybean policy became more influential in its domestic soybean production and had limited impacts on the US and Brazil production side. The weaker role that China's policy plays emphasizes the fact that China's supply behavior has less impact on Brazil and US production, and most of the impact power from China is on demand side. Non-soybean agricultural border policies relatively preferred Brazilian agricultural products to the US agricultural products. Brazilian soybean production was thus dampened, while the US soybean production was subsequently encouraged.

C.5 Sensitivity analysis of soybean productivity and policies

We also implement a ±10% change in each domestic soybean support driver to evaluate the corresponding magnitudes of responsiveness of soybean trade/production (Figure C.6 and Figure C.7). For example, the upper panel in Figure C.6 examines soybean output payments (left column) impacts from China, Brazil, and US (right column "policy countries") on China's total soybean imports (middle column "trade partners"). Consistent with the economic theory, a change in output payment leads to the greatest trade/production changes, and each county's trade/production is more responsive to its domestic policies. In contrast, a change in endowment (land/labor/capital) payments has limited effects on soybean trade/production.

Sensitivity analyses on soybean policies revealed the following telecoupled interactions:

1) China's total soybean imports/China's soybean production is more responsive to the US policy than Brazilian policy.
2) Brazil and the US are more sensitive to each other's soybean policies than China's policies.
3) The US is more responsive to Brazil's policy, but Brazil is less sensitive to the US policy.
4) Brazil is insensitive to China's policy, but the US is more sensitive to China's policy.
5) Land policy is more effective among endowment based payments. Only Brazil is sensitive to its own capital payments due to its more capital insensitive agricultural production cost structure.

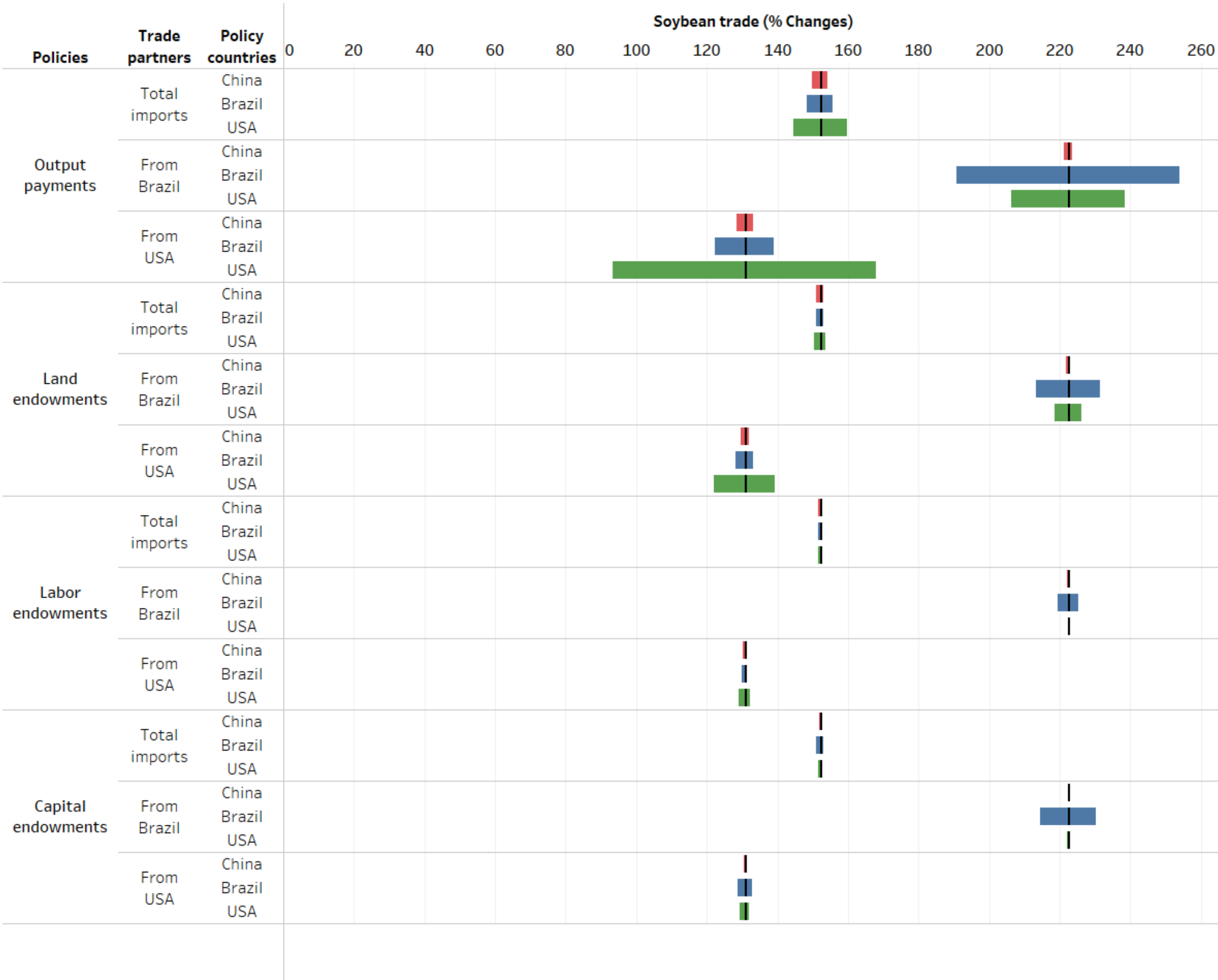

Figure C.6 China's soybean import sensitivity to domestic agricultural support changes. ±10% changes in each driver are applied. This figure presents the responses of China's soybean imports from Brazil, the US and China's total imports. The left column of vertical axis presents policy examined. The right column shows the country that each policy is implemented. The middle column shows the trade categories that we evaluate. For example, the first row shows China's total soybean imports responses to China's ±10% changes in soybean output payments.

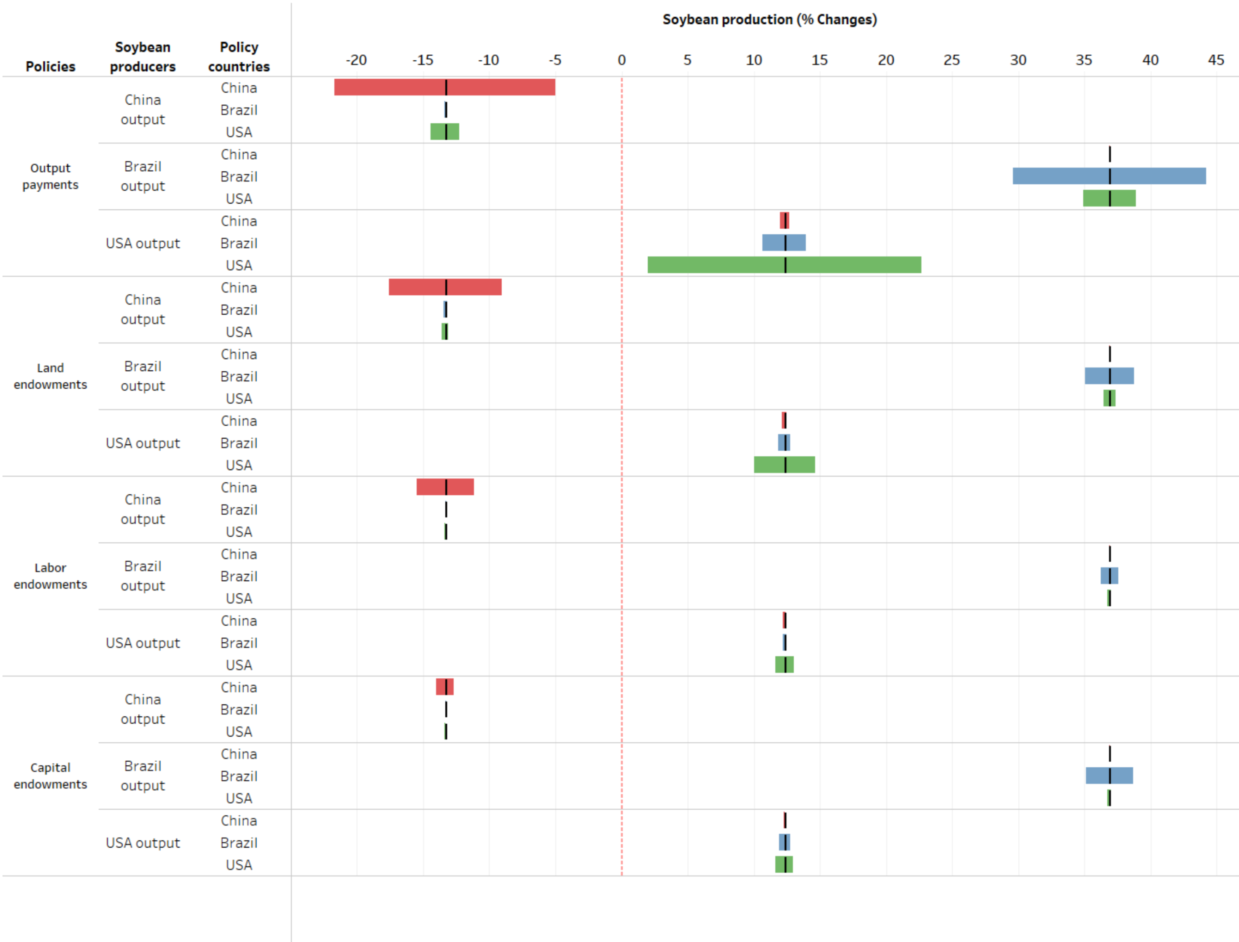

Figure C.7 Soybean production sensitivity to domestic agricultural support changes

±10% changes in each driver are applied. This figure presents the responses of soybean production in China, Brazil, the US. The left column of vertical axis presents policy examined. The right column shows the country that each policy is implemented. The middle column shows the soybean output categories that we evaluate. For example, the first row shows China's soybean production responses to China's ±10% changes in soybean output payments.

APPENDIX D. BEEF PRODUCTION AND TRADE SITUATION IN BRAZIL

Brazil's beef is the largest beef supplier for EU, composed of over 40% of total EU's beef imports (Aranoff et al. 2008). Bilateral beef trade from Brazil to EU has gone through two stages: a beef export surge due to a relaxed quota policy from EU before 2007, and a drastic beef export decline caused by the epidemic Foot and Mouth Disease (FMD) after 2007 (Schnepf et al. 2001b; Sapp 2008; Smyth 2008) . EU relaxed beef tariff quota for Mercosur countries since 2004, which significantly increased EU's beef imports from Brazil. Figure D.1 and Figure D.2 depicted this import surge from EU's import and Brazil's export perspectives, respectively. However, the FMD triggered a strict regulation from EU towards Brazil's beef imports, which significantly declined Brazil's beef exports to EU and Brazil's total beef exports. Over the period of 2004-2011, bilateral EU-Brazil traded beef quantity has declined by 37% accumulatively; EU's total soybean imports declined by 17% accumulatively; Brazil's total beef exports have declined by a surprisingly accumulative of 40%. Although EU's ban on Brazil's beef declined Brazil's beef production after 2007, its beef production still increased by 15% which indirectly increased its pasture land demands (Figure D.3).

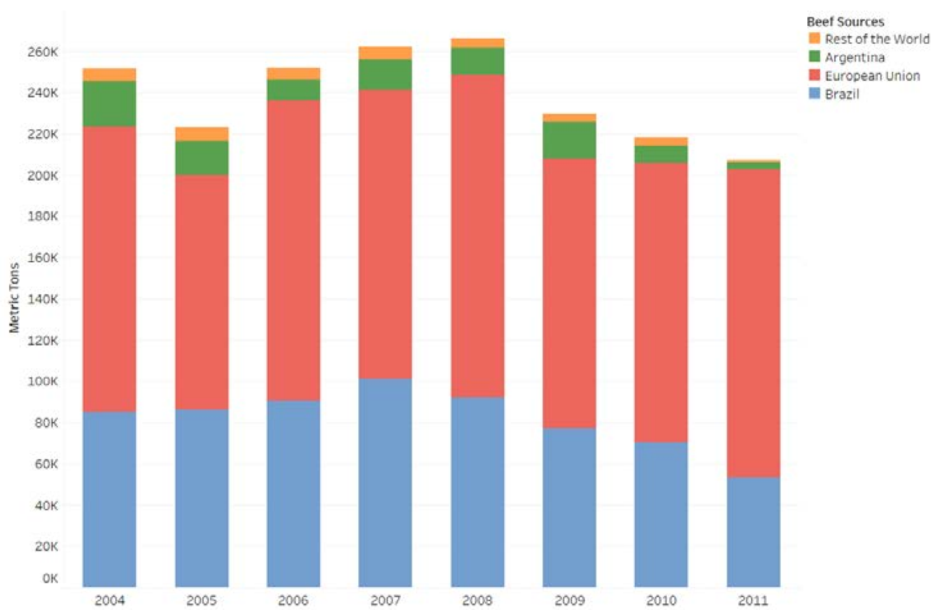

Figure D.1. EU's beef imports from different sources (2004-2011)

Source: FAO (2015) EU's reported bilateral imports of prepared beef

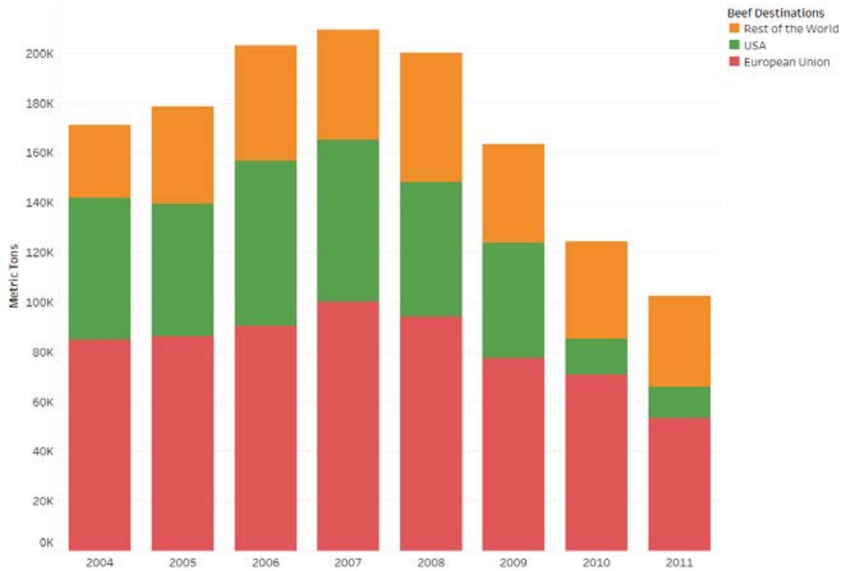

Figure D.2 Brazil's beef exports to different destinations (2004-2011)

Source: FAO (2015) Brazil's reported bilateral exports of prepared beef

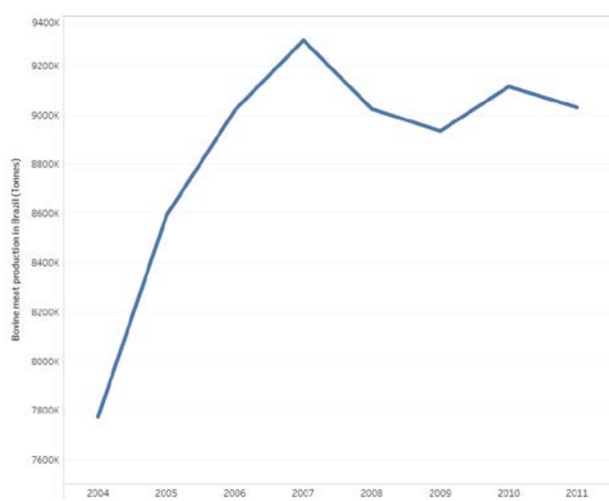

Figure D.3 Bovine meat production in Brazil in metric tons (2004-2011)

Source: FAO (2015)

APPENDIX E. SUPPLEMENTARY RESULTS FOR ELASTICITY ESTIMATION

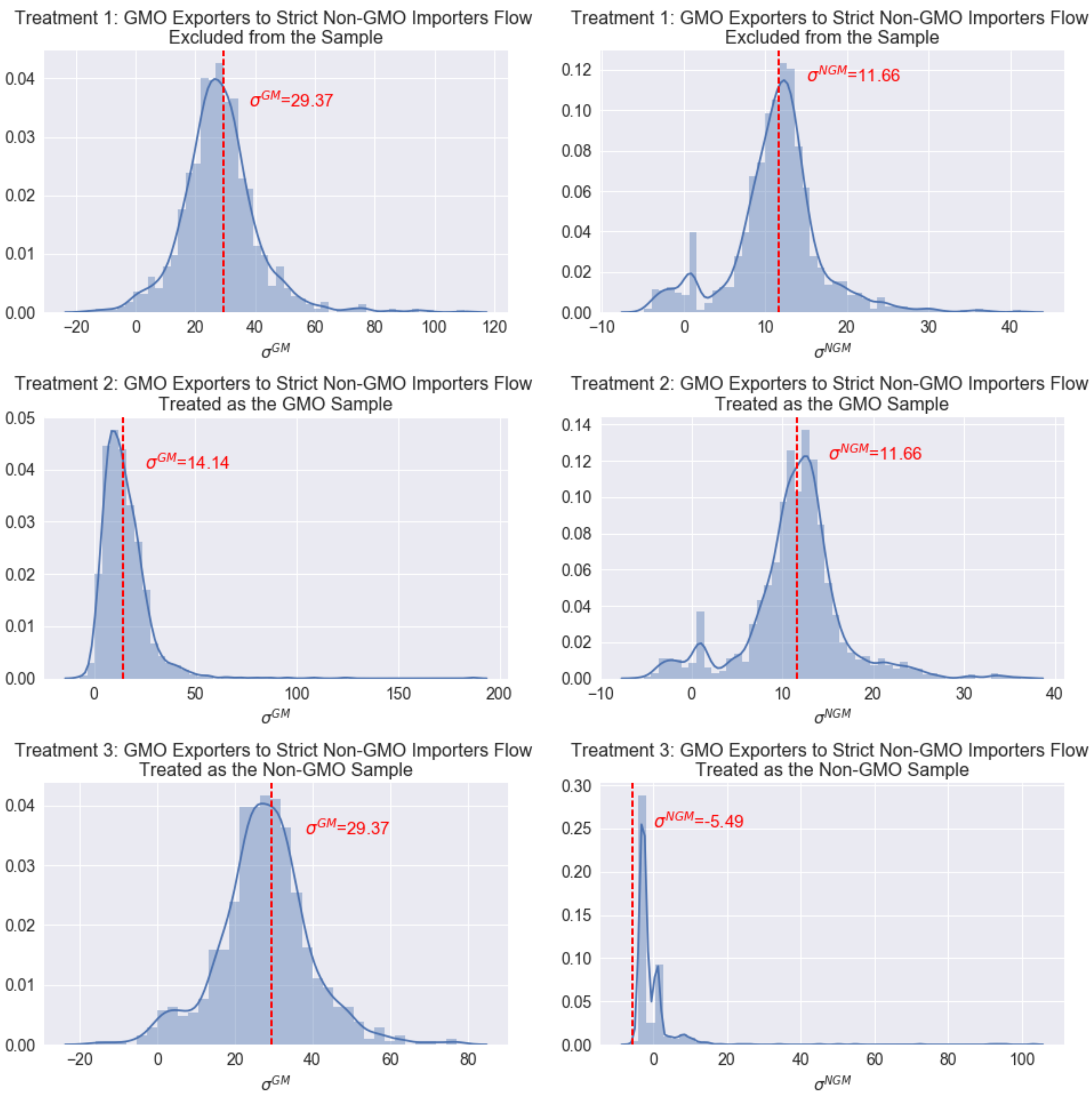

Figure E.1 Distribution of estimated trade elasticities for GMO and non-GMO samples of each treatment.

The vertical lines mark our sample estimates.

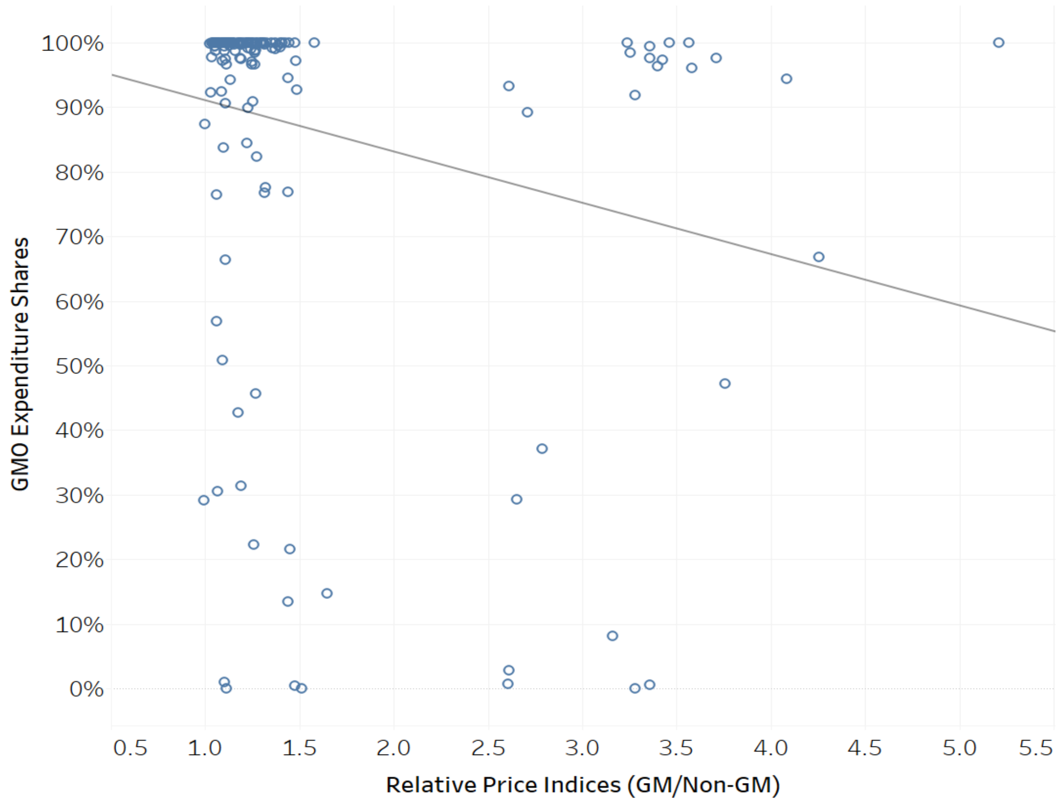

Figure E.2 GM soybean expenditure shares versus relative price indices (GM/non-GM)

The vertical axis shows the GMO expenditure shares out of total soybean expenditures. The horizontal axis represents the relative GM/non-GM soybean price indices derived from single nest CES.

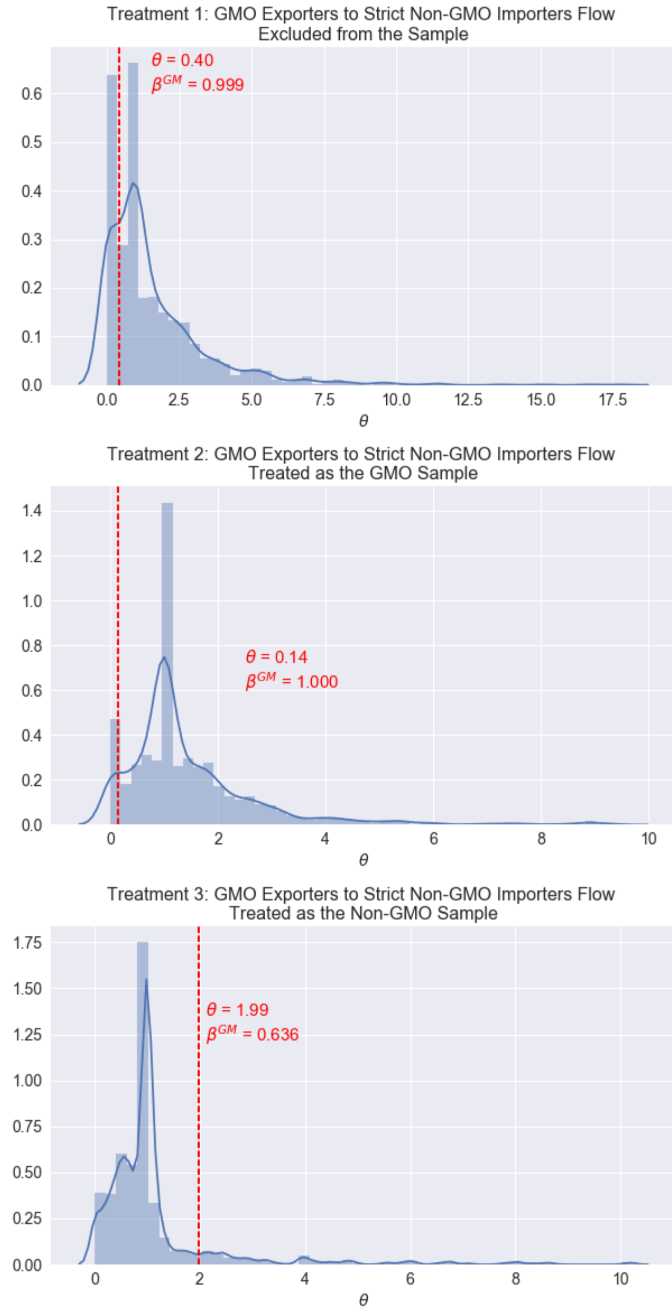

Figure E.3 Distribution of "elasticity of substitution between GM and non-GM soybeans" for each treatment

The vertical lines denote our estimates based on the samples. Historical observations in Treatment 1 and 2 show stronger GMO preferences, and Treatment 3 presents greater non-GMO preferences. The centered estimates (mode) have the GMO preference level between Treatment 1, 2 and 3. So our sample estimates are not centered.

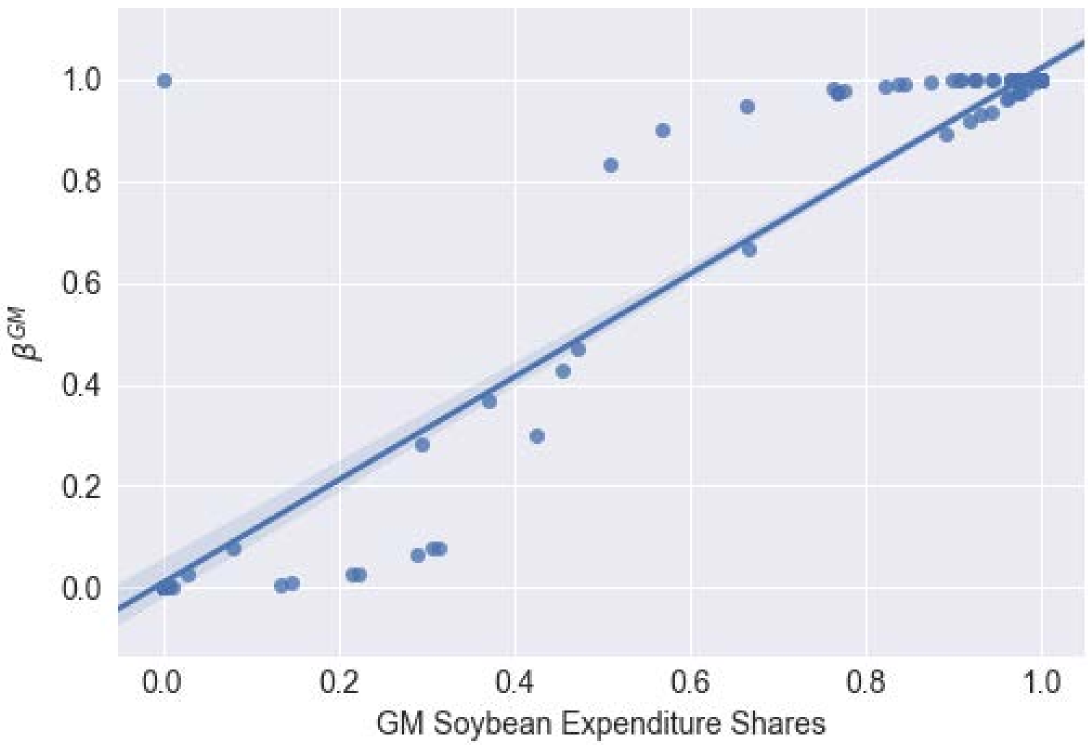

Figure E.4 Relationships between “preference weights of GM soybeans” and “GM soybean expenditure shares”

The vertical axis represents preference weights of GM soybeans”. The horizontal axis denotes GM soybean expenditure shares out of total soybean expenditures in each importer.

Table E.1 Heterogeneous soybean variety preference weights by each importer

Importers	beta(GM)	beta(Non-GM)	Importers	beta(GM)	beta(Non-GM)
Cambodia	1.00	0.00	Malawi	1.00	0.00
Belize	1.00	0.00	Estonia	1.00	0.00
Greenland	1.00	0.00	Syrian Arab Republic	1.00	0.00
Turks and Caicos Isl.	1.00	0.00	French Polynesia	1.00	0.00
Afghanistan	1.00	0.00	Argentina	0.99	0.01
Lithuania	1.00	0.00	Congo, Rep.	0.99	0.01
Uganda	1.00	0.00	Jordan	0.99	0.01
Lesotho	1.00	0.00	Brunei	0.99	0.01
Chad	1.00	0.00	Spain	0.98	0.02
Swaziland	1.00	0.00	St. Kitts and Nevis	0.98	0.02
Panama	1.00	0.00	Ukraine	0.98	0.02
Guyana	1.00	0.00	Japan	0.98	0.02
Barbados	1.00	0.00	Denmark	0.98	0.02
Morocco	1.00	0.00	Slovenia	0.97	0.03
Nicaragua	1.00	0.00	Germany	0.97	0.03
Saint Pierre and Miquelon	1.00	0.00	Macao	0.97	0.03
Brazil	1.00	0.00	France	0.96	0.04
Egypt, Arab Rep.	1.00	0.00	Canada	0.96	0.04
Paraguay	1.00	0.00	Tanzania	0.95	0.05
Liberia	1.00	0.00	South Africa	0.93	0.07
St. Vincent and the Grenadines	1.00	0.00	Greece	0.93	0.07
Antigua and Barbuda	1.00	0.00	United States	0.92	0.08
Cayman Islands	1.00	0.00	New Zealand	0.90	0.10
Cuba	1.00	0.00	Korea, Rep.	0.89	0.11
Azerbaijan	1.00	0.00	Cape Verde	0.83	0.17
Grenada	1.00	0.00	Italy	0.67	0.33
Kazakhstan	1.00		Romania	0.47	0.53
Thailand	1.00	0.00	India	0.43	0.57
El Salvador	1.00	0.00	Poland	0.37	0.63
Bangladesh	1.00	0.00	Iceland	0.30	0.70
St. Lucia	1.00	0.00	Slovak Republic	0.28	0.72

Table E.1 continued

Costa Rica	1.00	0.00	Kuwait	0.08	0.92
Chile	1.00	0.00	Croatia	0.08	0.92
Bahamas, The	1.00	0.00	Dominican Republic	0.08	0.92
Bermuda	1.00	0.00	Fm Sudan	0.07	0.93
Congo, Dem. Rep.	1.00	0.00	Sweden	0.03	0.97
Burundi	1.00	0.00	Czech Republic	0.03	0.97
Bolivia	1.00	0.00	Switzerland	0.03	0.97
Trinidad and Tobago	1.00	0.00	Korea, Dem. Rep.	0.01	0.99
Tunisia	1.00	0.00	Macedonia, FYR	0.01	0.99
Mexico	1.00	0.00	Bulgaria	0.01	0.99
Saudi Arabia	1.00	0.00	Austria	0.00	1.00
Mozambique	1.00	0.00	Hungary	0.00	1.00
Georgia	1.00	0.00	Australia	0.00	1.00
Jamaica	1.00	0.00	Luxembourg	0.00	1.00
Colombia	1.00	0.00	Bosnia and Herzegovina	0.00	1.00
Indonesia	1.00	0.00	Vanuatu	0.00	1.00
Norway	1.00	0.00	Rwanda	0.00	1.00
Namibia	1.00	0.00	Andorra	0.00	1.00
Iran, Islamic Rep.	1.00	0.00	Kenya	0.00	1.00
Nepal	1.00	0.00	Burkina Faso	0.00	1.00
United Arab Emirates	1.00	0.00	Gibraltar	0.00	1.00
Seychelles	1.00	0.00	Tonga	0.00	1.00
Guatemala	1.00	0.00	Senegal	0.00	1.00
Turkey	1.00	0.00	Mali	0.00	1.00
Cote d'Ivoire	1.00	0.00	Eritrea	0.00	1.00
Honduras	1.00	0.00	Madagascar	0.00	1.00
China	1.00	0.00	Sierra Leone	0.00	1.00
Israel	1.00	0.00	Lao PDR	0.00	1.00
Vietnam	1.00	0.00	New Caledonia	0.00	1.00
Philippines	1.00	0.00	Niger	0.00	1.00
United Kingdom	1.00	0.00	Gabon	0.00	1.00
Singapore	1.00	0.00	Comoros	0.00	1.00
Mauritius	1.00	0.00	Sri Lanka	0.00	1.00

Table E.1 continued

Ireland	1.00	0.00	Belarus	0.00	1.00
Suriname	1.00	0.00	Lebanon	0.00	1.00
Botswana	1.00	0.00	Mauritania	0.00	1.00
Portugal	1.00	0.00	Solomon Islands	0.00	1.00
Pakistan	1.00	0.00	Papua New Guinea	0.00	1.00
Ecuador	1.00	0.00	Ethiopia(excludes Eritrea)	0.00	1.00
Ghana	1.00	0.00	Cameroon	0.00	1.00
Bahrain	1.00	0.00	Fiji	0.00	1.00
Oman	1.00	0.00	Armenia	0.00	1.00
Zimbabwe	1.00	0.00	Moldova	0.00	1.00
Finland	1.00	0.00	Malta	0.00	1.00
Netherlands	1.00	0.00	Peru	0.00	1.00
Nigeria	1.00	0.00	Mongolia	0.00	1.00
Malaysia	1.00	0.00	Cyprus	0.00	1.00
Palau	1.00	0.00	Algeria	0.00	1.00
Uruguay	1.00	0.00	East Timor	0.00	1.00
Zambia	1.00	0.00	Latvia	0.00	1.00
Hong Kong, China	1.00	0.00	Russian Federation	0.00	1.00
Aruba	1.00	0.00	Serbia, FR(Serbia/Montenegro)	0.00	1.00
Angola	1.00	0.00	Qatar	0.00	1.00
Belgium	1.00	0.00	Samoa	0.00	1.00

APPENDIX F. GAMS CODE SAMPLE FOR ELASTICITY ESTIMATION

F.1 Sample Codes for Data Preparation

ppml_data.gams

```
$offdigit
option limrow=0,limcol=0 ;
option Decimals=8;

SET   j  Importer Regions
/
ABW   Aruba
AFG   Afghanistan
AGO   Angola
AND   Andorra
ARE   United Arab Emirates
ARG   Argentina
ARM   Armenia
ATG   Antigua and Barbuda
AUS   Australia
AUT   Austria
AZE   Azerbaijan
BDI   Burundi
BEL   Belgium
BFA   Burkina Faso
BGD   Bangladesh
BGR   Bulgaria
BHR   Bahrain
BHS   Bahamas The
BIH   Bosnia and Herzegovina
BLR   Belarus
BLZ   Belize
BMU   Bermuda
BOL   Bolivia
BRA   Brazil
BRB   Barbados
BRN   Brunei
BWA   Botswana
CAN   Canada
CHE   Switzerland
CHL   Chile
CHN   China
CIV   Cote d'Ivoire
CMR   Cameroon
COD   Congo Dem. Rep.
COG   Congo Rep.
COL   Colombia
COM   Comoros
CPV   Cape Verde
CRI   Costa Rica
CUB   Cuba
```

CYM	Cayman Islands
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
DOM	Dominican Republic
DZA	Algeria
ECU	Ecuador
EGY	Egypt Arab Rep.
ERI	Eritrea
ESP	Spain
EST	Estonia
ETH	Ethiopia(excludes Eritrea)
FIN	Finland
FJI	Fiji
FRA	France
GAB	Gabon
GBR	United Kingdom
GEO	Georgia
GHA	Ghana
GIB	Gibraltar
GRC	Greece
GRD	Grenada
GRL	Greenland
GTM	Guatemala
GUY	Guyana
HKG	Hong Kong China
HND	Honduras
HRV	Croatia
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
IRN	Iran Islamic Rep.
ISL	Iceland
ISR	Israel
ITA	Italy
JAM	Jamaica
JOR	Jordan
JPN	Japan
KAZ	Kazakhstan
KEN	Kenya
KGZ	Kyrgyz Republic
KHM	Cambodia
KNA	St. Kitts and Nevis
KOR	Korea Rep.
KWT	Kuwait
LAO	Lao PDR
LBN	Lebanon
LBR	Liberia
LCA	St. Lucia
LKA	Sri Lanka
LSO	Lesotho
LTU	Lithuania
LUX	Luxembourg
LVA	Latvia
MAC	Macao

MAR	Morocco
MDA	Moldova
MDG	Madagascar
MEX	Mexico
MKD	Macedonia FYR
MLI	Mali
MLT	Malta
MNG	Mongolia
MOZ	Mozambique
MRT	Mauritania
MUS	Mauritius
MWI	Malawi
MYS	Malaysia
NAM	Namibia
NCL	New Caledonia
NER	Niger
NGA	Nigeria
NIC	Nicaragua
NLD	Netherlands
NOR	Norway
NPL	Nepal
NZL	New Zealand
OMN	Oman
PAK	Pakistan
PAN	Panama
PER	Peru
PHL	Philippines
PLW	Palau
PNG	Papua New Guinea
POL	Poland
PRK	Korea Dem. Rep.
PRT	Portugal
PRY	Paraguay
PYF	French Polynesia
QAT	Qatar
ROU	Romania
RUS	Russian Federation
RWA	Rwanda
SAU	Saudi Arabia
SCG	Serbia FR(Serbia Montenegro)
SDN	Fm Sudan
SEN	Senegal
SGP	Singapore
SLB	Solomon Islands
SLE	Sierra Leone
SLV	El Salvador
SPM	Saint Pierre and Miquelon
SUR	Suriname
SVK	Slovak Republic
SVN	Slovenia
SWE	Sweden
SWZ	Swaziland
SYC	Seychelles
SYR	Syrian Arab Republic
TCA	Turks and Caicos Isl.
TCD	Chad
THA	Thailand

```
TLS   East Timor
TON   Tonga
TTO   Trinidad and Tobago
TUN   Tunisia
TUR   Turkey
TZA   Tanzania
UGA   Uganda
UKR   Ukraine
URY   Uruguay
USA   United States
VCT   St. Vincent and the Grenadines
VEN   Venezuela
VNM   Vietnam
VUT   Vanuatu
WSM   Samoa
ZAF   South Africa
ZMB   Zambia
ZWE   Zimbabwe
/;

SET      i(j)  Exporter Regions
/
BRA   Brazil
POL   Poland
SVN   Slovenia
AUT   Austria
SVK   Slovak Republic
ROU   Romania
CHN   China
JPN   Japan
CAN   Canada
HUN   Hungary
USA   United States
ZAF   South Africa
GRC   Greece
PRY   Paraguay
FRA   France
URY   Uruguay
KOR   Korea Rep.
ESP   Spain
CZE   Czech Republic
DEU   Germany
BGR   Bulgaria
ARG   Argentina
ITA   Italy
HRV   Croatia
/;

Alias(i,ex),(j,im);

SET    gi(i) GMO exporters
/
BRA   Brazil
USA   United States
ZAF   South Africa
ARG   Argentina
CAN   Canada
```

```
PRY   Paraguay
URY   Uruguay
/;

SET      ni(i) NonGMO exporters;
ni(i) = Yes - gi(i);

SET      nj(j) Strict NonGMO importers
/
PER   Peru
DZA   Algeria
MDG   Madagascar
RUS   Russian Federation
VEN   Venezuela
KGZ   Kyrgyz Republic
/;

SET     gj(j) GMO allowed importers;
gj(j) = Yes - nj(j);
display gi, ni, gj, nj;

SET m /g GMSoy,n NonGMSoy/;

* GMO trade flows: gi to gj
* NonGMO trade flows: ni to j


SET       k     Variable names for full datasets
/
$offlisting
$include fullnames.csv
$onlisting
/;

display k;

SET      k1(k)     Variable that doesn't belong to fixed effects
/intercept, ln1trf, lndist/;

SET      k2(k)     Fixed effect variables;
k2(k) = YES - k1(k);

SET      k2_exp(k) Export fixed effects
/
exp_ARG
exp_AUT
exp_BGR
exp_BRA
exp_CAN
exp_CHN
exp_CZE
exp_DEU
exp_ESP
exp_FRA
exp_GRC
exp_HRV
exp_HUN
```

```
exp_ITA
exp_JPN
exp_KOR
exp_POL
exp_PRY
exp_ROU
exp_SVK
exp_SVN
exp_URY
exp_USA
exp_ZAF
/;

SET      knc(k)   Normal variables exluding constant variables;
SET      kint(k)  Set that only contains intercept /intercept/;

knc(k) =  k1(k) - kint(k);

DISPLAY knc, kint;

SET      k2_imp(k) Import fixed effects;
k2_imp(k) = k2(k) - k2_exp(k);

DISPLAY k2, k2_imp,k2_exp;

SET      kc(k)     Intercept /intercept/;

SET      kc_imp(k) Constant plus import fixed effects;
kc_imp(k) = kc(k) + k2_imp(k);

SET      kc_exp(k) Constant plus export fixed effects;
kc_exp(k) = kc(k) + k2_exp(k);

DISPLAY kc, kc_exp, kc_imp;


PARAMETER value(i,j) Bilateral trade values between two countries
/
$offlisting
$ondelim
$include tradevalue.csv
$offdelim
$onlisting
/;

display value;

$ontext
PARAMETER expend(j)    Expenditures of importers on soybeans
/
$offlisting
$ondelim
$include tradevalue.csv
$offdelim
$onlisting
/;
$offtext
```

```
TABLE data(i,j,k) Independent variables for each pairs
$offlisting
$ondelim
$include data_dist.csv
$offdelim
$onlisting


PARAMETERS map(j,k) Mapping j with k;
map(j,k) = 0;
map(j,k)$(sum(i,data(i,j,k))=24)=1;

PARAMETERS mapx(i,k) Mapping i with k;
mapx(i,k) = 0;
mapx(i,k)$(sum(j,data(i,j,k))=171)=1;

DISPLAY map, mapx;

SET     sgg(i,j) Sample GMO set
/
$offlisting
$ondelim
$include expimp_GMO.csv
$offdelim
$onlisting
/
;

SET     snn(i,j) Sample GMO set
/
$offlisting
$ondelim
$include expimp_NGMO.csv
$offdelim
$onlisting
/
;

DISPLAY data, sgg, snn;

PARAMETER expdG(j) Expenditures on GM soybeans for country j
          expdN(j) Expenditures on Non-GM soybeans for country j
          expdA(j) Expenditures on soybeans for country j;
expdG(j) = sum(i$sgg(i,j),value(i,j));
expdN(j) = sum(i$snn(i,j),value(i,j));
expdA(j) = expdG(j) + expdN(j);
DISPLAY expdG,expdN,expdA;

SETS     sg(j)   Sample set that country j actually importing GM soy
         sn(j)   Sample set that country j actually importing NonGM soy
         sa(j)   Sample set that country j actually import soy;
sg(j) = YES;
sg(j)$(expdG(j)=0) = No;
sg(nj)=No;

sn(j) = YES;
```

```
sn(j)$(expdN(j)=0) = No;

sa(j) = YES;
sa(j)$(expdA(j)=0) = No;

DISPLAY sg,sn,sa;

PARAMETERS trf1p(i,j)   1 + trf
           dist(i,j)    distance;
trf1p(i,j) = exp(data(i,j,'ln1trf'));
dist(i,j) = exp(data(i,j,'lndist'));
DISPLAY trf1p, dist;
DISPLAY sgg, snn, value;
```

F.2 Sample Codes for Static Estimation

PPML_reg.gams

```
$offdigit
option limrow=0,limcol=0 ;
option Decimals=8;


$include ppml_data.gms



********Loglikelihood for GM soybeans with fixed effects********

VARIABLE b(k) Coefficients on each independent variable;
PARAMETERS b_result(k) Starting values on each independent variables
/
$offlisting
$ondelim
$include GMO_coef.csv
$offdelim
$onlisting
/;


VARIABLE L       Loglikelihood function;
EQUATIONS lobj   Loglikelihood objective function
          lcont  Loglikelihood constraints for coefficients;

lobj.. L =e= -sum((i,j)$sgg(i,j),exp(sum(k,data(i,j,k)*b(k))))
                 +
sum((i,j)$(sgg(i,j)),value(i,j)/1000*sum(k,data(i,j,k)*b(k)));

lcont(k2).. b('intercept') + b(k2)=G=0;
b.fx(k2)$(b_result(k2)=0) = 0;

MODEL likelihood/lobj,lcont/;
SOLVE likelihood using nlp maximizing L;
```

```
DISPLAY L.l, b.l;


********Loglikelihood for non-GMO soybeans with fixed effects********
VARIABLE bN(k) Coefficients on each independent variable;
PARAMETERS bN_result(k) Starting values on each independent variables
/
$offlisting
$ondelim
$include NGMO_coef.csv
$offdelim
$onlisting
/;


VARIABLE LN       Loglikelihood function;
EQUATIONS lobjN   Loglikelihood objective function
          lcontN  Loglikelihood constraints for coefficients;

lobjN.. LN =e= -sum((i,j)$snn(i,j),exp(sum(k,data(i,j,k)*bN(k))))
                 +
sum((i,j)$(snn(i,j)),value(i,j)/1000*sum(k,data(i,j,k)*bN(k)));

lcontN(k2).. bN('intercept') + bN(k2)=G=0;



bN.fx(k2)$(bN_result(k2)=0) = 0;


MODEL likelihoodN/lobjN,lcontN/;
SOLVE likelihoodN using nlp maximizing LN;
DISPLAY LN.l, bN.l;


SOLVE likelihoodN using nlp maximizing LN;
DISPLAY LN.l, bN.l;


********Calculate GM and non-GM price index from fixed effects********

PARAMETERS lnPG(j)   ln Price index for GM soybeans for country j
           lnPN(j)   ln Price index of non-GM soybeans for country j
           PG(j)     Price index for GM soybeans for country j
           PN(j)     Price index of non-GM soybeans for country j
           sigG      Elasticity of substitution for GM soybeans
           sigN      Elasticity of substitution for non-GM soybeans
           rhoG      Elasticity of distance for GM soybeans
           rhoN      Elasticity of distance for nonGM soybeans;




sigG = 1 - b.l('ln1trf');
sigN = 1 - bN.l('ln1trf');
rhoG = b.l('lndist')/(1-sigG);
rhoN = bN.l('lndist')/(1-sigN);
```

```
PARAMETER fx_effG(j) Fixed import effects for GM soybeans
          fx_effN(j) Fixed import effects for non-GM soybeans;
fx_effG(j) = sum(kc_imp,b.l(kc_imp)*map(j,kc_imp));
fx_effN(j) = sum(kc_imp,bN.l(kc_imp)*map(j,kc_imp));

DISPLAY fx_effG,fx_effN,sigG,sigN,rhoG,rhoN;


*** Exporter Fixed Effects, equivalent to ln[alpha(i)]+ln[pi]
PARAMETER fx_effxG(i) Fixed export effects for GM soybeans
          fx_effxN(i) Fixed export effects for non-GM soybeans;
fx_effxG(i) = sum(kc_exp,b.l(kc_exp)*mapx(i,kc_exp));
fx_effxN(i) = sum(kc_exp,bN.l(kc_exp)*mapx(i,kc_exp));

DISPLAY fx_effxG,fx_effxN;


PARAMETERS tot_sgg;
tot_sgg = sum((i,j)$sgg(i,j),1);

DISPLAY tot_sgg;

PARAMETERS tot_snn;
tot_snn = sum((i,j)$snn(i,j),1);

DISPLAY tot_snn;
```

F.3 Sample Codes for Bootstrapping

ppml_boot.gms

```
$offdigit
option limrow=0,limcol=0 ;
option Decimals=8;

options solprint=off;
$include ppml_data.gms

SET              obf               Total observations
/obs1*obs3307/;

PARAMETERS indg             loop index
           cardg(i,j)     cardinal value of the subset observation
            ;


indg = 0;

loop(sgg(i,j),
        indg = indg+1;
        cardg(i,j)=indg;
);
```

```
PARAMETER
        rdrawg        randomly draw with replacement over the 1155 observations;

SET          boot                  Iterations of bootstrap /ite1 * ite6/;
SET          bootobsg(obf)         Iterations of observations /obs1 * obs910/;
SET          boot2(boot)            A subset of boot;
SET          boot1(boot)            A initial value of boot /ite1/;
boot2(boot) = Yes - boot1(boot);

execseed = %seed% ;


PARAMETER     sbootg(boot,i,j)                  Contains which data is choosen
in each bootstrap;
PARAMETER    databootobsg(bootobsg,i,j,k)       Contains the new dataset which
the regression is based on;
PARAMETER    databootg(boot,bootobsg,i,j,k)     Contains the new dataset which
the regression is based on;
PARAMETER     vbootobsg(bootobsg,i,j)            Contains the new traded value
which the regression is based on;
PARAMETER     vbootg(boot,bootobsg,i,j)          Contains the new traded value
which the regression is based on;
PARAMETER    randbootg(boot,bootobsg)          Contains the boostrapped random
value;



******************Generate 1000 samples of datasets***********************
loop(boot,
sbootg(boot,i,j) = 0;
        loop(bootobsg,
        rdrawg=round(uniform(0.5,910.5));
        randbootg(boot,bootobsg) = rdrawg;
                loop((i,j)$(cardg(i,j) eq rdrawg),
*sbootg shows how many times that one data point has been drawn
                sbootg(boot,i,j)=sbootg(boot,i,j)+1;
*databootobsg keeps track of
                databootobsg(bootobsg,i,j,k) = data(i,j,k);
                vbootobsg(bootobsg,i,j) = value(i,j);
                );
databootg(boot,bootobsg,i,j,k)= databootobsg(bootobsg,i,j,k);
vbootg(boot,bootobsg,i,j)= vbootobsg(bootobsg,i,j);
        );
     );



DISPLAY databootg, vbootg, sbootg,randbootg,cardg;

**We have to make sure that 1155 values are chosen for each iteration.
PARAMETER total_sbootg(boot)  total number of observations for each iteration;
total_sbootg(boot) = sum((i,j),sbootg(boot,i,j));

DISPLAY total_sbootg;
```

```
* According to what we did for our central value analysis, trade pairs that
including
* in the set 1) chosen from boot iteration 2) Had exports 3) Had imports
PARAMETERS   expdGbt(boot,j)           Expenditures on GM soybeans for country
j for each iteration
             expvaGbt(boot,i)              Total export value for GM soybean
exporters for each iteration;

expdGbt(boot,j) = sum((bootobsg,i),vbootg(boot,bootobsg,i,j));
expvaGbt(boot,i) = sum((bootobsg,j),vbootg(boot,bootobsg,i,j));

SET sbootgs(boot,i,j)    Set showing which trade pairs is included in the set;
sbootgs(boot,i,j)$(sgg(i,j) and sbootg(boot,i,j)>0)=YES;


DISPLAY sbootgs;



PARAMETERS b_resultg(k) Starting values on each independent variables
/
$offlisting
$ondelim
$include GMO_coef.csv
$offdelim
$onlisting
/;

alias(bootobsg,og);

VARIABLE        bbtg(k)             Contains coefficients for each iteration
equivalent to b(k);
VARIABLE      Lbtg                  Loglikelihood function;
EQUATIONS     objbtg                Loglikelihood objective function
              contbtg               Loglikelihood constraints for coefficients;
PARAMETER     coefbtg                     Contains calculated coefficients for
each iteration from b(k)
              databtg_(og,i,j,k)        Contains data for each iteraction
              valuebtg_(og,i,j)       Contains traded value for each iteration;
SET           sggboot(i,j)              New set for GM trade flows;

**********Parameters for price calculation out of fixed effects

PARAMETERS
             lnPGbt(boot,og,j)             ln Price index for GM soybeans for
country j in each iteration
             PGbt(boot,og,j)                 Price index for GM soybeans for
country j for country j in each iteration
             lnPGbtS(boot,j)               ln Price index for GM soybeans for
country j in each iteration
             PGbtS(boot,j)           Price index for GM soybeans for country
j for country j in each iteration
             sigGbt(boot)                   Elasticity of substituion for GM
soybeans for country j in each iteration
```

```
             fx_effGbt(boot,og,j)         Fixed export effects for GM soybeans
for country j in each iteration
             fx_effxGbt(boot,og,i)       Fixed export effects for GM soybeans
for country i in each iteration;


PARAMETERS mapg(boot,bootobsg,j,k) Mapping j with k;
mapg(boot,bootobsg,j,kc_imp)$(sum(i,databootg(boot,bootobsg,i,j,kc_imp))<>0)=
1;

PARAMETERS mapxg(boot,bootobsg,i,k) Mapping i with k;
mapxg(boot,bootobsg,i,kc_exp)$(sum(j,databootg(boot,bootobsg,i,j,kc_exp))<>0)
=1;


objbtg..                     Lbtg                     =e=                    -
sum((i,j,og)$sggboot(i,j),exp(sum(k,databtg_(og,i,j,k)*bbtg(k))))
                 +
sum((i,j,og)$sggboot(i,j),valuebtg_(og,i,j)/100000*sum(k,databtg_(og,i,j,k)*b
btg(k)));

contbtg(k2).. bbtg('intercept') + bbtg(k2)=G=0;



MODEL llbootg/objbtg,contbtg/;

loop(boot,



         valuebtg_(og,i,j) = 0;
         databtg_(og,i,j,k)= 0;
         valuebtg_(og,i,j) = vbootg(boot,og,i,j);
         databtg_(og,i,j,k)= databootg(boot,og,i,j,k);
         sggboot(i,j)$(sbootgs(boot,i,j))=YES;

         bbtg.lo(k)=-INF;
         bbtg.up(k)=+INF;
         bbtg.fx(k2)$(b_resultg(k2)=0) = 0;



         SOLVE llbootg using nlp maximizing Lbtg;

         coefbtg(boot,k)$(llbootg.solvestat eq 1) = bbtg.l(k);


);

*Calculate PGj for each iteration
sigGbt(boot) = 1 - coefbtg(boot,'ln1trf');
fx_effGbt(boot,og,j) = sum(kc_imp,coefbtg(boot,kc_imp)*mapg(boot,og,j,kc_imp));
fx_effxGbt(boot,og,i)                                                        =
sum(kc_exp,coefbtg(boot,kc_exp)*mapxg(boot,og,i,kc_exp));
```

```
PARAMETERS fx_effGbtS(boot,j)   simplified fixed import effects for GM soybeans
           fx_effxGbtS(boot,i)     similified  fixed  export  effects  for  NGM
soybeans
           countG(boot,j)         count the number of exporter for each j in
each iteration
           countxG(boot,i)        count the number of importer for each i in
each iteration;
*Note: sboot(boot,i,j) presents the actual number that each flow is drawn.

countG(boot,j) = sum(og$(fx_effGbt(boot,og,j)>0),1);
countxG(boot,i) = sum(og$(fx_effxGbt(boot,og,i)>0),1);


fx_effGbtS(boot,j)$(countG(boot,j)>0)                                       =
sum(og,fx_effGbt(boot,og,j))/countG(boot,j);
fx_effxGbtS(boot,i)$(countxG(boot,i)>0)                                     =
sum(og,fx_effxGbt(boot,og,i))/countxG(boot,i);



PARAMETERS rhobtG                Distance elasticity for GM soybeans;
rhobtG(boot)$(coefbtg(boot,'ln1trf')<>0)                                    =
coefbtg(boot,'lndist')/(coefbtg(boot,'ln1trf'));

PARAMETERS lntaubtG(boot,og,i,j) Log Trade cost for GM soybeans;
lntaubtG(boot,og,i,j)                                                       =
databootg(boot,og,i,j,'ln1trf')+rhobtg(boot)*databootg(boot,og,i,j,'lndist');

PARAMETERS lntaubtGS(boot,i,j)   Simplified Log Trade cost for GM soybeans;
lntaubtGS(boot,i,j)$(sbootgs(boot,i,j))                                     =
sum(og,lntaubtG(boot,og,i,j))/sbootg(boot,i,j);

DISPLAY lntaubtG,lntaubtGS;



PARAMETERS taubtG(boot,og,i,j)     Trade cost for GM soybeans;
taubtG(boot,og,i,j)$(lntaubtG(boot,og,i,j)>0)= exp(lntaubtG(boot,og,i,j));
DISPLAY taubtG


PARAMETERS taubtGS(boot,i,j)     Trade cost for GM soybeans;
taubtGS(boot,i,j)= exp(lntaubtGS(boot,i,j));
DISPLAY taubtGS;



PARAMETERS alpha_pbtG(boot,og,i)   Alpha_p for GM soybeans;
alpha_pbtG(boot,og,i)$(coefbtg(boot,'ln1trf')<>0)=
exp(fx_effxGbt(boot,og,i)/(coefbtg(boot,'ln1trf')));

PARAMETERS alpha_pbtGS(boot,i)   Alpha_p for GM soybeans;
alpha_pbtGS(boot,i)$(coefbtg(boot,'ln1trf')<>0)=
exp(fx_effxGbtS(boot,i)/(coefbtg(boot,'ln1trf')));


DISPLAY alpha_pbtGS,taubtGS,sigGbt;
```

```
***************Bootstrap for Non-GM soybeans*********************
PARAMETERS indn             loop index
           cardn(i,j)       cardinal value of the subset observation
            ;


indn = 0;

loop(snn(i,j),
        indn = indn+1;
        cardn(i,j)=indn;
);


PARAMETER
              rdrawn            Randomly draw with replacement over the 2397
observations;

SET          bootobsn(obf)      Iterations of observations /obs911 * obs3307/;


PARAMETER     sbootn(boot,i,j)                  Contains which data is choosen
in each bootstrap;
PARAMETER     databootobsn(bootobsn,i,j,k)      Contains the new dataset which
the regression is based on;
PARAMETER     databootn(boot,bootobsn,i,j,k)    Contains the new dataset which
the regression is based on;
PARAMETER     vbootobsn(bootobsn,i,j)           Contains the new traded value
which the regression is based on;
PARAMETER     vbootn(boot,bootobsn,i,j)         Contains the new traded value
which the regression is based on;
PARAMETER     randbootn(boot,bootobsn)         Contains the boostrapped random
value;



******************Generate 1000 samples of datasets***********************
loop(boot,
sbootn(boot,i,j) = 0;
        loop(bootobsn,
        rdrawn=round(uniform(0.5,2397.5));
        randbootn(boot,bootobsn)=rdrawn;
                loop((i,j)$(cardn(i,j) eq rdrawn),
*sbootg shows how many times that one data point has been drawn
                sbootn(boot,i,j)=sbootn(boot,i,j)+1;
*databootobsg keeps track of
                databootobsn(bootobsn,i,j,k) = data(i,j,k);
                vbootobsn(bootobsn,i,j) = value(i,j);
                );
databootn(boot,bootobsn,i,j,k)= databootobsn(bootobsn,i,j,k);
vbootn(boot,bootobsn,i,j)= vbootobsn(bootobsn,i,j);
        );
     );
```

```
**We have to make sure that 1155 values are chosen for each iteration.
PARAMETER total_sbootn(boot)  total number of observations for each iteration;
total_sbootn(boot) = sum((i,j),sbootn(boot,i,j));



PARAMETERS
             expdNbt(boot,j)                Expenditures on NonGM soybeans for
country j for each iteration
             expvaNbt(boot,i)             Total export value for NonGM soybean
exporters for each iteration;

expdNbt(boot,j) = sum((bootobsn,i),vbootn(boot,bootobsn,i,j));
expvaNbt(boot,i) = sum((bootobsn,j),vbootn(boot,bootobsn,i,j));


SET sbootns(boot,i,j)    Set showing which trade pairs are included in the set;

sbootns(boot,i,j)$(snn(i,j) and sbootn(boot,i,j)>0)=YES;


DISPLAY sbootns;

PARAMETERS b_resultn(k) Starting values on each independent variables
/
$offlisting
$ondelim
$include NGMO_coef.csv
$offdelim
$onlisting
/;

alias(bootobsn,on);

VARIABLE      bbtn(k)                  Contains coefficients for each iteration
equivalent to b(k);
VARIABLE      Lbtn                       Loglikelihood function;
EQUATIONS     objbtn                     Loglikelihood objective function
              contbtn                Loglikelihood constraints for coefficients;
PARAMETER     coefbtn                      Contains calculated coefficients for
each iteration from b(k)
              databtn_(on,i,j,k)         Contains data for each iteraction
              valuebtn_(on,i,j)        Contains traded value for each iteration;
SET            snnboot(i,j)                New set for non-GM soybeans for each
boot;

**********Parameters for price calculation out of fixed effects

PARAMETERS
             lnPNbt(boot,on,j)               ln Price index for NonGM soybeans
for country j in each iteration
             PNbt(boot,on,j)                Price index for NonGM soybeans for
country j for country j in each iteration
             lnPNbtS(boot,j)            ln Price index for NonGM soybeans for
country j in each iteration
```

```
             PNbtS(boot,j)                  Price index for NonGM soybeans for
country j for country j in each iteration
             sigNbt(boot)                   Elasticity of substituion for NonGM
soybeans for country j in each iteration
             fx_effNbt(boot,on,j)               Fixed export effects for NonGM
soybeans for country j in each iteration
             fx_effxNbt(boot,on,j)              Fixed export effects for NonGM
soybeans for country j in each iteration;


PARAMETERS mapn(boot,bootobsn,j,k) Mapping j with k;
mapn(boot,bootobsn,j,kc_imp)$(sum(i,databootn(boot,bootobsn,i,j,kc_imp))<>0)=
1;


PARAMETERS mapxn(boot,bootobsn,i,k) Mapping i with k;
mapxn(boot,bootobsn,i,kc_exp)$(sum(j,databootn(boot,bootobsn,i,j,kc_exp))<>0)
=1;



objbtn..                     Lbtn                     =e=                    -
sum((i,j,on)$snnboot(i,j),exp(sum(k,databtn_(on,i,j,k)*bbtn(k))))
                 +
sum((i,j,on)$snnboot(i,j),valuebtn_(on,i,j)/100000*sum(k,databtn_(on,i,j,k)*b
btn(k)));

contbtn(k2).. bbtn('intercept') + bbtn(k2)=G=0;



MODEL llbootn/objbtn,contbtn/;

loop(boot,



         valuebtn_(on,i,j) = 0;
         databtn_(on,i,j,k)= 0;
         valuebtn_(on,i,j) = vbootn(boot,on,i,j);
         databtn_(on,i,j,k)= databootn(boot,on,i,j,k);
         snnboot(i,j)$(sbootns(boot,i,j))=YES;

         bbtn.lo(k)=-INF;
         bbtn.up(k)=+INF;
         bbtn.fx(k2)$(b_resultn(k2)=0) = 0;



         SOLVE llbootn using nlp maximizing Lbtn;

         coefbtn(boot,k)$(llbootn.solvestat eq 1) = bbtn.l(k);


);

*Calculate PNj for each iteration
```

```
sigNbt(boot) = 1 - coefbtn(boot,'ln1trf');
fx_effNbt(boot,on,j) = sum(kc_imp,coefbtn(boot,kc_imp)*mapn(boot,on,j,kc_imp));
fx_effxNbt(boot,on,i)                                                          =
sum(kc_exp,coefbtn(boot,kc_exp)*mapxn(boot,on,i,kc_exp));



PARAMETERS fx_effNbtS(boot,j)   simplified fixed import effects for GM soybeans
           fx_effxNbtS(boot,i)     similified  fixed  export  effects  for  NGM
soybeans
           countN(boot,j)         count  the  number  of  exporter  for  each  j  in
each iteration
           countxN(boot,i)        count  the  number  of  importer  for  each  i  in
each iteration;

*Note: sboot(boot,i,j) presents the actual number that each flow is drawn.

countN(boot,j) = sum(on$(fx_effNbt(boot,on,j)>0),1);
countxN(boot,i) = sum(on$(fx_effxNbt(boot,on,i)>0),1);

fx_effNbtS(boot,j)$(countN(boot,j)>0)                                          =
sum(on,fx_effNbt(boot,on,j))/countN(boot,j);
fx_effxNbtS(boot,i)$(countxN(boot,i)>0)                                        =
sum(on,fx_effxNbt(boot,on,i))/countxN(boot,i);

DISPLAY fx_effNbtS, fx_effxNbtS;


PARAMETERS rhobtN        Distance elasticity for NonGM soybeans;
rhobtN(boot)$(coefbtn(boot,'ln1trf')<>0)                                       =
coefbtn(boot,'lndist')/(coefbtn(boot,'ln1trf'));

PARAMETERS lntaubtN(boot,on,i,j)        Log Trade cost for NonGM soybeans;
lntaubtN(boot,on,i,j)                                                          =
databootn(boot,on,i,j,'ln1trf')+rhobtn(boot)*databootn(boot,on,i,j,'lndist');


PARAMETERS taubtN(boot,on,i,j)          Trade cost for NonGM soybeans;
taubtN(boot,on,i,j)$(sbootns(boot,i,j)) = exp(lntaubtN(boot,on,i,j));



PARAMETERS  lntaubtNS(boot,i,j)           Simplified  Log  Trade  cost  for  NonGM
soybeans;;
lntaubtNS(boot,i,j)$(sbootns(boot,i,j))                                        =
sum(on,lntaubtN(boot,on,i,j))/sbootn(boot,i,j);


PARAMETERS taubtNS(boot,i,j)          Trade cost for NonGM soybeans;
taubtNS(boot,i,j)$(sbootns(boot,i,j)) = exp(lntaubtNS(boot,i,j));

DISPLAY taubtNS;

PARAMETERS alpha_pbtN(boot,on,i)      Alpha_p for NonGM soybeans;
alpha_pbtN(boot,on,i)$(coefbtn(boot,'ln1trf')<>0)                              =
exp(fx_effxNbt(boot,on,i)/(coefbtn(boot,'ln1trf')));
```

```
PARAMETERS alphа_pbtNS(boot,i)      Alpha_p for NonGM soybeans;

alpha_pbtNS(boot,i)$(coefbtn(boot,'ln1trf')<>0)                              =
exp(fx_effxNbtS(boot,i)/(coefbtn(boot,'ln1trf')));


********************Combine GM and non-GM soybean data sources***************
PARAMETERS       sboota(boot,i,j,m)             Determine which trade flow is
chosen for each iteration;

sboota(boot,i,j,'g') = sbootg(boot,i,j);
sboota(boot,i,j,'n') = sbootn(boot,i,j);

SET               sbootas(boot,i,j,m)             Comprehensive set of GM and
non-GM soybeans;
sbootas(boot,i,j,'g')$sbootgs(boot,i,j)=YES;
sbootas(boot,i,j,'n')$sbootns(boot,i,j)=YES;

PARAMETERS       databootf(boot,obf,i,j,m,k)      Full bootstrapped database
                 valuebootf_(boot,obf,i,j,m)      Traded value from i to j of
GM or NonGM soybeans
                 valuebootfS_(boot,i,j,m)        Simplified Traded value from
i to j of GM or NonGM soybeans;;

databootf(boot,og,i,j,'g',k)$sbootas(boot,i,j,'g') = databootg(boot,og,i,j,k);
databootf(boot,on,i,j,'n',k)$sbootas(boot,i,j,'n') = databootn(boot,on,i,j,k);

valuebootf_(boot,og,i,j,'g')$sbootas(boot,i,j,'g') = vbootg(boot,og,i,j);
valuebootf_(boot,on,i,j,'n')$sbootas(boot,i,j,'n') = vbootn(boot,on,i,j);

valuebootfS_(boot,i,j,'g')$(sbootas(boot,i,j,'g'))                           =
sum(og,valuebootf_(boot,og,i,j,'g'))/sboota(boot,i,j,'g');
valuebootfS_(boot,i,j,'n')$(sbootas(boot,i,j,'n'))                           =
sum(on,valuebootf_(boot,on,i,j,'n'))/sboota(boot,i,j,'n');



DISPLAY vbootg, vbootn, valuebootf_, valuebootfS_,sboota;



PARAMETERS       expdAbt(boot,j)              Total expenditures
                 expvaAbt(boot,i)             Total export revenues
                 lnexpdAbt(boot,j)            Log of total expenditures
                 sbootj(boot,j)               Importers in each boot iteration
                 sbooti(boot,i)              Exporters in each boot iteration;

sbootj(boot,j) = sum((i,m),sboota(boot,i,j,m));
sbooti(boot,i) = sum((j,m),sboota(boot,i,j,m));


expdAbt(boot,j)$(expdGbt(boot,j)>0 or expdNbt(boot,j)>0) = expdGbt(boot,j) +
expdNbt(boot,j);
lnexpdAbt(boot,j)$(expdAbt(boot,j)>0) = log(expdAbt(boot,j));
```

```
expvaAbt(boot,i)$(expvaGbt(boot,i)>0 or expvaNbt(boot,i)>0) = expvaGbt(boot,i)
+ expvaNbt(boot,i);



*********GM************
DISPLAY expdAbt, sbootj;


PARAMETERS cnt_expd, cnt_imp, cnt_expva, cnt_exp;
cnt_expd(boot) = sum(j$(expdAbt(boot,j)>0),1);
cnt_imp(boot) = sum(j$(sbootj(boot,j)>0),1);

cnt_expva(boot) = sum(i$(expvaAbt(boot,i)>0),1);
cnt_exp(boot) = sum(i$(sbooti(boot,i)>0),1)

DISPLAY cnt_expd, cnt_imp,cnt_expva,cnt_exp;

PARAMETERS temp_lnPGbt;
temp_lnPGbt(boot,og,j)$(sbootj(boot,j)>0)
=sum(i$((alpha_pbtG(boot,og,i)*taubtG(boot,og,i,j)>0)),
                         (alpha_pbtG(boot,og,i)*taubtG(boot,og,i,j))**(1-
sigGbt(boot)));


lnPGbt(boot,og,j)$(temp_lnPGbt(boot,og,j)>0)             =              1/(1-
sigGbt(boot))*log(temp_lnPGbt(boot,og,j));


PARAMETERS temp_lnPGbtS;
temp_lnPGbtS(boot,j)$(sbootj(boot,j)>0)
=sum(i$((alpha_pbtGS(boot,i)*taubtGS(boot,i,j)>0)),
                         (alpha_pbtGS(boot,i)*taubtGS(boot,i,j))**(1-
sigGbt(boot)));


lnPGbtS(boot,j)$(temp_lnPGbtS(boot,j)>0)                =                1/(1-
sigGbt(boot))*log(temp_lnPGbtS(boot,j));



PGbtS(boot,j)$(sbootj(boot,j)>0) = exp(lnPGbtS(boot,j));

DISPLAY PGbtS,sigGbt;


*********NGM***********


PARAMETERS temp_lnPNbt;
temp_lnPNbt(boot,on,j) =sum(i$(alpha_pbtN(boot,on,i)*taubtN(boot,on,i,j)>0),
                         (alpha_pbtN(boot,on,i)*taubtN(boot,on,i,j))**(1-
sigNbt(boot)));


lnPNbt(boot,on,j)$(temp_lnPNbt(boot,on,j)>0)             =              1/(1-
sigNbt(boot))*log(temp_lnPNbt(boot,on,j));
```

```
PNbt(boot,on,j)$(expdAbt(boot,j)>0) = exp(lnPNbt(boot,on,j));




PARAMETERS temp_lnPNbtS;
temp_lnPNbtS(boot,j) =sum(i$(alpha_pbtNS(boot,i)*taubtNS(boot,i,j)>0),
                         (alpha_pbtNS(boot,i)*taubtNS(boot,i,j))**(1-
sigNbt(boot)));


lnPNbtS(boot,j)$(temp_lnPNbtS(boot,j)>0)          =          1/(1-
sigNbt(boot))*log(temp_lnPNbtS(boot,j));

PNbtS(boot,j)$(expdAbt(boot,j)>0) = exp(lnPNbtS(boot,j));


**Create a variable that summarize all price variables

PARAMETERS        lnPJbt(boot,obf,j,m)             Log Price index for GM and
non-GM variables
                 PJbt(boot,obf,j,m)             Price index for GM and non-GM
variables;

lnPJbt(boot,og,j,'g') = lnPGbt(boot,og,j);
lnPJbt(boot,on,j,'n') = lnPNbt(boot,on,j);

PARAMETERS       lnPJbtS(boot,j,m)            Log Price index for GM and non-
GM variables
                 PJbtS(boot,j,m)                Price index for GM and non-GM
variables;

lnPJbtS(boot,j,'g') = lnPGbtS(boot,j);
lnPJbtS(boot,j,'n') = lnPNbtS(boot,j);

PARAMETERS       xknown_bt(boot,obf,i,j,m)       Known variables from previous
regressions;
xknown_bt(boot,og,i,j,'g')$(sbootas(boot,i,j,'g'))  =  fx_effxGbt(boot,og,i)  +
(1-sigGbt(boot))*lntaubtG(boot,og,i,j)+sigGbt(boot)*lnPJbt(boot,og,j,'g');
xknown_bt(boot,on,i,j,'n')$(sbootas(boot,i,j,'n'))  =  fx_effxNbt(boot,on,i)  +
(1-sigNbt(boot))*lntaubtN(boot,on,i,j)+sigNbt(boot)*lnPJbt(boot,on,j,'n');


PARAMETERS        xknown_btS(boot,i,j,m)        Known variables from previous
regressions;
xknown_btS(boot,i,j,'g')$(sbootas(boot,i,j,'g'))  =  fx_effxGbtS(boot,i)  +  (1-
sigGbt(boot))*lntaubtGS(boot,i,j)+sigGbt(boot)*lnPJbtS(boot,j,'g');
xknown_btS(boot,i,j,'n')$(sbootas(boot,i,j,'n'))  =  fx_effxNbtS(boot,i)  +  (1-
sigNbt(boot))*lntaubtNS(boot,i,j)+sigNbt(boot)*lnPJbtS(boot,j,'n');


POSITIVE VARIABLES
           thetabt                                Elasticity of substitution
between GM and non-GM soybeans;

VARIABLES
```

```
          lnbetabt(m)                          Preferences for GM and nonGM
soybeans for each j
          lnPJJbt(j)                           Price index for GM and nonGM
soybeans for each j;

VARIABLES
          LAbt                                  Objective variable for log-
likelihood function;

Equations
                lobjabt                         Objective equation
                PJJconbt                        Price index constraints
                betaconbt                       Beta constraints
                betaconbt2
                thetacon1
                thetacon2;

PARAMETER      xknownbt_(i,j,m)                 Known variables from previous
regressions;
PARAMETER      value_bt(i,j,m)                  Traded value from i to j;
PARAMETER      lnexpdAbt_(j)                  Total expenditures on soybeans;
PARAMETER      expvaAbt_(i)                    Total soybean export revenues;
PARAMETER      lnPJbt_(j,m)                   Log Price index for GM and non-
GM variables;
SET      sboota_(i,j,m)                  Determine which trade flow is chosen
for each iteration;
PARAMETER sboota_no(i,j,m)                 Number of each trade flow that is
chosen;


lobjabt..                                                  LAbt       =e=       -
sum((i,j,m)$sboota_(i,j,m),sboota_no(i,j,m)*exp(xknownbt_(i,j,m)-
thetabt*lnPJbt_(j,m)+(thetabt-
1)*lnPJJbt(j)+thetabt*lnbetabt(m)+lnexpdAbt_(j)-log(100000)))
                +
sum((i,j,m)$sboota_(i,j,m),sboota_no(i,j,m)*value_bt(i,j,m)/100000*(xknownbt_
(i,j,m)-thetabt*lnPJbt_(j,m)+(thetabt-
1)*lnPJJbt(j)+thetabt*lnbetabt(m)+lnexpdAbt_(j)-log(100000)));


betaconbt..   sum(m,exp(lnbetabt(m)))-1=e=0;

PJJconbt(j)..                             (1-thetabt)*lnPJJbt(j)          =e=
log(sum(m,exp(lnbetabt(m))**thetabt*exp(lnPJbt_(j,m))**(1-thetabt)));

MODEL likelihoodabt/lobjabt,betaconbt,PJJconbt/;

PARAMETERS       result_theta(boot)             Result for theta
                 result_lnbeta(boot,m)          Result for lnbeta
                 result_beta(boot,m)            Result for beta
                 result_lnPJJbt(boot,j)         Result for lnPJJbt
                 result_PJJbt(boot,j)           Result for lnPJJbt;

PARAMETERS       thetaboot(boot)                Initial values for theta;
thetaboot('ite1') = 0.4;
thetaboot(boot2) = 0.4;
loop(boot,
```

```
        value_bt(i,j,m) = 0;
        xknownbt_(i,j,m)=0;
        lnexpdAbt_(j) = 0;
        expvaAbt_(i) = 0;
        sboota_no(i,j,m) = 0;

        value_bt(i,j,m) = valuebootfS_(boot,i,j,m);
        xknownbt_(i,j,m) = xknown_btS(boot,i,j,m);
        lnexpdAbt_(j) = lnexpdAbt(boot,j);
        expvaAbt_(i) = expvaAbt(boot,i);
        lnPJbt_(j,m) = lnPJbtS(boot,j,m);
        sboota_(i,j,m)= sbootas(boot,i,j,m);
        sboota_no(i,j,m) = sboota(boot,i,j,m);

         thetabt.l = thetaboot(boot);
         thetabt.up = +INF;
         thetabt.lo = 0;
         lnbetabt.up(m)=0;

        SOLVE likelihoodabt using nlp maximizing LAbt;

        result_theta(boot)$(likelihoodabt.solvestat eq 1) = thetabt.l;
        result_lnbeta(boot,m)$(likelihoodabt.solvestat eq 1) = lnbetabt.l(m);
        result_beta(boot,m)$(likelihoodabt.solvestat       eq       1)       =
exp(lnbetabt.l(m));
        result_lnPJJbt(boot,j)$(likelihoodabt.solvestat eq 1) = lnPJJbt.l(j);
        result_PJJbt(boot,j)$(likelihoodabt.solvestat      eq      1)      =
exp(lnPJJbt.l(j));


);

PARAMETERS expd_ratio(boot,j) Expenditure on GM soybeans to expenditure on non-
GM soybeans;
expd_ratio(boot,j)$(expdNbt(boot,j)>0)= expdGbt(boot,j)/expdNbt(boot,j);

DISPLAY   result_theta,   result_beta,   result_PJJbt,thetaboot,sigGbt,sigNbt,
expdGbt,expdNbt,alpha_pbtGS,alpha_pbtNS,expd_ratio;
PARAMETER sboot_final(boot,i,j,m) final set;
sboot_final(boot,i,j,m)$sbootas(boot,i,j,m)=sboota(boot,i,j,m);



PARAMETERS total_sboota;
total_sboota(boot) = sum((i,j,m),sboota(boot,i,j,m));
DISPLAY total_sboota;



file main_results / main_results.csv / ;
if(%ifAppend% eq 1,
   main_results.ap = 1 ;
   main_results.pc = 5 ;
   main_results.nd = 9 ;
   put main_results ;
else
```

```
   main_results.ap = 0 ;
   put main_results;
   put "Seed,iteration,sigmaGM,sigmaNGM,theta,RhoGM,RhoNGM,betaGM,betaNGM" / ;
   main_results.pc = 5 ;
   main_results.nd = 9 ;
) ;


loop(boot,
   put  %seed%:12:0,    boot.tl,  sigGbt(boot),sigNbt(boot),result_theta(boot),
rhobtG(boot), rhobtN(boot),result_beta(boot,'g'),result_beta(boot,'n')/ ;

) ;

PUTCLOSE main_results;

file exp_results / exp_results.csv / ;
if(%ifAppend% eq 1,
   exp_results.ap = 1 ;
   exp_results.pc = 5 ;
   exp_results.nd = 9 ;
   put exp_results ;
else
   exp_results.ap = 0 ;
   put exp_results ;
   put "Seed,iteration,exporter,alpha_pG, alpha_pNG" / ;
   exp_results.pc = 5 ;
   exp_results.nd = 9 ;
) ;


loop(boot,
         loop(i,
                 put        %seed%:12:0,                 boot.tl,        i.tl,
alpha_pbtGS(boot,i),alpha_pbtNS(boot,i) / ;
   );
) ;

PUTCLOSE exp_results;

file imp_results / imp_results.csv / ;
if(%ifAppend% eq 1,
   imp_results.ap = 1 ;
   imp_results.pc = 5 ;
   imp_results.nd = 9 ;
   put imp_results ;
else
   imp_results.ap = 0 ;
   put imp_results ;
   put "Seed,iteration,importer, PriceIndexGM, PriceIndex_NGM, PriceIndex_Soy"
/ ;
   imp_results.pc = 5 ;
   imp_results.nd = 9 ;
) ;


loop(boot,
```

```
        loop(j,
                put        %seed%:12:0,                boot.tl,        j.tl,
PGbtS(boot,j),PNbtS(boot,j),result_PJJbt(boot,j) / ;
   );
) ;

PUTCLOSE imp_results;


file set_results / set_results.csv / ;
if(%ifAppend% eq 1,
   set_results.ap = 1 ;
   set_results.pc = 5 ;
   set_results.nd = 9 ;
   put set_results ;
else
   set_results.ap = 0 ;
   put set_results ;
   put "Seed,iteration, exporter,importer, GM_NGM, chosen" / ;
   set_results.pc = 5 ;
   set_results.nd = 9 ;
) ;


loop(boot,
        loop(i,
                loop(j,
                        loop(m,
                                put %seed%:12:0,  boot.tl, i.tl, j.tl, m.tl,
sboot_final(boot,i,j,m) / ;
                );
        );
   );
) ;

PUTCLOSE set_results;
```

APPENDIX G. A DESCRIPTION OF FIVE GROUPS OF DRIVERS

Table G.1 Historical socio-economic drivers in the model

A Categories of drivers	Sub-categories of drivers	Explanation	Data sources
Macroeconomic	GDP growth	Driven by labor productivity growth in non-agricultural industries	World Development Indicators, World Bank (2016)
	Population growth	Total population growth	World Development Indicators, World Bank (2016)
	Labor accumulation	Includes skilled and unskilled labor	Global Bilateral Migration Data Base (GMig2 database), (Walmsley et al. 2013)
	Capital accumulation	Capital stock	Penn World Table (PWT), (Feenstra et al. 2013)
	Investment growth	Investment flow	World Development Indicators, World Bank (2016)
	Feed industry restructure in China	Protein intensity, feed production expansion	USDA (2016a), Gale (2015)
Soybean Productivity	GM soybean productivity growth	Labor, capital, and fertilizer productivity Hicks neutral productivity adjustments Land productivity to target land use changes	GMO Compass (2015), FAO (2015)
	Non-GM soybean productivity growth	Labor, capital, and fertilizer productivity Hicks neutral productivity adjustments Land productivity to target land use changes	GMO Compass (2015), FAO (2015)
Other Crop Productivity	Non-soybean labor, capital and fertilizer productivity	National average labor, capital, and fertilizer productivity in agricultural and crop production	Fuglie and Rada (2013a)
	Other cropland use productivity (including multiple cropping)	Land productivity improvement and intensification due to multiple cropping	FAO (2015)
Policy	Domestic agricultural policies	Output payments, intermediate input payments, endowment-based payments, all factor payments	Producer Support Estimates (PSEs), OECD (2016a)
	Trade border policies	Bilateral tariff changes	Tariff Analytical and Simulation Tool for Economists (TASTE), Horridge and Laborde (2008a)
	Biofuel policies	Ethanol and biodiesel	Taheripour et al. (2007)
Pasture and Forestry Changes	Land, capital and labor productivity, and other factors in forestry, pasture, and cropland-pasture	Pasture, cropland-pasture, and forestry land use changes driven by pasture, cropland-pasture, and forestry productivity changes and other factors	FAO (2015)

APPENDIX H. GLOBAL BIOFUEL DECOMPOSITIONS

Over 2004-2011, global biofuel production mainly includes corn-ethanol production in the US, sugarcane-ethanol production in Brazil, corn-ethanol, sugarcane ethanol, soy-biodiesel, and rapeseed-biodiesel production in the EU. Among these biofuel policies, the US biofuel production over this period had some implications for soybean production. Biofuels in the US were mainly corn-ethanol and soy-biodiesel production in the period of 2004-2011. Production of soy-biodiesel directly impacted demand for soybeans and its production, while corn-ethanol influenced soybean production through its effects on corn production. To better understand how each type of global biofuel production impacted percentage changes in US' and Brazil's soybean production and exports to China, as well as the production and export indices, we isolate global biofuel policy contributions to these changes from a historical simulation with full sets of drivers listed in Table G.1. It is achieved through three steps: first, we run a historical simulation with all five groups of drivers in Table G.1; then, we decompose percentage changes in US' and Brazil's soybean production and exports to China, as well as the production and export indices into subcategories of these five groups drivers (second column in Table G.1); finally, we pick up the biofuel policy share of these changes and decompose them into contributions of each individual biofuel policy (e.g., the US corn-ethanol, the US soy-biodiesel, Brazil sugarcane-ethanol, etc.).

The decomposition result of global biofuel policies is shown in Figure H.1. It shows the global biofuel policies shares of contributions to the US' (upper panel), Brazil's (middle panel) and US/Brazil's (lower panel) production (left stacked bar) and exports to China (right stacked bar). The net contributions of global biofuel policies to these changes are shown as black bars crossing the stacked bars. These net contributions of global biofuel policies comprise individual contributions of each biofuel production denoted by each color. For example, orange color in exports to China column and the US panel shows the contribution of US corn-ethanol to percentage changes in the US soybean exports to China.

The decomposition results of global biofuel policies confirm that the production and export indices (lower panel) were dominated by the US corn-ethanol (orange bar) and soy-biodiesel production (green bar). Soy-biodiesel production successfully spurred its domestic demands for soybeans and its soybean production, leading to an increase in the production index (the green bar in the left column of the lower panel). In contrast, the US corn-ethanol mandates encouraged corn production and impeded its soybean production, resulting in a reduction in the production index (the orange bar in the left column of the lower panel). However, the US soy-biodiesel policy diverted its potential soybean exports to domestic biodiesel production, declining the export index (the green bar in the right column of the lower panel). Contrarily, the US corn-ethanol production declined the US soybean supply and encouraged Brazilian supply, resulting in a reduction in the export index as well (the orange bar in the right column of the lower panel. Positive impacts from the US soy-biodiesel policy on the production index is smaller than the negative effects imposed by the US corn-ethanol policy, leading to a net decline in the production index. Both the US corn-ethanol and soy-biodiesel policies discouraged the export index with similar impacts.

Other biofuel policies had limited impacts on the two indices. Among other biofuel policies, Brazilian sugarcane-ethanol (blue bars) and EU’s soy-biodiesel production (purple bars) had relatively higher impacts. Brazilian sugarcane-ethanol production drew land and labor resources from soybean production to sugarcane production. It declined Brazilian soybean production and exports to China (blue bars in the middle panel) and increased the US relative production and exports advantages (blue bars in the upper and lower panel). EU’s soy-biodiesel production increased EU’s demands for Brazilian soybeans, declined Brazilian soybean exports to China (the purple bar in the right column of the middle panel), and increased the US soybean exports to China (the purple bar in the right column of the upper panel). Consequently, EU’s soy-biodiesel production increased the export index (the purple bar in the right column of the lower panel).

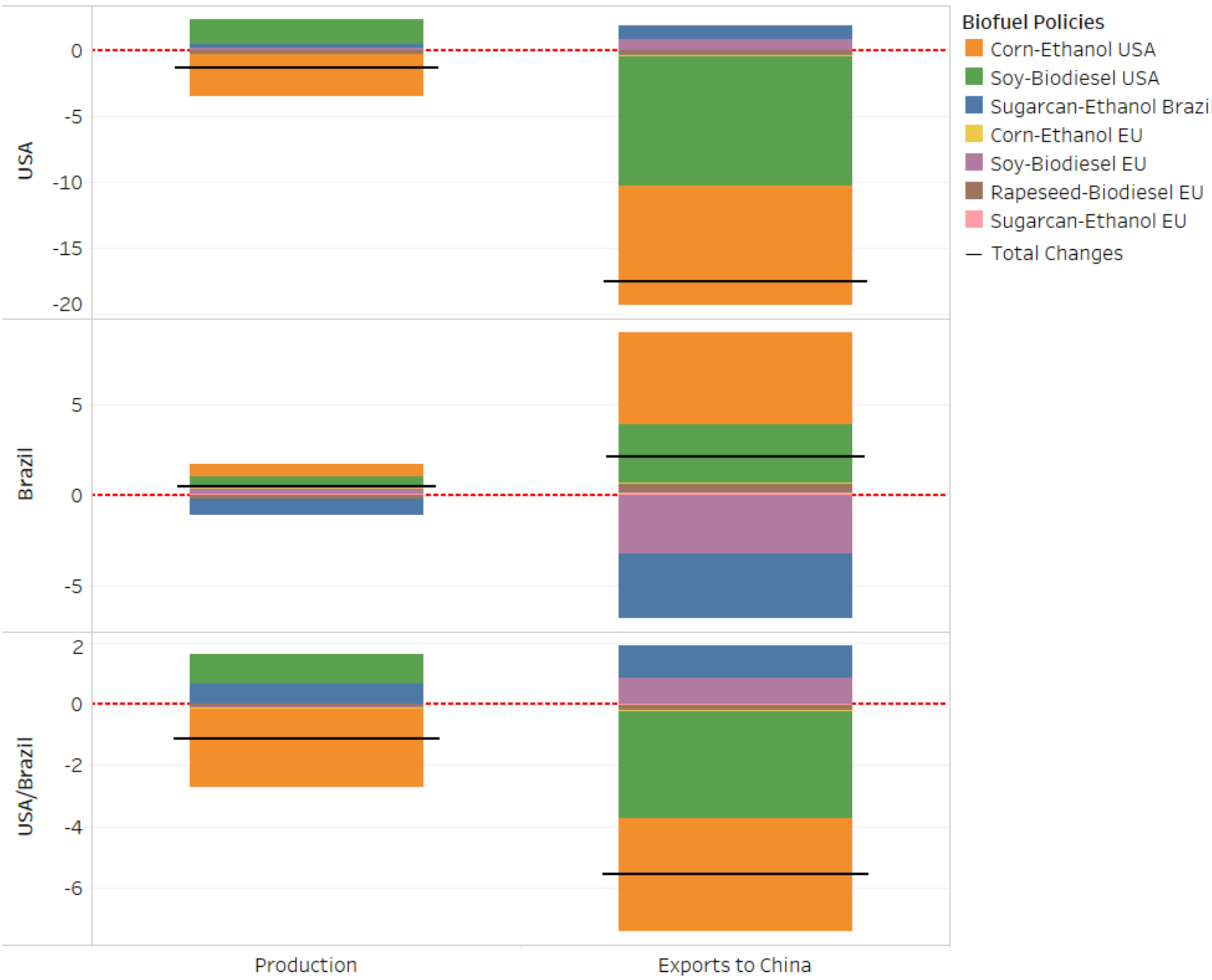

Figure H.1 Contributions of global biofuel policies to the US, Brazil, relative US/Brazil production and exports to China indices

Net contributions of global biofuel policies to the US' (upper panel), Brazil's (middle panel) and relative US/Brazil's (lower panel) production index and exports to China index are shown as the black horizontal bars crossing the stacked bars. Each of these net contributions is decomposed into individual biofuel policy. For example, orange color in exports to China column and the US panel shows the contribution of US corn-ethanol to percentage changes in the US soybean exports to China.

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VITA

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