THE UNITED STATES AND BRAZIL – SPATIAL AND LOGISTICAL INTERDEPENDENCE FOR SOYBEAN SHIPMENTS TO CHINA

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

Analyzing the United States/Brazil competition for market share of Chinese soybean imports requires a detailed, stochastic approach. Using data from 2013 to 2019, this thesis attempts to model and explain the change in market share for each producing country as different variables fluctuate or enter the equation. Using five origins in each country, the PNW, USG, Santos, Paranaguá, and the northern arc of ports in Brazil, various transportation routes from origin to port, congestion and quality metrics, and ocean freight, a least-cost *optimized Monte Carlo* simulation is performed using time-series forecasting distributions for monthly variables. A distribution of outcomes for changes in market share over the crop year demonstrates that Chinese importers favor U.S, soybeans from December to March and Brazil soybeans the alternate months. In the base case Brazil captures almost two-thirds of China's soybean imports. Sensitivity analyses include trade disputes, quality discounts, improved infrastructure, and congestion costs.

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Lastly, I want to thank God for blessing me with these people and opportunities and giving me the strength to see through the challenging times and bring to fruition these endeavors for the future of my family.

DEDICATION

I wish to dedicate this thesis to all of the dear friends I have lost in my teens and twenties but especially to Brooke Nicole Schroeder. I can only imagine the type of friends we would be today, how wonderful you would be in your career as an Agriculture Education teacher, and how much you would love Graham. I miss your silliness, laughter, fortitude, wisdom, and faith.

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LIST OF ABBREVIATIONS

MMT ....Million Metric Ton

PNW..Pacific Northwest Port located in the United States

USG...U.S. Gulf port

DCV ....Daily Car Value in dollars per car in the U.S. secondary car market

COT...Certificate of Transportation

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1. INTRODUCTION

1.1. Introduction

In 2020/21, 363 million metric tons (MMT) of soybeans were produced in the world (USDA FAS, 2021). Of those, 165 MMT were exported/imported by being transported across the globe from surplus regions to deficit regions. One outstanding deficit region is China which imports almost 60% of the world's soybean exports (USDA FAS, 2021). This study focuses on this very concentrated trade relationship that exists in the global soybean trade between China and the two main origins it buys soybean from, the United States and Brazil. This section describes the three countries' trade relationships as well as the associated factors such as spatial markets, commodity markets, and rail markets. The problem statement, objectives, procedures, and hypothesis are provided. Organization of the thesis is discussed to provide structure as well.

1.2. The United States/Brazil/China Soybean Trade

The world soybean trade centers on two main producing origins, the United States and Brazil, and the world's largest soybean importer by far, China. In the 2020/21 crop year, U.S. production was 112 MMT, exports were 62 MMT, and 56% of exports were exported to China (USDA FAS, 2021; USDA FGIS, 2021). In Brazil, during the 2020/21 crop year, soybean production totaled 137 MMT, with 83 MMT exported, and 75% of exports are estimated to have been exported to China (USDA FAS, 2021; S&P Global Platts, 2020). Both countries are relatively new to producing soybeans, compared to China where soybeans have been grown for thousands of years. The United States passed China to be the leading producer of soybeans in 1942, and Brazil passed China to be the second most producing country in 1975 (Shurtleff and Aoyagi, 2004). The competition has increased since, with Brazil taking over the United States to be the leading soybean exporter in 2013, and both countries producing 120 MMT of soybeans during the 17/18 crop year, after which Brazil would pass the United States in production (Gale et. al, 2019).

Considering these export quantities and the continued expansion of production in the United States and Brazil, the two countries along with China are considered in the literature to be interdependent on one another in the world's most concentrated agriculture trade sector (Gale et. al, 2019). Their interconnectedness is explored through three layers of markets: spatial markets, commodity markets, and rail markets.

1.3. Spatial Markets

Spatial markets emerge due to geographical features and production nature of different regions. As areas specialize in production, they produce a surplus of a good, and other areas that are specialized in different goods will have a deficit. In this thesis' soybean focus, Brazil and the United States are surplus regions, and China is a deficit region. While spatial markets in theory reach equilibrium, the trade between the three countries is occurring constantly and changing in response to cost fluctuations.

The boundaries of spatial markets can shift according to economic, geographic, and political constraints, as well as temporal factors. A boundary is considered as the point to which it is not economically or physically feasible to ship a good. Within spatial markets competition exists to deliver the least-cost good for any specific quality type to the buyer. A trader with a network of origins would be more competitive since they have more originating and transportation options available to them. This thesis model is a cost minimization model similar to a network flow commonly discussed in commodity literature. The conjunction of spatial and temporal considerations is considered and developed further in Chapters 2 and 3.

1.4. Commodity Markets

Commodity markets are a complex network of thousands of originating locations in a producing region. To begin, commodity markets consist of a local cash market. Elevators and grain processing facilities source commodities for their uses. A grain processing facility requires grain for an end-use such as milling, meal, or biofuels. Elevators may sell grain to processing facilities, or they may contract it for export.

For many commodities, there are also futures contracts available. The futures market exists to mitigate or take on price risk, depending on an individual's or facility's strategy. Hedging and options can create price floors or ceilings for those holding a cash commodity, expecting to buy one. Speculators are also involved in the futures market; they assist with price discovery by seeking arbitrage opportunities.

Forwarding contracting cash grain and trading the futures lead to movement of grain. Many modes of transportation exist within commodity markets, with some of the most common in many countries being trucks, railways, and barges. Transportation costs represent an important feature of commodity markets since transportation of grain connects producing regions to exporting or end-use regions. This thesis focuses primarily on the cash markets and transportation costs involved in moving commodities.

The basis is critical to all market participants. In this thesis, the buyer buys soybeans at U.S. and Brazil origins at basis levels, and this is a component of total costs for shipments to China These basis values vary spatially, and inter-temporally, and have important seasonal characteristics.

1.5. Rail Markets

Rail markets are a unique mode of transportation that requires various mechanisms to assist with price discovery and allocation of resources. Since railcars can only be filled at certain facilities, a lot of pre-planning is necessary to ensure efficient use of railways. In the United States, rail markets include a primary market and a secondary market. Cars are purchased ahead of time in the primary market in units such as entire trains or trips using a bid-ask system. Cancellation penalties disincentivize shippers from reserving too large a quantity, and transferability provisions allow extra cars to be sold. This occurs in the secondary market. Individual cars can be bought by shippers in need of extra cars and sold by shippers who over-allocated. The value of a car in the secondary market on any given day is referred to as the Daily Car Value (DCV). The DCV is volatile and in recent years has ranged anywhere from -$1000 to $5000 per car (TradeWest Market Reports). These cars are also bought and sold using a bid-ask auctions.

The United States is not the only country where transferability has been implemented. A 2011 law in Brazil require railroad companies to sell excess rail capacity to increase efficiency (Salin and Somwaru, 2020). Brazil has also continued to invest in railways in efforts to connect its north-central production area with northern and southern ports. Limited price data is available for Brazil's rail industry, but the volatility of rail markets in the United States and its effects on outcome variables demonstrates the importance of railways in each country.

1.6. Problem Statement

A trader or shipper providing soybeans to China through buying from the United States and Brazil has a variety of factors to consider. Volatility in origin basis offerings and transportation costs pose risk to traders. Delay times and costs incurred due to delays are important to account for. A trader with positions in each originating country can source soybeans from each location at any given point in time to provide sales to China. This trader would hope to find the least-cost originating location for each month and would choose to fulfill its bushels from that origin to seek a profit through cost-minimization. In this analysis, the trader has five origins in each country, 2-3 export locations, various modes of transportation where available, and ocean freight routes to reach China. The trader is supplying 1 MMT of soybeans to China each month from U.S. and Brazil origins.

1.7. Objectives and Procedures

This model is formulated as an optimized Monte Carlo simulation that minimizes the costs of fulfilling the contract or trade. It uses input variables, many of which are random and specified as random, and cost equations to illustrate the proposed solutions to the problem statement. The objectives are to model the current soybean trade between the United States, Brazil, and China by using crop year market share as a point of focus to demonstrate logistic competition as well as changes to the market. Another objective is to compare the cost delivered of a bushel of soybeans to China from three locations: Brazil, the U.S. Gulf (USG) port, and the Pacific Northwest (PNW) port, for each month in the crop year.

The crop year market share is the share of China's imports that the originating countries, United States and Brazil, capture, as if they are the only two suppliers to China. Thus, the market shares always add up to 100% of China's demand in the model scenario. The crop year market share is found through running an optimized Monte Carlo simulation and forming a distribution of outcomes from the least-cost solutions. The average percent of China's demand filled by an originating country for any given month is that country's market share for that month. It can be interpreted as the probability that the origin country is the least-cost option at that time. For example, if in March, the model finds that the least-cost option is to ship all of March's soybeans from Brazil 56% percent of the time, that is interpreted as there is a 56% probability that Brazil is the least-cost option for the trader in March. This market share value/probability is analyzed in depth in the base case. The, the model is adjusted according to events that change the input variables to demonstrate the crop year market share's sensitivity to the change for each origin country. Similarly, the cost delivered from Brazil, USG, and PNW is analyzed in depth pertaining to the base case and is monitored throughout the sensitivity analysis to demonstrate the effects of each adjusted variable. Sensitivity analysis includes modeling changes in transportation costs, delay times, quality differences, structural variable changes in the market, and supply-side shocks.

The procedure is a stochastic Monte Carlo simulation and solved using Palisade @Risk technology and Excel Solver. First, time series distributions are fit to the random variables using their historical data. Non-random variables are also included in the model. A cost equation is formulated and used to determine delivered cost from each origin, using the various modes of transportation, for each month. The model uses the minimum costs available for the origin countries and then allocates the entirety of the monthly shipping requirement to be from that origin. Over the course of many optimized Monte Carlo simulations, the results form a distribution of outcomes that communicate the results of the simulation.

1.8. Hypothesis

U.S. market share has been declining in recent years due to Brazilian competitiveness, and it is expected to continue to decrease (Salin and Somwaru, 2020). By modeling which transportation and congestion variables increase or decrease U.S. market share, it can be illustrated which variables would have the most positive impact on U.S. market share. It is expected that improvements in transportation efficiency that lower transportation costs will cause the United States to be more competitive and capture more market share. Likewise, the hypothesis is that the U.S. market share is likely less than 40% at present times and that improvements in Brazilian infrastructure shown through transportation and wait times will decrease U.S. market share further. Decreasing costs in transportation and structural variables in the United States is expected to increase U.S. market share, and a shock to the marketplace is likely to fall in the favor of U.S. market share as well. Exploring this hypothesis is done through forming the base case and performing the sensitivity analyses.

1.9. Organization

This thesis contains six chapters. The introductory Chapter 1 provides pertinent background information on the United States/Brazil/China soybean trade, introductions to various types of markets, and the objectives and procedures for the analysis. Chapter 2 discusses the history of soybean production in the United States and Brazil as well as China's growing demand. The unique features of these soybean trade relationships are presented. Previous literature explains the details discovered by other researchers, focusing on basis studies, rail trading, and spatial arbitrage/optimization. Chapter 3 provides theoretical context for the model. Price discovery, basis theory, spatial markets, and cost minimization build on one another to provide a framework from which to conceive a proper model. Chapter 4 provides the empirical model, its data specifications and conversions, and the procedures for optimization. The base case scenario is defined along with the planned sensitivities. Chapter 5 presents the results from the base case along with the sensitivity analysis to describe the market conditions and how changes in the marketplace affect the variables of interest. Finally, the implications of results, limitations, and suggestions for further research are provided in Chapter 6.

2. BACKGROUND AND LITERATURE REVIEW

2.1. Introduction

The United States and Brazil have experienced similar histories having attained rapid growth in an agriculture commodity such as soybean production, but they did not experience the growth simultaneously. In this chapter, a brief history of each country's soybean industry is provided along with reasons behind the demand for soybeans. China's position in the soybean trade is discussed, and the interdependence of China, Brazil, and the United States is established. Unique features of marketing and trading for soybean distribution to China are presented. Previous literature is also presented, specifically around the topics of origin and export basis, rail trading in the United States, and spatial arbitrage. The tenet of finding and mitigating risk is intertwined throughout the literature discussion, as this forms the motivation for problem-solving for risk and the base for much of the research performed on soybean market systems.

2.2. Background

Soybean cultivation began over 3000 years ago in China but has only been of existence in the United States for about 180 years (Soy Info Center). Given the U.S.' short lifespan as a country compared to China, this is logical, but there is a remarkable story behind the rapid success story of U.S. soybeans from the 1940's to the 1970's and now the equally as impressive expansion in Brazil in recent times. What started out as a forage crop in both countries has become the number one cash crop for many years. Soybean production in the United States and Brazil and consequently their efforts to meet global soybean demand efficiently are some of the most dominant topics in commodities and risk literature. Exploring this story and previous literature lays a strong foundation for study and gives way to an optimization analysis of the current state of the soybean trade that satisfies the country from which soybeans originated, China.

2.2.1. Brief History of U.S. Soybean Production

From 1804 to the mid-1910s soybeans were viewed as a forage crop in the United States. In the 1920s soybeans began to be more widely produced, but only 25% of soybeans were harvested for the actual seed (Shurtleff and Aoyagi, 2004). Soybean production in the United States as a cash crop began as a wartime necessity during World War II. In need of soybean meal as well as fats and oils, the United States increased its soy production by 77% in 1942 (Shurtleff and Aoyagi, 2004), and it became the leading producer of soybean worldwide that year as well. During these early years, incredible amounts of research were put into optimizing soybean varieties, feed rations using soybeans, harvesting and processing techniques, and general care.

After WWII and into the 1970s, rising exports, machinery developments, weed control, hybrid breeding, and global demand for animal protein led to the United States producing over three-quarters of the globe's soybeans by 1969 (Shurtleff and Aoyagi, 2004). Domestic subsidies that included soybeans rather than just corn and wheat ushered in increased soybean acreage so that by the turn of the century the U.S. planted as much soybeans as corn and less wheat than both (Gale et. al, 2019).

U.S. soybean production was able to expand and move northward to the Great Plains due to breeding efforts and genetically engineered (GE) soybeans. GE soybeans were first planted for commercial use in 1996, and by 2020 90% of corn, cotton, and soybeans grown in the United States comes from GE seed (USDA 2020). GE crops can include genes for herbicide-tolerance, insect-resistance, drought-resistance, and increased content of valuable materials such as oil or protein (USDA 2020). Early adoption of herbicide-resistant soybeans allowed U.S. farmers to spray their fields with herbicides to kill weeds, decrease competition for the soybean crop, and increase yield.

Soybean varieties bred to reach maturity in shorter-growing seasons such as those in the Dakotas allowed production to expand northward. States in the upper Midwest once thought to be too cold to grow soybeans are now some of the top-producing states, and soybean production in the deep south has decreased severely. The movement of soybean production northward in the United States simultaneously as China's demand grew has led to the Pacific Northwest port (PNW) being a gateway for Chinese buyers to procure U.S. soybeans.

The PNW port is extremely reliant on soybean exports to China. Figure 2.1 shows the PNW soybeans inspected for export and their country of destination, split by year. The exports are almost exclusively to China, with a few other south Asian countries such as Vietnam and Thailand buying soybeans through the PNW. China is the only country to buy over 1 MMT in any given crop year in recent history.

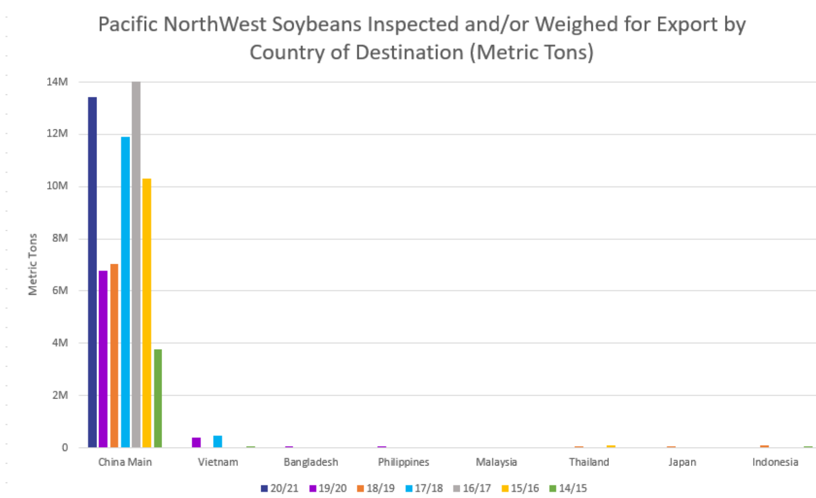


Figure 2.1: PNW cumulative soybean inspected and/or weight for export by country of destination in metric tons (USDA).

The United States in total is less reliant than the PNW is on China, as there are quite a few countries that buy a few million metric tons of soybeans each crop year. However, Figure

2.2 shows most U.S. soybeans still go to China. The trade dispute between the United States and China can be seen in the drop-off for 2018/19 and 2019/20 crop years. In either case, it was not until the 2020/21 crop year that U.S. exports to China rose back to levels similar to previous.

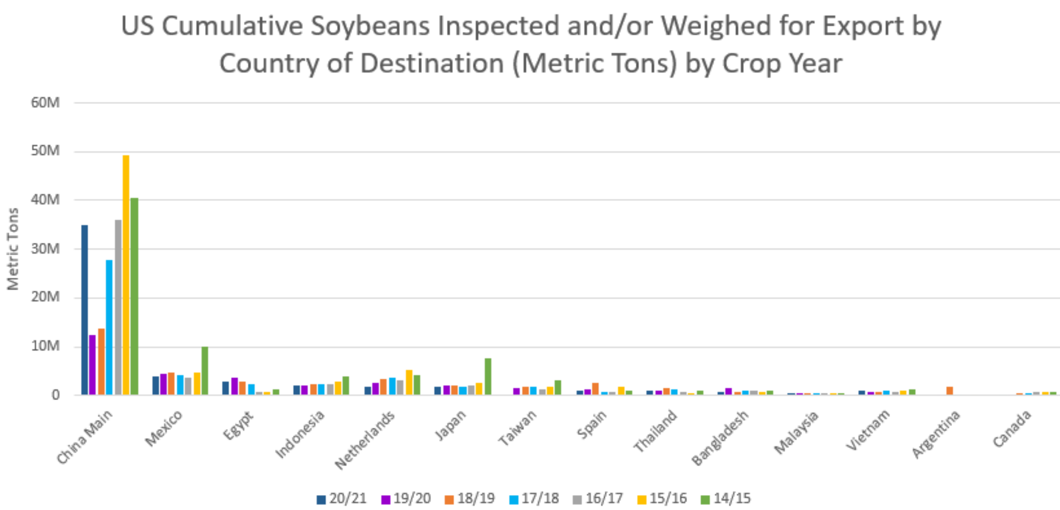


Figure 2.2: U.S. cumulative soybeans inspected and/or weighed for export by country of destination in metric tons (USDA).

The total U.S. soybean exports and PNW exports demonstrate the reliance the U.S. soybean industry has on China in particular. Salin and Somwaru (2020) establish that the global soybean trade has reached an equilibrium, so as the trade continues to grow with new entries into the market, U.S. market share is expected to continue to shrink. Without farm-to-port improvements to raise transportation efficiency and lower cost, U.S. market share could continue its decline due to Brazil's own investments in infrastructure and grain transportation. Salin and Somwaru perform calculations based on the World Agricultural Supply and Demand Estimates (WASDE) and FAS September 2020 report, the world soybean trade is 166 MMT. A decline of one percentage point in U.S. market share is equal to half of a billion U.S. dollars lost in exports (Salin and Somwaru, 2020). This represents a significant gain for the U.S. agriculture industry and poses good reason for infrastructure investments and long-term solutions for lower-cost transportation.

2.2.2. Brief History of Brazil Soybean Production

Soybean production in Brazil has an even shorter history that that of the United States, as soybeans were introduced as one alternative to coffee in the 1960s (Gale et. al, 2020). In 1969, the same year that the United States produced three-quarters of the world's soybeans, Brazil passed 1 MMT of production (Shurtleff and Aoyagi, 2004). Brazil began its own meteoric production increases and became the second largest producer by 1975, producing over 11 MMT (Shurtleff and Aoyagi, 2004). Many factors attributed to this including macropolitical events such as the U.S. soybean export embargo and more stable governance in Brazil (Gale et. al, 2020), Brazilian soybeans' higher oil and protein content, and the country's arable land and production abilities that are unique to its geography.

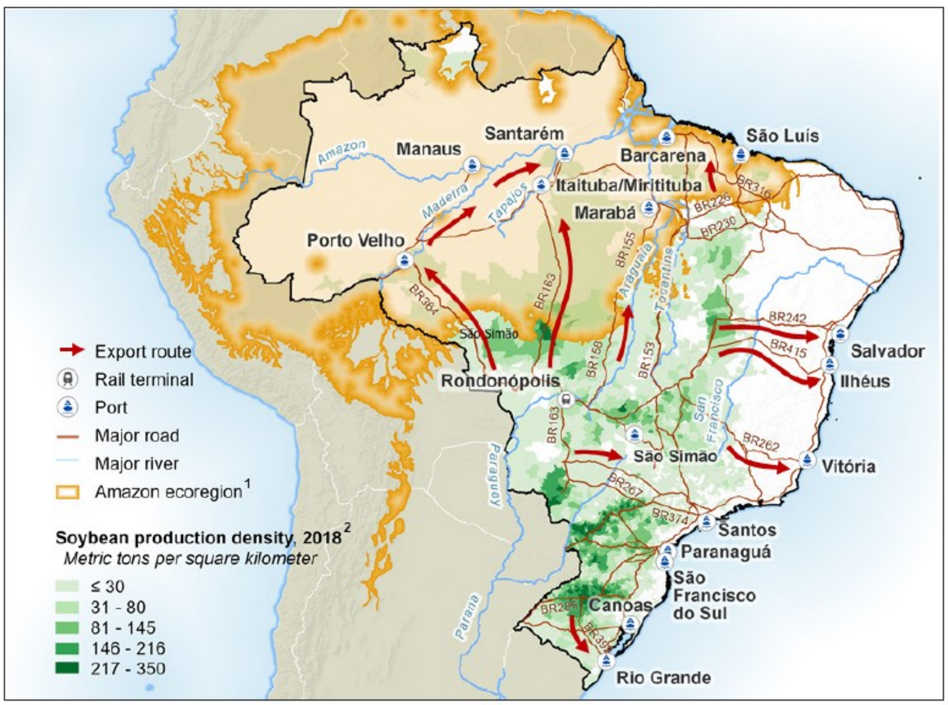
Soybean cultivation has crept northwards through Brazil, beginning in the southern states such as Paraná, Rio Grande do Sul, Santa Catarina, and Sao Paulo and expanding northward into the Cerrado region which includes states such as Mato Grosso, Mato Grosso do Sul, Goiás, Minas Gerais, and Bahia as farmers create an increase in arable land. According Gale et. al, states considered on the soybean frontier are responsible for 65% of Brazil's soybean output growth from 1997 to 2017 (2020). During this time farmers continued to increase yields as well as practices improved. Additionally, double cropping with corn allows Brazilian farmers to have two harvests each year, taking advantage of the tropical climate. Between 2012 and 2016, Brazil's market share hovered below 50%, and in the 2017/18 crop year, both the United States and Brazil produced 120 MMT (Gale et. al 2019). In 2028/29 the USDA predicts that Brazil's production will surpass 160 MMT, whereas that of the United States will be 34 MMT behind (Gale et. al 2019).

Brazil's rapid soybean output increase has played a large role in the United States/Brazil competition. Brazilian soybeans have been cutting into U.S. market share since the 1990's (Salin and Somwaru, 2020). Brazil became the most dominant soybean exporter in the world in 2013, and U.S. market share in 2019 was 32 percent compared to 66 percent in 1992 (Salin and Somwaru, 2020). Brazil has increased production dramatically, but an increase in transportation efficiency has been an equally important factor in Brazil establishing itself as a key player for China's soybean purchases (Thomson Reuters, 2021).

Brazilian infrastructure was and still is limited compared to that of the United States. The main form of transportation for grains is by truck, and in 2018, 86% of roads were unpaved in Brazil as compared to 32% of those in the United States (Salin, 2020). As recently as 2013, Brazil's infrastructure was referred to as "19th century logistics with 21st century agriculture" (Osava/IPS 2013). Soybeans are trucked from centrally-located soybean-producing states of Bahia, Goiás, Paraná, and Mato Grosso to ports located on the Amazon River and the Southern Brazilian coast. In 2013, trucks accounted for 60 percent of the transportation methods, waiting lines to unload in the largest port Santos could be 12 to 24 hours long, and transporting a metric ton of soybeans in Brazil cost 70 dollars more than in the United States (Osava/IPS 2013). At the time, Santos was the export location of 60 percent of Brazil´s soybeans, even though the majority of production takes place 2000 kilometers away in Mato Grosso and the neighboring states (Osava/IPS 2013).

In the late 2000´s, Brazil began implementing comprehensive investments and reforms to railways, roadways, and waterways. A new law in 2011 implemented the selling of excess rail capacity between railroads, and a new intermodal facility was built in Rondonópolis, Mato Grosso that connects to Santos (Salin and Somwaru, 2020). A new export route between two Amazon River locations, western Mirititub a, Para, and eastern Barcarena was implemented. The highway that connects Sorriso to Miritituba, BR-163, was paved in 2019, and this addition reduced the travel time on that route from many days to just 35 hours (Salin and Somwaru, 2020). Figure 2.3 displays the state of Brazil's production and transportation in 2018 (Salin, 2019). A clear lack of rail terminals and routes is apparent as well is the reliance on highways.

Main export routes for soybeans



[1]World Wildlife Fund.
[2]Brazilian Institute of Geography and Statistics—Produção Agricola Municipal.
Source: USDA/Agricultural Marketing Service (AMS) and USDA/Foreign Agricultural Service (FAS).

Figure 2.3: Soybean transportation in Brazil (USDA, 2019).

Investing in infrastructure such as paved highways and more developed barge and railways has and continues to pay off for Brazil. After over a decade of improvements, increased efficiency, and a Chinese tariff on U.S. soybeans lead to Brazil becoming both the largest producer and largest exporter of soybeans in 2018 (Salin and Somwaru, 2020). Whereas U.S.

soybeans are more expensive to produce per bushel due to large, fixed land and capital costs, and transportation and ocean freight are more stable for the United States, Brazil's investments in transportation have given Brazil a competitive advantage (Salin and Somwaru, 2020). Truck rates in Brazil decreased anywhere from 12-18% from 2018 to 2019, in part due to depreciation of the Brazilian real, and transportation's share of the total cost delivered from northern Mato Grasso to Shanghai, China decreased from 34% in 2008 to 28% in 2019 (Salin 2020).

For the annual *USDA Soybean Transportation Guide: Brazil 2019*, Salin calculates many locations' transportation costs in 2018 from farm to China: Sorriso, MT through Santos via truck (122.08) and via rail (107.10), Sioux Falls, SD (92.59), and Fargo, ND through PNW (91.60), Davenport, IA through USG (88.80), a Southern MA state origin in Brazil through a northern port Sao Luis (71.48), and a Northwest RS origin, through Rio Grande in the far south of Brazil (60.27) (Salin 2020). The most expensive route in Salin's calculations to China is from Sorriso. Sorriso is located in a booming area of Brazil and is of particular interest in Brazil's production growth. Both other Brazil origins that Salin uses are more cost effective than the U.S. routes. Figure 2.4 shows the USDA cost calculations for specified routes from Brazil and the United States to China.

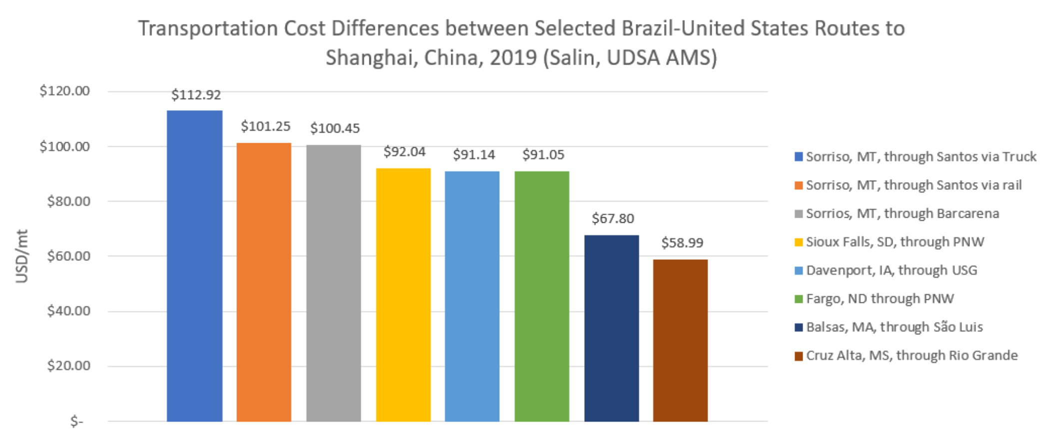


Figure 2.4: Transportation cost differences between selected Brazil-U.S. routes to Shanghai, China, 2019 (Salin, USDA AMS).

Incentive exists for investment in interior infrastructure in Brazil, especially for increasing the northern arc of ports which are currently more expensive that their domestic and international competitors. Historically, Brazil's southern ports were the only main threat to U.S. soybean producers, but due to expansion of paved roads and barge terminals and new laws regarding sharing rail capacity, the northern arc of ports have begun to explode with soybean traffic. In five years, Amazon River port Barcarena increased its grain movement over 400%, moving from 1.1 MMT in 2014 to 5.8 MMT in 2019 (Salin and Somwaru, 2020). Currently in Brazil, three of the five largest ports are in the south: Santos, Rio Grande, and Paranaguá. Two of the largest five are now northern ports: Sao Luis and Barcarena. Diversifying between southern and northern ports has also decreased congestion in the southern ports (Salin and Somwaru, 2020).

Incentives to reduce cost are driven by goals to make profit and capture market share. The market share that Brazil and other soybean producers are after is China's soybean consumption. China's demand for soybeans is one of the most dominant factors in Brazil's recent expansions in soybean export capacity.

2.2.3. China's Demand for Soy

Global soybean trade is the most concentrated segment in agriculture (Gale et. al, 2019). The United States and Brazil offer two large soybean markets for Chinese importers looking to fill China's demand for soybeans. China imports more than 60 percent of the world's soybeans, and the United States and Brazil supply the world with 80 percent of its exports (Gale et. al, 2019). Comparatively, the top two importers of pork, cotton, corn, poultry, and wheat import a combined 66, 52, 56, 64, and 31 percent of the world's imports, respectively (Gale et. al, 2019). China's soybeans imports surpass all of those handily, explaining the attention soybeans receive in agriculture economics literature. China's imports of soybeans passed the entirety of the European Union's (EU) soybean imports in 2002 (Gale et. al, 2019). Clearly exports to China are a main driver in the growth of the soybean industry, and Gale et. al describe the three countries as being interdependent on one another in this relationship. While growth in China's demand is expected to slow, China is predicted to continue to import 85% of the world's soybeans into 2028.

Worldwide and in China, various combinations of growing populations, rise in income, and increase in quality of life contribute to more demand for meat and other proteins and oils that are fed at least in part by soybeans (Lee et. al, 2016). Beginning with poultry and then continuing into pork and beef, developing countries are hungry for high-quality and more efficient protein. Each year, China needs to be able to feed its pork industry.

Of note, as of 2016 import tariffs on soybeans were lower than soybean meal or oil (Lee et. al, 2016), which is an explanation to China's raw soybean imports and growing crush industry. The soybean crushing industry in China is now so large, with almost 10,000 companies. Most are state-owned, multinational, or private in ownership type, and they employ almost half a million people (Gale et. al, 2019). The industry is so competitive that importers buy soybeans simply to maintain some capacity and cash flow, even if prices are not ideal (Gale et. al, 2019).

There are events that can negatively impact China's demand for soybeans as well, as their demand does not increase at all moments. In 2018, African swine fever reduced livestock population and therefore the quantity of feed demanded (Gale et. al, 2019). Government policies such as environmental policies on farm locations, reduced or eliminated tariffs on soybeans from nearby Asian countries, allowing meal imports from other oilseeds, and lowering the protein standard in livestock feed are all examples of recent events that can shift demand from imports from the United States and Brazil (Gale et. al 2019). However, the overall trend for China's demand exhibits growth.

Another notable sign of continued growth is China's investment in Latin American infrastructure including acquiring terminals and trading companies in Santos and investments in rail and road projects to connect production states with export locations (Gale et. al, 2020).

2.2.4. Features of Marketing and Trading for Soybean Distribution to China

To supply soybeans to China, there are many factors that shippers and traders must consider in their decision-making. Some of the most critical factors include quality differences, transportation factors, and trade policies and interventions.

2.2.4.1. Quality Differences

Soybean quality discrepancies are one unique feature in the grain trade between China and its trade partners. Traditionally, it is common knowledge that the international grain traders and buyers regard U.S. soybeans as deficient relative to Brazil. As such, traditionally, the discounts are as below (RJO'Brien Market Report May 23, 2017).

> Given predominantly tropical conditions in Brazilian growing regions, Brazilian soybeans tend to sport higher protein and oil content than soybeans in the US as well as Argentina. Basis Brazilian soybeans at quality par in the eyes of Chinese and EU industrial crushers: US Gulf soybeans at 10c per bu discount (but subject specific seed fill weather in a specific year…have seen this discount has high as 25c). US PNW soybeans at 15c per bu discount (have seen as high as 30c discount). Argentina soybeans at 20-25c per bu discount (have seen has high as 35c discount). Again, all relative to Brazilian soybean quality at par.

These discounts generally persist and in recent years were summarized by Thomson Reuters, discussing how Brazilian soybeans often receive a premium of 5 to 10 U.S. dollars per metric ton (February 2, 2018). This is the equivalent of 13 to 27 cents per bushel, a sizeable premium in a margin-based industry. Discounts on U.S. soybeans can vary by year and are generally based on reported protein content but can include foreign matter discounts as well (Reuters 2018).

Hertsgaard et. al (2018) studied these quality discounts through the framework of testing soybeans for quality variables. They found measuring quality variability through protein results in mispricing due to heterogeneity of quality indicators across spatial markets. Traders face the risk of implicit and explicit discounts that are applied to whole regions commonly thought to have lower protein and also the risk of rejected shipments (Hertsgaard et. al, 2018). Based off of their research and modeling, Hertsgaard et. al (2018) made recommendations for mitigating the costs of quality disparities that include: research and developments to improve protein in certain production areas, sellers executing a strategy to deliver soybeans that meet buyers' requirements, testing for end-use traits, and firms positioning themselves in various originating geographies to assist their ability to change end-use quality factors are of interest to buyers.

2.2.4.2. Transportation

The United States and Brazil have distinct methods of transportation that traders must consider. The United States employs the use of truck, barge, and rail. Barge rates and rail rates in the secondary car market change often. Brazil continues to have higher interior costs altogether as the country continues to move from almost total reliance on trucks to employing truck, rail, and barge as well. Even with improving interior transportation conditions, wait times in Brazil are substantial; wait times and demurrage costs are developed more in Chapter 4.

It can be argued that the United States is currently not improving transportation to the same degree as Brazil. From 2018 to 2019, transportation costs from Iowa to port increased 3% (Salin 2020). Since U.S. Gulf ports and Brazilian Paranaguá port prices closely mirror the Chicago Board of Trade (CBOT) futures price, each trending about 5 percent higher than the

CBOT price, the prices for each exporter are highly competitive (Gale et. al, 2020). Brazil's Paranaguá prices have a higher standard deviation from the CBOT price, 6.6 percentage points compared to the USG 2.3 percentage points (Gale et. al, 2020), but as previously discussed in Brazil's background information, lowering transportation costs has, in a way, offset the greater volatility of Brazilian prices. As transportation costs are expected to fall in Brazil, and exporting prices trend to move together, any rise in transportation cost in the United States could be expected to capture more market share for Brazil.

2.2.4.3. Trade Policy and Interventions

Another unique factor of the U.S./Brazil/China soybean trade is the major differences that arise between U.S. and Chinese leadership. Trade tensions between world leaders, colloquially referred to as trade wars, have significant economic impacts, especially on agriculture exports. In July of 2018 China enacted a 25% tariff on U.S. soybeans which resulted in a major shift in preferences towards Brazilian soybeans. Retaliatory tariffs placed on U.S. agriculture and food products are estimated to have resulted in the United States losing 15.6 billion USD in trade with countries who were retaliating against the United States (Carter and Steinbach, 2020). Carter and Steinbach estimate that countries without tariffs placed on their goods gained 13.5 billion USD in trade. These figures are for agriculture and food in general, and logically includes the impacts of the tariff on the United States and the lack of tariff on Brazil in terms of soybeans. It was found that Canada and the European Union became a replacement destination for U.S. soybeans, and South American countries benefitted the most from the tariff (Carter and Steinbach, 2020).

Adjemian et. al (2019) estimated that the tariff lowered U.S. prices by 74 c/bu and increased Brazil's prices by 97 c/bu on average over the duration of the trade war. They found the impacts to be non-uniform, with North Dakota and South Dakota receiving greater impact, suggesting that there are spatial factors that limit or intensify impact (Adjemian et. al, 2019) When the initial tariff was put in place, U.S. exports to China totaled 8.2 MMT, compared to 31.7 MMT from the same months in 2017 (Adjemian et. al, 2019). They also found that while the impact on prices adjusted after five months when truce talks and Brazil's harvest simultaneously began, U.S. export volume needed until the end of the 2019/20 crop year to reach average levels again (Adjemian et al., 2019). U.S. exports were forced to adjust by sending soybeans to other countries and through attempted trade deals. The tensions remain between the two countries due to very different governance styles (Adjemian et. al, 2019). Additionally, the trade dispute reduced Chinese buyers' willingness to rely on the United States, and while the three countries are still very interdependent on each other, the dispute along with Brazil's investments into infrastructure have increased Brazil's position as a major supplier (Thompson Reuters, 2021).

Taking into account the history of soybean production in the United States and Brazil along with all of the factors that Chinese buyers consider when choosing between the two countries for purchases provides context when reviewing previous studies done around similar topics.

2.3. Previous Studies

Given the size of the market for soybeans, researchers have dedicated much time to exploring various topics at great length within the soybean trade. Origin and export basis, their correlation, and their composition factors are a focus. Composition factors of basis prices lead to a greater understanding of the cost of buying and selling physical soybeans.

Transportation serves a major role within studying basis prices and provides a transition into two more main topics. Research of development and current status of rail trading within the

United States provides opportunity to find and limit cost risk in one of the most volatile transportation costs. Rail trading analysis in the United States can advise other countries on best practices and policies for efficiency and low standard deviation of costs.

Spatial arbitrage combines basis, transportation, and geographic factors into an overarching theme of optimizing locations from which soybeans are bought and shipped overseas. Monte Carlo studies provide a foundation for further exploration into spatial arbitrage.

2.3.1. Basis Studies

Supply of and demand for a commodity can be reflected in many ways, two of which are the futures price and the local cash, or spot price. The futures price is an over-arching state of supply and demand for a region as large as worldwide, such as the CBOT futures price. The spot cash price is a localized state of demand and is more commonly reported using a conversion to basis price. The basis price is the difference between the local cash price and the futures price (Kolb and Overdahl, 2006). When discussing originating basis, for example the basis at a country elevator near where grain is produced, the cash spot is almost always lower than the futures price, especially at significant distances to port. This is due to the costs associated with carrying a commodity such as interest, insurance, storage, and transportation (Kolb and Overdahl, 2006). Therefore, the basis price is reported as a negative value. If the basis becomes more negative, it is weakening, and if the basis moves closer to 0, it is strengthening. Terminal, or destination basis is calculated the same way as origin basis, but the cash price used is that of an exporting location such as the USG ports.

A basis value reflects many factors. Many studies have been performed testing the significance of different factors for near-terminal or terminal basis (Tilley and Campbell, 1988, Zhang and Houston, 2005, Bullock and Wilson, 2019, Lakkakula and Wilson, 2020), and that of origin basis has also been analyzed (Baldwin, 1986, Wilson and Dahl, 2011, Hart and Olson, 2017). Much literature focuses on origin basis or does not distinguish. Baldwin (1986) outlined supply and demand, protein/quality measures, conditions of the crop such as moisture, transportation and storage availability and costs, and seasonality and location differences as some of the most important factors. Over time the market has become more complex; Wilson and Dahl (2011) found that the shipping costs, ocean rate spreads between the USG and PNW, export sales, rail efficiency, stocks to storage capacity ratio, futures prices, and varying futures/destination spreads are significant explanatory variables as to basis volatility at the origin (Wilson and Dahl 2011). Basis in a trade is said to converge to the futures price at the end of a futures contract due to the cash price needing to match added storage costs over a contract period and trade occurring due to arbitrage opportunities (Baldwin, 1986). However, the literature discussed above also points to many factors that cause fluctuations in basis over a continuous time period, such as monthly or annually. Many of the aforementioned factors are discussed individually to thoroughly outline the components that are significant to basis prices.

Shipping costs are often cited as some of the most obvious components of basis. Hart and Olson (2017) found that higher transportation costs are highly statistically significant in weakening the local basis. They examined North Dakota origins and found that the rail tariff and secondary car market prices were statistically significant. Steadman et. al (2019) provide a thorough overview of transportation costs in soy and corn. They calculated where rail was available in their scenario, rail cost made up the largest share of the route cost compared to truck and barge. Bullock and Wilson (2019) concurred, finding that the export basis for a marketing year is more sensitive to interior rail shipping than barge or ocean freights. Given the importance and complexity of the U.S. rail transportation system, a separate section follows to discuss rail trading.

Wait times can directly affect transportation costs as they disrupt the flow of the supply chain by failing to meet the expectations of buyers and sellers. In 1998, Wilson et. al stated that post-harvest delays and logistical issues had been discussed in agriculture marketing publications but that rail car allocation issues had not made their way into the literature yet, only the general issues of supply allocation. Since the article's publication, an increasing amount of attention has been given to researching and proposing solutions for defining and limiting delays. Steadman et. al (2019) paid special attention to delay cost such as congestion and wait time, which is a key part of this thesis. The analysis found that 12% to 58% of transportation cost can come from delay costs (Steadman et. al, 2019). Delay costs can be found in each main mode of transportation in the United States: truck, barge, and rail.

Both barge and ocean rates as necessary modes of grain transportation have been found to influence prices through their own volatility (Haigh and Bryant 2000). As the shipping industry becomes more efficient, spreads between different locations for a given variable have become of importance because shippers are more able to choose the more favorable side of the spread. Ocean rate spreads cause traders to favor exports from one port or the other, which can be especially true in the case of USG and PNW ports, as the PNW has a distance advantage to eastern importers (Thomson Reuters, 2018). Greater demand for exports from a certain port strengthens the origin basis in the areas that serve that port.

Export sales reflect demand for exported soybeans. Many studies establish that higher export sales raise origin basis (Wilson and Dahl, 2011, Hart and Olson, 2017), and Wilson and Dahl (2011) concluded that, throughout time, exports have occurred more in seasonal peaks, which has effects in capacity and logistical abilities in the United States. Bullock and Wilson (2019) found that China's total imports of soybeans had a significant and positive effect on both the PNW and USG export basis values.

Considering these factors and their effects on originating and terminal basis, Hart and Olson (2017) found terminal basis to have a positive statistical significance for origin basis. More recently, Lakkakula and Wilson (2020) found that simultaneous discovery of the origin and terminal basis occurs. Changes in the factors previously discussed in reference to origin basis are also factors in the terminal basis. For example, a rise in transportation costs decreases the origin basis and increases the export basis, demonstrating that the change in cost is absorbed by the buyer and seller. In cases where the transportation costs rose 1 USD, the seller or grower experiences a 19 c/bu weaker basis, and the buyer sees an 82 c/bu increase in basis. Both observations suggest a negative impact for the sellers' respective positions and a larger impact for the grain buyer (Lakkakula and Wilson, 2020). Thus, a congestion factor such as late rail cars would have a greater cost impact on the grain buyer.

There are some factors that are more obvious in determining the terminal basis relative to the origin basis. One is that terminal export basis moves in response to international competition. Zhang and Houston (2005) concluded in their study that general futures volatility and competitive soybean production in South America had a negative impact on the spot par CBOT basis. Bullock and Wilson (2019) and Lakkakula and Wilson (2020) found that changes in the Brazilian export basis had significant and positive impacts upon the USG and PNW terminal basis.

Literature points to the conclusion that seasonality is not a consistent indicator of terminal basis because events such farmer basis trading activity and conditions of the barge and rail systems have non-seasonal trends (Bullock and Wilson, 2019, Lakkakula and Wilson, 2020). Since Lakkakula and Wilson (2020) illustrate that the origin and destination basis are found in tandem, the items discussed in terms of terminal basis can be thought to have effects on the origin basis and vice versa since those factors contribute to the changes in the origin basis rather than the two basis values impacting one another.

Basis prices and their components can be unpredictable due to uncertainty and a lack of information regarding the probability of any given outcome in a complex system such as that of predicting a future basis value (Vose, 2008). Risk is measured using a standard deviation, and the larger the standard deviation, the less predictable a variable or outcome becomes. This unpredictability and wide deviation of prices is also known as volatility. Volatility in basis values pose risk to growers, traders, and shippers. Wilson and Dahl (2011) illustrated that over time basis values have experienced increased volatility which has also caused shipping demand volatility. Uncertainty in basis price, or any of its components such as transportation costs, creates an opportunity for traders to take on or mitigate risk. Volatility in futures can be managed through hedging while variability in the basis can be managed through basis contracts (Wilson and Dahl, 2011) while more elaborate mechanisms to reduce risks, involving more elaborate forms of forward coverage especially in rail shipping, are likely to develop.

2.3.2. Rail Trading Within the United States

Similar to price and basis risk, transportation variables also pose risk to traders. Transportation costs vary as demand changes. In large, complex transportation systems such as the U.S. grain transportation system, various methods have evolved to transport grain and mitigate the cost risks involved in grain transportation. Rail freight prices are no exception to price risk, but many methods and strategies have been developed to allow shippers and traders to mitigate risk.

Prior to 1988, there was an inability to access rail cars in advance through any sort of reservation (Wilson, Priewe, and Dahl, 1998). During that time, rail price discovery was performed via confidential contracts (Lakkakula and Wilson, 2020) which were an inefficient price discovery system. In 1988, the Certificate of Transportation (COT) program was created by the rail company that now operates as the Burlington Northern & Santa Fe Railway (BNSF) (Lakkakula and Wilson, 2020). The COT guidelines contained provisions for forward shipping guarantees and penalties for buyer and/or seller defaults as well as transferability (Lakkakula and Wilson, 2020). Wilson and Dahl (2011) found that, overall, the COTs provided visibility to the railcar market in the United States, and this transparency created risk mitigation opportunities.

Other railroads adopted forward markets similar to COTs, and while specifications have changed over the years, the bid allocation system remains. In the primary car market, shippers bid to secure allocation of cars or trips for a certain time in the future and can transfer cars to another shipper but will receive a penalty if they cancel the order (Lakkakula and Wilson, 2020). It is not uncommon for a car holder to experience a period where their quantity of grain does not meet or exceed the cars they purchased on the primary market since quantities can be difficult to predict. The inclusion of cancellation penalties and transferability of car provisions in the COT contracts set the foundation for the secondary rail market that exists today (Wilson and Dahl, 2011).

The secondary car market in the United States consists of the buying and selling of railcars that were purchased in the primary market (Landman 2017). The shipper no longer has capacity or the need for the total number of cars previously reserved and prefers to sell them rather than pay a cancellation charge. The cars are sold via bid and ask prices that are quoted as a positive (premium) or negative (discount) margin relative to the rail tariff price. Secondary market prices for rail in the United States can vary between a discount of $1000 USD/car and a premium of $5000 USD/car (TradeWest).

Wilson and Dahl (2011) studied the effects secondary car prices can have on basis values. Wilson et. al (2020) show that the secondary car market is much more volatile than the primary car market due to the immediate needs of shippers who, in a nearby time, may require more/less cars than they had previously purchased. These shippers are exposed to the risk of a cancellation fee if they have purchased too many railcars relative to the quantity of grain to ship, or the risk of demurrage if they have too few railcars on order. The bid/ask price spread that stems from mitigating these risks is illustrated by the large standard deviation of the historical secondary railcar market price (Wilson et. al, 2020). However, understanding the secondary car market gives shippers an opportunity to either acquire or mitigate risk. The secondary car market provides additional efficiency of allocation of cars and price discovery in addition to the primary car market, or shippers would not use both in their efforts.

As a result of the primary and secondary railcar markets, the costs involved in rail shipping decreased because the industry was more efficient at placing cars where they will be filled and moving more cars per week, a term known as velocity (Wilson and Dahl, 2011). A better velocity decreases the secondary railcar market price, which strengthens the export basis (Wilson et. al, 2020). The secondary car market is a way to quickly serve nearby demand which is present when a better export basis value is offered than previously (Wilson et. al, 2020). Because of the volatility of secondary railcar market prices and the ability to quickly serve demand over space and time, the U.S. railcar trading industry is a well-studied and intriguing venue for shippers to utilize in improving overall transportation efficiency while reducing cost variability.

2.3.3. Spatial Arbitrage Studies

Arbitrage is the purchase of a good in one market and the sale of it in another in order to profit from spatial, temporal, or form price disparity (Weisweiller, 1986). Not all arbitrage is free of risk, as price and market information are rarely perfect across time and space. The person attempting arbitrage takes on the risk of a failed endeavor, motivated by the reward of profit (Weisweiller, 1986). The arbitrageur needs to correctly estimate the locations and quantities of which to buy and sell that will be successful without taking on more financial risk than he/she can manage (Weisweiller, 1986). Without market players searching out points of arbitrage, price differences would subsist, and equilibrium of prices again would not be obtained (Weisweiller, 1986).

In a system as complex as commodity markets, with thousands of originating locations in just one country, vast regions, intermodal transportation opportunities, and multiple exporting locations, as well as merchandisers trading futures or basis, it is comprehendible that arbitrage opportunities are available. Kub (2014) defines arbitrage in commodities as the buying and selling of grain simultaneously to absorb the spread between each price as a profit, after transaction costs, transportation, and handling are considered. The spread can be in the context of quality, inter-market, or a geographical spread (Kub, 2014). An example of a geographical spread is the soybean spread between two locations, such as two different prices, one in North Dakota and one in Minnesota. This forms the basis of spatial arbitrage, and in concurrence with Weisweiller (1986), Kub (2014) credits arbitrage with keeping the markets efficient through "the very act of the merchandiser selling the overpriced asset and buying the underpriced asset" (p.47).

Spatial arbitrage in the literature is often demonstrated through modeling a scenario to find optimal decisions in the case of arbitrage opportunities under various assumptions and risks. Skadberg et. al (2015) created a spatial competition analysis that optimized scenarios with various origin locations, transportation routes, and export locations. They found that a firm with the choice of origin, route, and export location can find arbitrage in a spatial context and capture the advantage. This study showed the strength of vertical integration, which is enjoyed by many of the biggest grain trading companies that own exporting locations in the USG, PNW, and other U.S. and world ports. Included variables for transportation were fuel service charges, the secondary rail market, and rail tariffs.

Relevant to this study is spatial arbitrage in the soybean industry that serves Chinese demand. According to Gale et. al (2019), differences in basis offerings, volatility in interior shipping, port and vessel wait times, and exchange rate fluctuations are just some of the variables involved when marketing soybeans to China.

2.4. Conclusion

This chapter provided a historical background of the international soybean trade between the United States, Brazil, and China. The United States and Brazil are unique in their explosive soybean production growth, with Brazil's growth being more recent. While the United States remained the largest producer and exporter of soybeans for decades, Brazil by the mid-2000s was catching up and would match the U.S. production in 2017. Previous to World War II, China was the world's largest producer, but the United States and Brazil were able to produce lower-cost soybeans, and China eventually became the world's most prolific importer of soybeans to feed their population. These three countries have been and remain entwined in a complex trade marketplace that bears the effects of logistical challenges, subsequent transportation developments, quality discrepancies, macropolitical events, and major differences in the infrastructure, trade systems, and climates in the two producing countries. Given their contrasts, the U.S. Heartland and the Brazilian Cerrado share a common goal competing each year to capture market share from their most important customer, China. This chapter's background provides understanding of the historical context in which the thesis model in set.

Additionally, the previous literature contributes to the discussion and formation of a model by providing examples for comparison and contrast. Understanding how origin and terminal basis are comprised and comparing their similarities provides flexibility in the development of the thesis model, particularly when creating a cost equation which is heavily dependent on the variables suggested for analysis in the previous literature. The importance of U.S. rail trading stands out in particular as a transportation variable and is established as a key component to any major U.S. commodity analysis. Lastly, studies on spatial arbitrage, particularly stochastic optimization, are presented as an outline from which to build an optimization model that contains the most significant portions of the marketplace, such as originating basis, transportation costs including delay costs, ocean freight, and quality considerations. An examination of the previous literature allows for guidance and a contribution of a new model that can add to the overall state of knowledge in spatial optimization. Even though the model represents just a portion of world trade (ie., the soybean trade between the United States, Brazil, and China), the sheer amount of dollars and effort represented in this trade relationship is paramount to global agriculture. Using significant variables and correct procedures based off of previous literature, the thesis model presents a highly-detailed analysis of the competition between the United States and Brazil for the Chinese soybean import market.

3. THEORY CONCEPTS

3.1. Introduction

Markets have many functions which include storage, transportation, and transfer of ownership. Each of these functions helps move commodities to different places in the market. For commodities to move, price discovery is necessary and happens through the interaction of supply and demand. One of the most important prices in the commodity supply chain is the basis price, and the related theory behind its components and predictability. Along with this exists the interaction between the Law of One Price, spatial market competition, spatial arbitrage, cost minimization, and network markets, which all facilitate market efficiency across markets in the commodity trade space. Each component introduced is discussed in this chapter.

3.2. Price Discovery

Price discovery is an important function in any market. Supply and demand for a good work together in different manners through the actions buyers and sellers take to establish prices at which they are willing to sell/buy a good. This interaction happens at an individual level with a single buyer and seller, between two companies, or between one entity and many buyers or sellers. This individual price discovery can be aggregated into a marketplace of price discovery.

3.2.1. Function of Price Discovery

There is a magnitude of imperfect information in any system. Perfect price discovery would require all players to have equal access to the same, accurate information (Tomek and Robinson, 2003). Logistically, temporally, and economically, this cannot be the case, as individuals and groups have different preferences on how they access and use information. However, there are mechanisms adopted by various entities that facilitate finding an equilibrium price.

Different types of pricing mechanisms can include private negotiations, list price such as when an administrator sets a price, auctions that entail competitive bidding, and real-time pricing such as the futures market (Tomek and Robinson 2003). A private negotiation is any price agreed upon by two parties in a contract or verbal agreement. List prices are what consumers receive in the store when company employees set prices based on any given factor. Auctions occur when there is a bidding system for a good or service, either anonymously or publicly, and the highest bid receives the right to purchase that item for the bid price. The futures market is a double auction where the buyer and seller are making bids and offers simultaneously until a mutual price is found. None of these mechanisms are perfect all the time, but as an aggregate, they help the market distribute goods and services efficiently.

Price discovery happens at different levels and complexities. Tomek and Robinson (2003) describe price discovery as a searching process using information amongst noise. In a complex system such as the global soybean trade, price discovery happens at each level: local, regional, national, and global. As the size of the price discovery market increases, so does the complexity and noise. There are also individuals or groups, such as non-commercial players, who are not directly involved in the market but join in to seek profit. Their actions as well as those of the commercial entities can directly affect prices even down to the local level.

Due to the complex nature of the price discovery system, this thesis relies more on basis theory to conduct research and make assumptions for the model. All terminal and origin basis prices are derived in part from the futures price. Since the origin basis is dependent on the local cash price and its factors, basis theory is an important focus of this thesis.

3.2.2. Individual Price Discovery

A simple way to understand how local supply and demand guide the market to a price is to first discuss the process on an individual level. An individual's demand curve represents a desire to purchase a basket of goods with a set income. The assumptions and theory behind an individual's demand curve are comprised of their utility function, which is represented by an indifference curve.

The utility function is the person's tastes and preferences that affects their desire for the basket of goods, and this can change over time. Any single indifference curve represents receiving the same amount of utility from the purchase of a combination of goods. Figure 3.1 (Tomek and Robinson, 2003) shows two goods, X and Y, and three indifference curves, U_1, U_2, and U_3. The more to the upper right the indifference curve is, the more utility it represents. The downward-sloping straight lines in Figure 3.1 represent the individual's budget constraints and the combination of good X and Y that can be purchased with that budget. The point of tangency of an indifference curve and budget line forms a demand scenario for the individual.

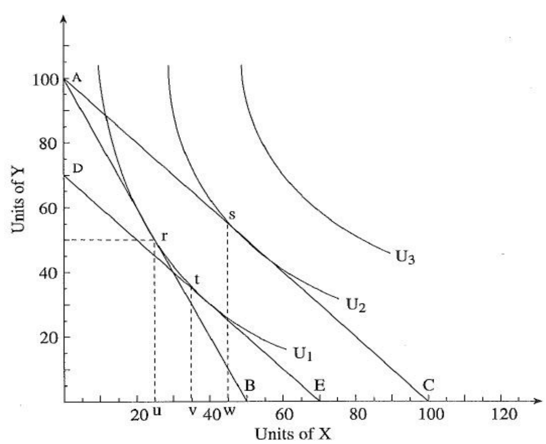


Figure 3.1: Individual consumer preferences (Tomek and Robinson, 2003).

There are different classifications of goods based off their behavior under an income or price change. Consumption of a normal good increases as income increases, and consumption of an inferior good decreases as income increases. Both normal and inferior goods have downward sloping demand curves (Nicholson and Snyder, 2008). When the price of a normal good declines, the income and substitution effects cause more of it to be demanded. In contrast, the fall in price of an inferior good causes more of it to be consumed per the substitution effect; however, the change due to the real income effect may cause less consumption of the good, so the net result of a price fall is indeterminate for the inferior good (Nicholson and Snyder, 2008). Giffen goods are another type of good that in essence defy the laws of demand; when a supposedly inferior good's price goes up enough to reduce purchasing power very drastically, the consumption of that good will increase because it is all that can be afforded (Nicholson and Snyder, 2008).

Normal goods are separated into luxuries and necessities. Necessary goods are those that when income increases, the percentage change in demand is less than the change in income. Luxury goods are those that when income increases, the ratio of demand increase to that of income is greater than one. Classification of a good will predict what a change in income does to the amount purchased of that good. Individual preferences aggregate to form market demand.

3.2.3. Market Price Discovery

There are two ways to describe different movements concerning market demand. A shift is demand moves the demand curve itself when a market changes in characteristics such as: real income, population, tastes and preferences, and prices of complements or substitutes. Each change creates a scenario where the demand curve changes locations on the graph, whether down and to left when demand is reduced or up and to the right when demand is increased. (Hudson, 2007). Demand can also change in terms of quantity demanded. This contrasts with the demand curve for a good or service moving, rather it signifies a movement along the curve in response to a change in price. Figure 3.2 illustrates the distinction between a demand change and a change in quantity demanded, as well a structural change to the market.

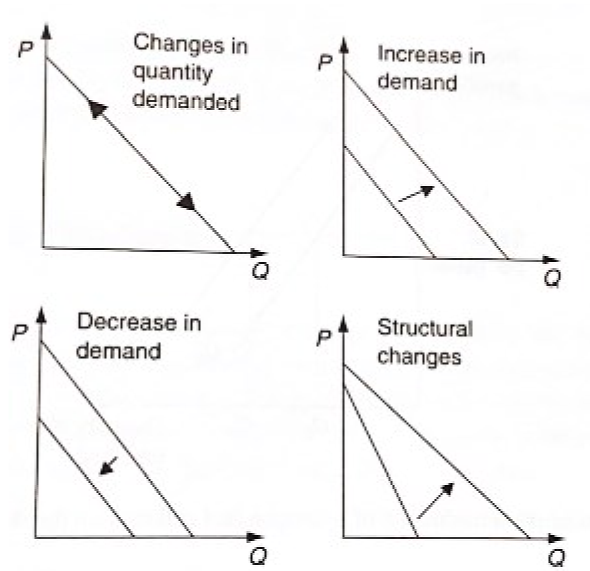


Figure 3.2: Changes in demand and quantity demand (Hudson, 2007).

Another important function of market price discovery is the concept of elasticity. Own-price elasticity shows how responsive demand is when a price changes for a good. Equation 3.1 illustrates that own-price elasticity is the percent change in quantity (Q_i) over the percent change in price (P_i). Using percentages takes away the problems of converting or comparing different units, and it creates a simple system for showing if a good is elastic, inelastic, or unitary. An own-price elasticity greater than one signifies an elastic good, an own-price elasticity of less than one signifies an inelastic good, and an elasticity of one is a unitary good (Hudson, 2007).

$$Eii = \frac{\frac{\partial Qi}{Qi}}{\frac{\partial Pi}{Pi}} \tag{3.1}$$

There is also cross-price elasticity, which determines substitutes and complements, and income elasticity, which determines normal and inferior goods and within normal goods, luxury and necessity goods. To focus on substitutes and complements, cross-price elasticity compares the change in quantity demanded of one good, B, in reaction to the change in price of another good, A. If the elasticity is greater than zero, the goods are substitutes because as price increases for good A, the demand for the good B increases. Therefore, if cross-price elasticity is less than one, the goods are complements because as the price of good A increases, the demand for good B decreases alongside that of good A (Hudson, 2007). In this thesis, soybeans from one area compared to another are widely considered a substitute good with the exception of a possible quality discount included to make substitution appropriate for the buyer.

Agriculture is commonly described as one of the most accurate examples of perfect competition. While no true perfectly competitive market exists, agriculture can be a close example. Perfect competition exists when these assumptions are met: price information for a homogenous product is readily available to a large number of buyers and sellers that act rationally and can enter and exit the market with ease (Kohls and Uhl, 2002). In this theory, the supply and demand curves would find the equilibrium shown in Figure 3.3. Notice that farmers are price-takers. However, since imperfect information exists, the commodity market in the short run creates areas of deficit and surplus which can be seen in the basis market in particular.

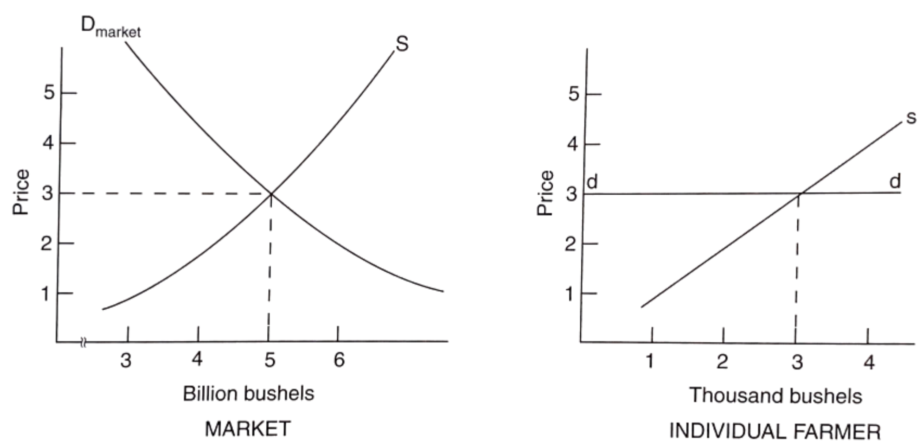


Figure 3.3: Supply and demand curves for the market and the farmer under perfect competition (Kohls and Uhl, 2002).

3.3. Basis Theory

Basis values are one of the most important features of this analysis. Since the analysis focuses on cost minimization, basis theory shows how price discovery and spatial markets come together to form the theoretical background in an analysis that is solely focused on cost minimization. In this way, the theoretical concepts are not all together ignored, and instead the basis data used in practice holds the theoretical founding within its own historical movement.

3.3.1. Theoretical Concept/Components of Basis

Kolb and Overdahl (2006) define the basis as the relationship that a cash price shares with the futures price for a good. More specifically, the basis is equal to a specific cash price at a location minus the futures contract price that corresponds with that cash commodity. Equation 3.2 illustrates the basis price calculation below. For example, the soybean basis in a given location, i, such as Ayr, ND is found by subtracting the Chicago Board of Trade (CBOT) soybeans futures price from the *i* spot cash price, which is the Ayr, ND cash price. Using the most current futures contract and spot cash price derives the nearby basis. One can also derive a forward basis by using deferred a deferred futures contract in the calculation.

$$Basis_i = \ Current\ Cash\ Price_i - Futures\ Price \tag{3.2}$$

Literature in Chapter 2 discussed the many factors that can change basis levels and the components. Compared to the futures price, basis prices are thought to be more predictable because a similar set of factors is always affecting the basis. The basis price is made up of the cost to store, transportation costs, and likely a premium or discount for quality differences. The supply and demand for storage is illustrated Figure 3.4.

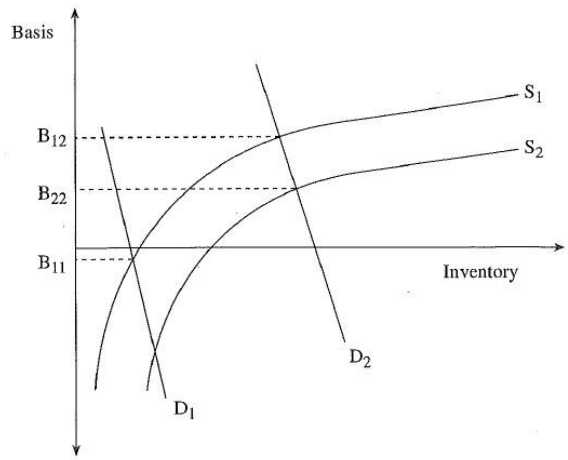


Figure 3.4: Storage supply and demand curve (Tomek and Robinson, 2003).

The storage supply curve does not have a linear shape because of variable costs such as labor and interest rate over time and economies of scale after much inventory is stored. When not enough storage is available even at economies of scale, the cost of storing increases once again due to higher cost of storage with greater inventories. The storage supply curve shifts upward and left or downward and right in response to change in costs. The corresponding demand curve is more upward and to the right, or greater, when production is high, and the storage demand is lower when production is low. Therefore, at harvest, producers prefer to store, and as they sell throughout the marketing year, demand will fall, decreasing storage price. Storage cost allows for basis predictability because the basis is expected to converge as storage costs fall until it is equal to only the transaction or delivery cost (Kolb and Overdahl, 2006). For this reason, this thesis uses basis prices as a representation of origin prices rather than cash or futures.

3.3.2. Changes in Basis and Predictability Relative to Futures

While storage cost allows for basis predictability, it does not make up the entirety of the basis due to commodities being sold across regions. As introduced in Chapter 2, transportation cost becomes a factor as a commodity is bought in the market that efficiently produces it and is delivered to a different market that demands it. Basic transportation costs include rail, barge, truck, and ocean freight rates in this analysis along with costs of delay. There are numerous other elements of shipping cost including Daily Car Value, load/unload costs, insurance, etc. Wilson and Dahl (2011) provide four different basis definition equations and their variables in Figure 3.5.

Basis definition	Comment
1. $B_o = C_o - F$	Basis is constant and highly predictable.
2. $B_o = B_d - M - T$	More complex, but, still simple and predictable
3. $B_o = B_d - \text{MAX}[(B_{d1} - T_{o1}), (B_{d2} - T_{o2}), (B_{d3} - T_{o3})] - M - F$	Includes impacts of multiple destination markets; the basis is derived from that market yielding the maximum net returns.
4. $B_o = B_d - [R_{oj} + FSC_{oj} + CAR\text{-}EP] - M - F$	Includes impacts of each of the primary elements of shipping by rail

Note: Variable definitions: C_o = cash price at origin; F = futures price; B_o = basis value at origin o; B_d = basis value at destination d; B_{dj} = basis value at destination dj; T = transport costs; T_{oj} = transport costs from o to j; R_{oj} = rail tariff rates from o to j; FSC_{oj} = fuel service charge from o to j; CAR = rail car values from either primary or secondary market; EP = efficiency payments (OEP, DEP); M = margins.

Figure 3.5: Alternative formulations of grain pricing or basis values (Wilson and Dahl, 2011).

Wilson and Dahl's (2011) Equation 1 refers to the most basic form of origin basis derived from the cash and futures prices. Equation 2 uses destination basis, margin, and transportation, which involves more factors but is still predictable. Equation 3 recognizes that an origin has the possibility of delivering grain to multiple destination markets, and so the origin basis reflects the maximum net returns from the optimal destination. Equation 4 include rail tariff rates, fuel service charges, and primary and secondary rail values. By considering these variables, basis values can be predicted in large part and used to conduct this thesis analysis.

3.4. Law of One Price

In a perfectly competitive price system, there is said to be a large number of homogenous goods, no transfer costs, low barriers to entry, and many buyers and sellers (Nicholson and Snyder, 2008). The world soybean market studied in this analysis has a large supply of relatively homogenous soybean sources and their factors of production. Supply and demand determine the equilibrium price for the good, which holds to the law of one price over time.

3.4.1. Definition of Theory

The law of one price simply states that a good trades at the same price between markets (Nicholson and Snyder, 2008). Immediately, it is known that a good such as soybeans is not priced the same even in towns near each other. The idea is that where the good trades at a low price, buyers will want to buy, and where it trades at a high price, sellers want to sell. These two actions taken together equalize the price (Nicholson and Snyder, 2008). In the context of soybean trade, in the short run differences in basis offering exist due to disparities in supply and demand, and this directs the flow of soybeans to where they are valued most.

It should be mentioned that there is discussion about if the law of one price can be applied to agriculture due to transfer costs. Goodwin et. al (2011) found transfer costs to be a random variable. This thesis focuses on the transportation costs aspect of the differences between regions to demonstrate where arbitrage might be available in the short run, which leads to the law of one price in perfect competition holding in the long run.

3.5. Spatial Markets Competition and Spatial Arbitrage

Hudson (2007) describes arbitrage as "essential in determining the proper allocation of product across space and equilibrating prices" (p.96). Hudson's definition is a consideration in this thesis. Discussing spatial competition and arbitrage's role across markets guides analysis into the concentrated world soybean trade.

3.5.1. Regional Spatial Equilibrium

Supply and demand in a region determine the local origin basis, and spatial price relationships are a result of differing regional prices. As prices change, the flow of commodities changes in response to find equilibrium. To begin, Figure 3.5 displays a spatial equilibrium model between two regions. Region A has a surplus of 15 units, and Region B has a matching deficit. In theory, the entirety of the 15 units would be traded. However, the model at equilibrium does not consider transfer costs such as insurance, financing, loading/unloading, any delay time or fees, or even contract failure costs (Tomek and Robinson, 2003). Using the third graph in Figure 3.6, the price less the transfer costs would provide a new, lower trade quantity as transfer costs increase.

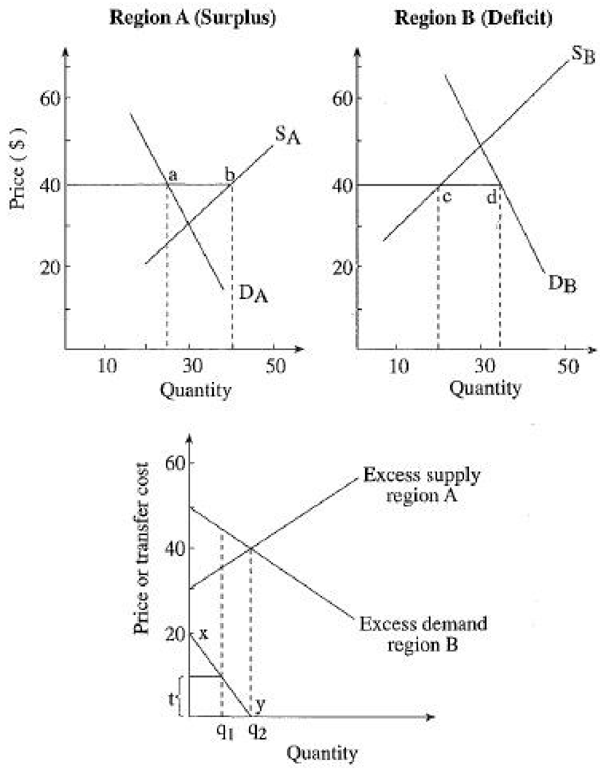


Figure 3.6: Two-region spatial equilibrium graph (Tomek and Robinson, 2003).

In most situations there are more than one surplus and deficit regions. For example, in this thesis Brazil and the United States are surplus regions, and China is a deficit region. Tomek and Robinson (2003) establish a hypothetical spatial model shown in Figure 3.7 where two regions X and Y produce excess supply, and regions A and B have excess demand for the good. Given the costs displayed, B would buy from either region X or Y, where A would only buy from X.

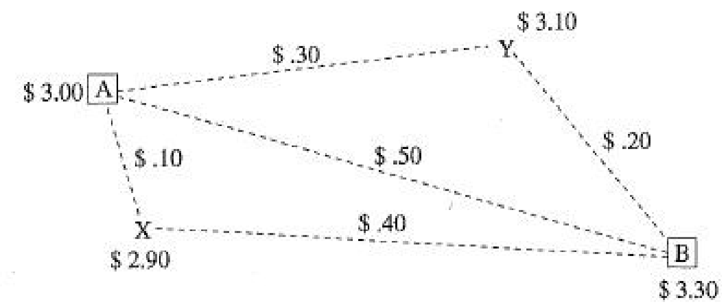


Figure 3.7: Market scenario with two surplus and two deficit regions (Tomek and Robinson, 2003).

Tomek and Robinson (2003) refer to transfer costs as the most important variable in spatial price relationships. Transfer costs include any cost involved in the physical and ownership movement of a good including transportation and fixed variables such as insurance or load/unload costs. Transfer cost increases at a decreasing rate as distance between locations increases (Tomek and Robinson, 2003). For these reasons, Hudson (2007) cautions researchers to not use average transportation costs for transfer costs.

Market boundaries are established when no economic argument can be made to ship a good (Hudson, 2007). Market boundaries can also arise from political or geographical constraints. Figure 3.8 provides an example of a spatial market scenario with an established market boundary. Modeled after the previous Figure 3.7 from Tomek and Robinson (2003), Hudson (2007) displays the market boundary to illustrate how Farmer Y will not be able to sell to importing region US because of the transfer costs exceeding the price difference.

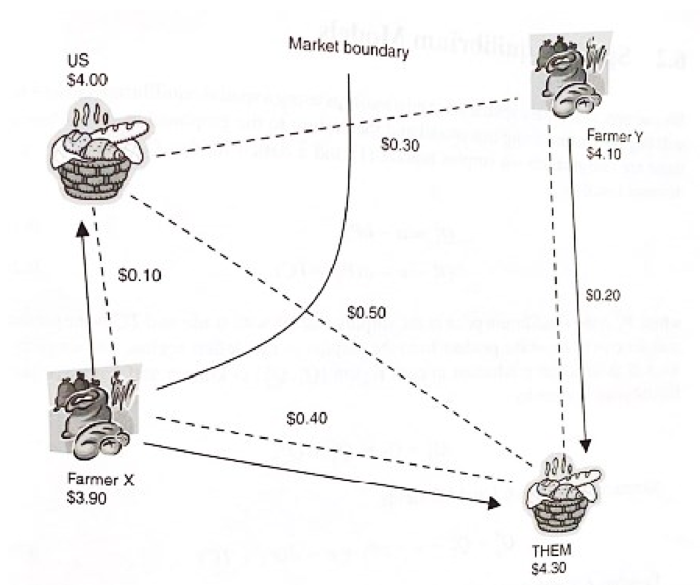


Figure 3.8: Hypothetical market for wheat with two suppliers and two markets (Hudson, 2007).

This is an illustrative example, not meant to be all-inclusive but rather to establish a foundation from which to discuss spatial arbitrage. Since factors like transportation costs, transfer costs, and market boundaries are constantly shifting, there are opportunities for arbitrage to take place.

It is important to discuss supply and demand in their traditional theoretical form to introduce other theoretical concepts such as price discovery and spatial equilibrium. So, it is noted that demand in theory is considered to be downward-sloping. However, to model the intended scenario, in practice it is assumed that a prolific buyer such a China always has some level of demand due to the many factors described in Chapter 2. China's demand is known, and in the empirical model, import demand for soybeans by China, is assumed perfectly price inelastic.

3.5.2. Spatial Arbitrage

There is an interdependence of the concepts and events of spatial competition, spatial arbitrage, and the law of one price. The law of one price was previously introduced in which it was stated that the theory holds in the long run but may not in the short run due. Spatial competition exists due to differences in local supply and demand, mainly due to specialization of production and geographical qualities, that create distinct basis values.

Because spatial competition exists across space and time, a person seeking an arbitrage opportunity is still at risk due to the good they wish to buy or sell needing time to move across markets. A basis price or any other associated cost may move prior to delivery, so any price that is not locked in a contract can shift and cause the arbitrage opportunity to become less profitable or a loss. However, forward contracts for basis or transportation variables can be employed to mitigate risk.

The theoretical equations for spatial arbitrage are given by Baulch (1997) beginning in Equation 3.3 shown below:

$$P_t^i + K_t^{ij} = P_t^j \tag{3.3}$$

where:

P_t^i	=	price of good at time *t* in the exporting market *i*
P_t^j	=	price of good at time *t* in the importing market *j*, and
K_t^{ij}	=	transfer costs between markets *i* and *j* during time period *t*.

In this case, the export market price plus transfer costs are equal to the import price, so trade can occur, but there are no arbitrage opportunities. Equation 3.3 represents no incentive to trade normally due to the price in the exporting market plus the transfer costs totaling greater than the price in the importing market. However, in that scenario, an arbitrage trade could occur by bringing a good from the import market to the export market.

$$P_t^i + K_t^{ij} > P_t^j \tag{3.4}$$

Equation 3.4 represents an opportunity for arbitrage from the exporting market to the importing market because the export market price with the transfer costs are less than the importing market price.

$$P_t^i + K_t^{ij} < P_t^j \tag{3.4}$$

Opportunity for profit seen by arbitrageurs and players within the industry looking to secure a better financial outlook for their trading activity are what drive the theory of the law of one price to fulfillment in the long run. There are risks associated with seeking profits, but the traders who find arbitrage opportunities can mitigate risk and take arbitrage positions through mechanisms that exist in the marketplace such as forward contracting. While there may be barriers and imperfect information, traders can be aware of basis prices and their components, transportation, and other spatial variables that can carry risk and therefore opportunities for profit.

In this particular research, transportation variables are heavily relied upon to define spatial markets because they represent a portion of spatial relationship that buyers and sellers can minimize, in contrast with fixed charges. Due to neither Brazil or the United States having a true distance advantage, Chinese soybean buyers take fixed costs into consideration and minimize variable costs. This reality leads into the discussion of minimizing cost in spatial markets.

3.6. Cost Minimization in Network Models

The main tenet of the empirical analysis is to conduct cost minimization given the theoretical concepts of the movement of prices and the market factors unique to the United States, Brazil, and China. Ballou (1992) describes cost reduction as having the same goal as profit maximization through minimizing variable costs related to logistics. Cost alternatives can be making least-cost decisions when sourcing goods and choosing transportation methods.

The problem statement of configuring a supply network is determining where points of origin/source should be located, what transport mechanisms should be used between them, and how to serve the demand (Ballou, 1992). There are both temporal and spatial aspects to a network model. The spatial aspects are in reference to the regional spatial issues previously discussed but, in a network model, they involve establishing locations by balancing geographic and production nature against carrying costs, overhead fixed costs, storage and handling costs, and transportation costs to the next step in the network (Ballou, 1992). The location of an origin and the costs associated with that origin must still allow for the customer/buyer to be serviced.

The temporal aspect of a network model involves choosing origins that allow for the customer/buyer to be sold to in their demand period, or more plainly stated, origins must be able to serve demand in the months the buyer has demand, The customer, in this case China, is concerned with the time it takes to acquire the product, soybeans. Processing costs and transportation costs are temporal aspects as well, and temporal concerns also affect how to choose optimal origins to supply the customer with a good (Ballou, 1992).

Ballou (1992) outlines the process behind simulation models that seek to perform a sample experiment on the network model:

> Simulating the network ordinarily involves replicating the cost structures, constraints, and other factors that represent that network in a reasonable manner. This replication is usually done by means of mathematical relationships, which are often stochastic in nature" (p. 294).

By repeating the simulation on a network model, it is possible to generate statistics that can be used to compare between different model structures and solve logistical planning problems. Simulation represents a common method of choice when the problem is very complex and detailed, contain stochastic elements, and is not in need of one single optimal solution (Ballou, 1992). For these reasons, the theoretical backgrounds support the use of stochastic simulation in the thesis model, which closely resembles a network model containing many logistical and sourcing.

3.7. Conclusion

Establishing the theoretical foundation serves as a guide for constructing a least-cost spatial optimization model. Price discovery occurs when corresponding supply and demand find their equilibrium price point that satisfies each. Markets function as an aggregate of individual price discovery in order to find a market price equilibrium. The law of one price is theoretically shown through the actions of arbitrageurs in a highly competitive marketplace. General spatial relationships and how arbitrage functions across them leads into researching the specific relationship between the United States and Brazil as soybean-producing countries and China as an importing country. The soybean trade, as a whole, is considered a highly competitive marketplace, but this research will explore deeper into the relationship between the three main players and evaluate where costs and risks have disparities that are crucial for Chinese importers and their choice of origin.

4. EMPIRICAL MODEL

4.1. Introduction

Competition between the United States and Brazil for China's soybean purchases is impacted by factors that are reflected in costs incurred by Chinese soybean importers. Previous literature discussed in Chapter 2 points to the recent investments in Brazilian infrastructure and the need to study differences between the U.S. and Brazilian soybean markets. As time progresses, Brazil and the United States are set to remain competitors in the Chinese soybean market. Predicting the timing of China's purchases from each country is important for U.S. and Brazilian soybean merchandising to understand and plan for.

The thesis model has two main objectives. The first is to establish a scenario that reflects the shipping outcomes for soybeans to China throughout the year by detailing the origin country and the least-cost route through the port. The second objective is to specify factors that shipping demand is most sensitive to and show relative sensitivity to factors that a soybean exporter will face.

The hypothetical role of a soybean merchandising company is assumed to present the model. The merchandising company has five originating locations in each country as well as various transportation routes to exporting ports, where such realistic routes exist. The merchandising company's goal is cost minimization, and since it has locations in each country it has no bias as to how it allocates grain sales and shipments. The shipments must total 1 million metric ton (MMT) per month for 12 months.

Costs in the model are defined below and include origin basis, interior shipping costs, port basis, port wait time, ocean shipping costs, and structural variables that resemble current market conditions. Many of these costs are random and are correlated with one another. As the costs change, the optimal origin and country of origin change. The model reflects these changes. The model is based on previous work done in a special report by Wilson, Bullock, and Lakkakula concerning spatial competition for importing wheat into Mexico (Wilson et. al 2020). The model is adapted to represent two competing countries and their origins rather than a list of origin locations from one similar market. The model is an optimized Monte Carlo simulation.

4.2. Empirical Specification

4.2.1. Basic Structure of Model

The model consists of five origins in each country. The origins in the United States stretch along the eastern state lines of North Dakota down to Missouri: Arthur Companies in Ayr, ND; Cargill, Inc. in Jasper, MN; CHS Inc. in Jasper, MN; Landus Cooperative in Ida Grover, IA; and Bartlett Grain Co. in St. Joseph, MO. The five origins in Brazil are from popular, robust soybean producing states of Bahia, Goiás, Mato Grasso, and Paraná. They are Barreiras, Bahia; Rio Verde, Goiás; Rondonópolis, Mato Grosso; Sorriso, Mato Grosso; and Ponta Grossa, Paraná.

Grain from the origins in the United States can take two transportation routes to port. Either grain is shipped via railroad shuttles to the Pacific Northwest port (PNW) located near Portland, Oregon, or grain is trucked in semis and then loaded onto river barge locations in the Mississippi River Valley to reach the U.S. Gulf ports (USG), represented in this study by New Orleans, Louisiana. The U.S. ports were chosen due to popularity among soybean exporters which is large part due to their location and long history of being established export markets. All U.S. origins can ship soybeans to either port to allow for arbitrage situations between the two. Figure 4.1 displays the origins and ports in each country.

Figure 4.1: Model origin and port locations.

The PNW port can ship directly from the west coast of the United States to Shanghai, China. The USG port is located on the Gulf of Mexico in the southern United States, accepts soybeans from barges coming down the rivers in the Mississippi River Valley, and can ship the soybeans to China through the Panama Canal and around Cape Hope if fuel prices are low. The data used for the USG ocean freight to China is for the route through the Panama Canal.

In Brazil, grain from origin locations can be trucked north to the Amazon River barge locations or the northeast ports. The entirety of the northern barge and port locations in Brazil are still developing in terms of data representation, so the study's northern port is referred to as North and comprised of data from Port of Rotterdam International; Pecém, a northeast port; and Cargill in Santarem, an Amazon River port. Grain is also trucked south to ADM in Santos and Bunge Paranaguá ports.

From the ports, the grain is shipped via ocean shipping routes that are as follows: PNW across the Pacific Ocean to Shanghai, China; USG to Shanghai, China, through the Panama

Canal; Southern Brazil around Cape Hope to Shanghai, China; and Northern Brazil through the Panama Canal to Shanghai, China. Figure 4.2 shows the path of soybean from the place of growth to the destination in China.

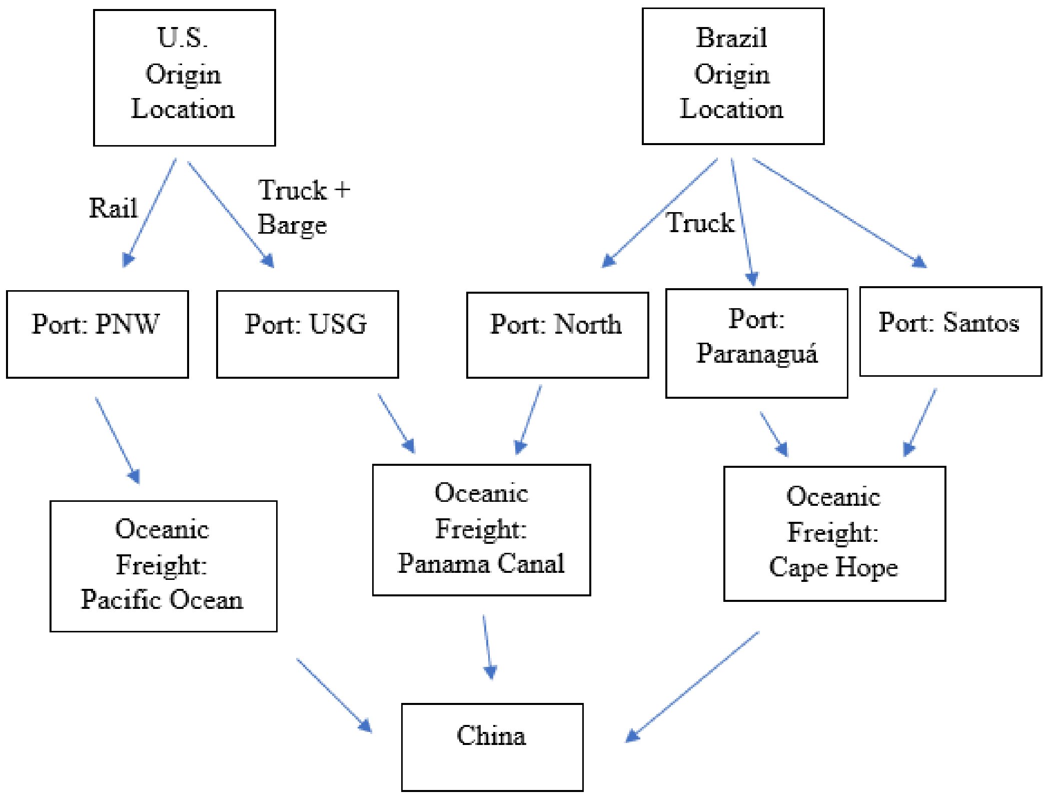


Figure 4.2: Soybean path from origin to destination China.

The model considers these routes as equally realistic when it aggregates the cost for each and compares the total costs for the routes to perform the optimization.

4.2.2. Mathematical Specification

The model is referred to as a stochastic optimized Monte Carlo simulation (Wilson et. al 2020). In this type of simulation model, the decision maker finds the best solution via deterministic optimization after knowing, with certainty, the ex-post values of the random variables. The model sequence begins by generating the random values for the particular iteration and then finding the optimal solution to the cost minimization problem. Therefore, each iteration is itself an individual optimization, and the collection of optimal results form a distribution of outcomes. This process differs from the more commonly known Monte Carlo optimization where the decision maker only knows the distribution of the random variable's value and must decide before the iteration is realized. This is an important distinction because in a regular Monte Carlo optimization, the decision maker's lack of perfect foresight regarding the iterated random values present a scenario where the decision maker must make the optimal choices under risk. On the other hand, the optimized Monte Carlo simulation used in this study presents a statistical summary of deterministic optimization results that use plausible historical or projected values for a select number of random variables in the model.

The model used in this thesis is a cost-minimizing spatial model where the optimal soybean procurement location is found for each month. The mathematical expression for Equation 4.1 is as follows:

$$\min_{x_{i,t}} C = \sum_{i=1}^{n} \sum_{t=1}^{12} \tilde{c}_{i,t} \cdot x_{i,t}, \tag{4.1}$$

subject to:

$$x_{i,t} \geq 0 \text{ for all } i, t;$$

$$\sum_{i=1}^{n} x_{i,t} \geq \bar{Q}_t \text{ for all } t;$$

where:

C = the total purchase cost for the Chinese buyer (in USD/bushel)

i = subscript for origin ($i = 1, \ldots, n$),

t = subscript for month of year ($t = 1, \ldots, 12$),

$x_{i,t}$ = quantity of purchase for export at origin i in month t (in bushels),

$\tilde{c}_{i,t}$ = randomly generated net purchase cost from origin i in month t (in USD/bushel),

$\bar{Q}_t$ = total required quantity purchased in month t (= 1 million metric ton).

The constraint requires that the quantity shipped from each country be between 0 and the maximum constrained value, also known as the total monthly shipping requirement in this model. The maximum constrained value is 1 MMT for each month across all simulations.

4.3. Detailed Data Specification/Empirical Model

4.3.1. Calculation of Basis

Origin basis values are sourced from DTN *Prophet X* for U.S. origins and Thomson Reuters Eikon for Brazilian origins. The exact shuttle elevator is specified in the case of the U.S. origins, whereas the Brazilian origins are represented by the town or city’s soybean basis reported through Bloomberg by Escola Superior de Agricultura Luiz de Queiroz (ESALQ). In each case the value is sourced first as a cash price, and the basis is calculated by the cash price less the Chicago Board of Trade (CBOT) soybean futures price. In the Brazilian case, the cash price is converted from Real to U.S. Dollar (USD) before the basis calculation is performed. Equation 4.2 demonstrates how basis for each origin and port is derived. Basis is equal to the cash price less the futures price.

$$Basis_i = Cash_i - Futures_{CBOT} \tag{4.2}$$

The calculated interior basis for Brazil origins is shown in Figure 4.3, and the interior basis for U.S. origins is shown in Figure 4.4. Both are displayed from 2013 to 2019, showing the data used in the study.

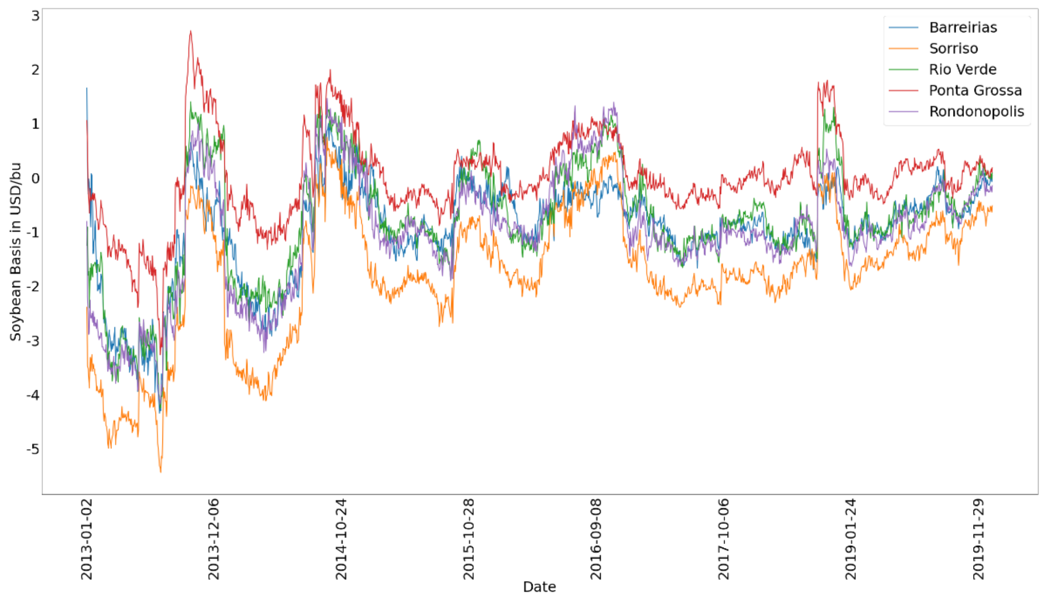


Figure 4.3: Brazil origin basis January 2013 to December 2019.

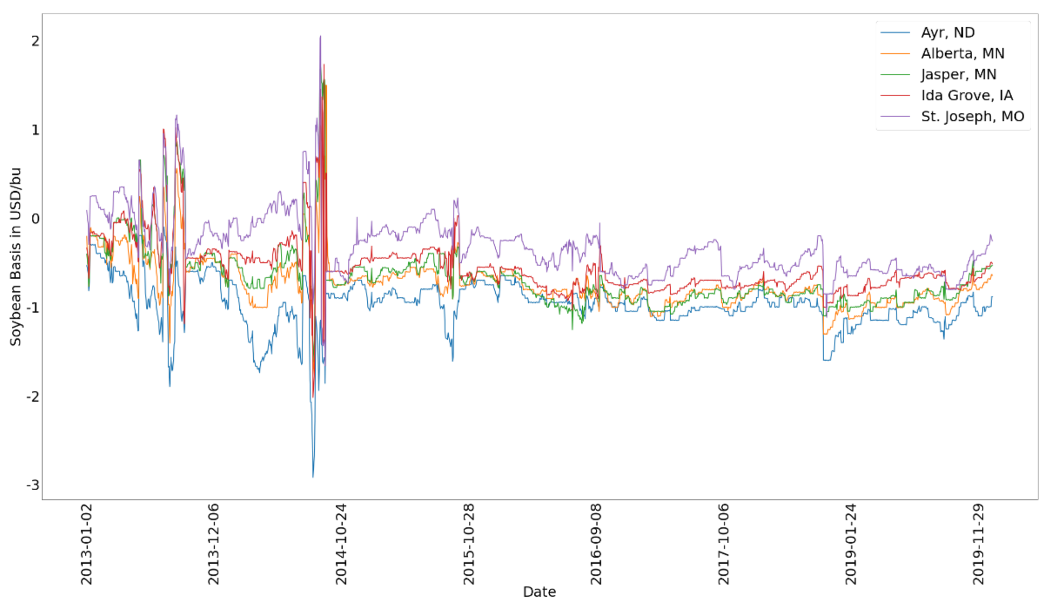


Figure 4.4: US origin basis January 2013 to December 2019.

Given the axis on each graph, it is clear that Brazil's origin basis values in the past were more volatile than that of the United States. Both countries experienced very volatile price movements in the years of 2013 and 2014, and volatility continues to persist, especially in Brazil.

4.3.2. Interior Transportation Cost

Transportation to ports involves trucking in both countries. In Brazil, only a limited rail system exists, so soybeans are trucked to the origins by farmers and then to the ports by truckers as well. Interior shipping costs for Brazil are sourced from Brazilian sources: the Brazilian National Company of Supply (CONAB) and the Instituto Mato-Grossense de Economia Agropecuária (IMEA).

U.S. truck costs are the UDSA AMS North Central Region rate per mile, per truckload multiplied by miles between the origination elevator and the barge locations. The cost is then converted to dollars per bushel based on standard 1000-bushel truckloads.

Barge rates are in dollars per bushel from the USDA for the barge-loading locations of: Twin Cities (TWC), Mid-Mississippi (MM), Lower Illinois River (ILL), St. Louis (STL), Cincinnati (CINC), Lower Ohio River (LOH), and Cairo to Memphis (CAR-MEM). Transportation to the USG port is equal to the minimum trucking cost plus barge rate for each origin. Equation 4.3 shows a transportation cost example for soybeans moving south to the gulf. $JANTransCost_{AyrtoUSG}$ is the shipping costs for January from Ayr to the USG.

$$\begin{aligned}
&JANTransCost_{AyrtoUSG} = \\
&MIN\big(Truck_{AyrtoTWC} + JANBarge_{TWC}, Truck_{AyrtoMM} + \\
&JANBarge_{MM}, Truck_{AyrtoILL} + JANBarge_{ILL}, Truck_{AyrtoSTL} + \\
&JANBarge_{STL}, Truck_{AyrtoCINC} + JANBarge_{CINC}, Truck_{AyrtoLOH} + \\
&JANBarge_{LOH}, Truck_{AyrtoCAR} + JANBarge_{CAR-MEM}\big) \qquad (4.3)
\end{aligned}$$

U.S. soybeans are also transported west via the rail system. This cost is represented by two components: rail tariff and daily car value (DCV). The rail tariff is obtained Burlington Northern Santa Fe Railway (BNSF) and Union Pacific Railway (UP). Rail tariff is non-random and is obtained in dollars per loaded railcar. The fuel service charge during the period of collected data was embedded into the rail tariff rate. The DCV is obtained from the average of the bid and ask values from weekly TradeWest brokerage reports and is a random variable for which a distribution is derived. The DCV over time is displayed in Figure 4.5.

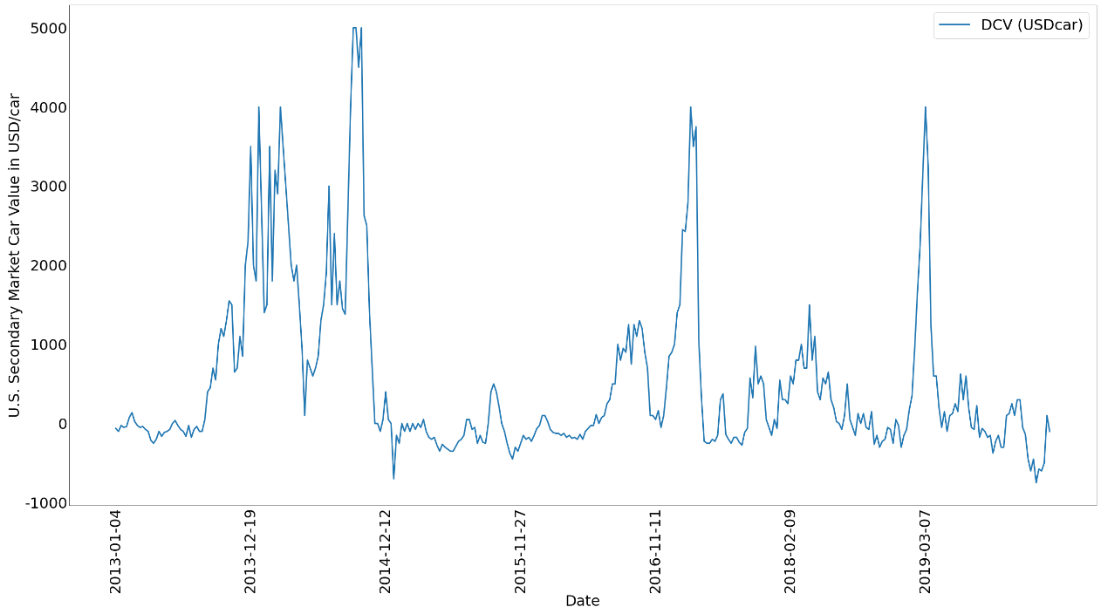


Figure 4.5: Daily Car Value (DCV) from 2013 to 2019 in the United States.

The sum of the constant rail tariff from each origin and the DCV is the total rail cost to the PNW. Equation 4.4 shows the transportation cost example for soybeans traveling west. $JANTransCost_{AyrtoPNW}$ is the shipping costs for January from Ayr to the PNW.

$$JANTransCost_{AyrtoPNW} = JANDCV + RailTariff_{AyrtoPNW} \tag{4.4}$$

4.3.3. Wait Time and Demurrage Specifications

Vessel wait time refers to vessels waiting at ports to be filled in Brazil. Vessel demurrage costs are cost incurred from waiting; the demurrage costs are specific to Brazil and its struggles with inconsistent supply at the ports caused by trucking/shipping inefficiencies. Average wait times are sourced from Agência Marítima CARGONAVE Ltda. (CARGONAVE) of Brazil for the largest grain elevator at each port and are used to derive a mean across years and therefore an expected value of wait time. Figure 4.6 displays the monthly average wait times measured in days from 2013 to 2019 for three ports in Brazil, Santarem, Paranaguá, and Santos.

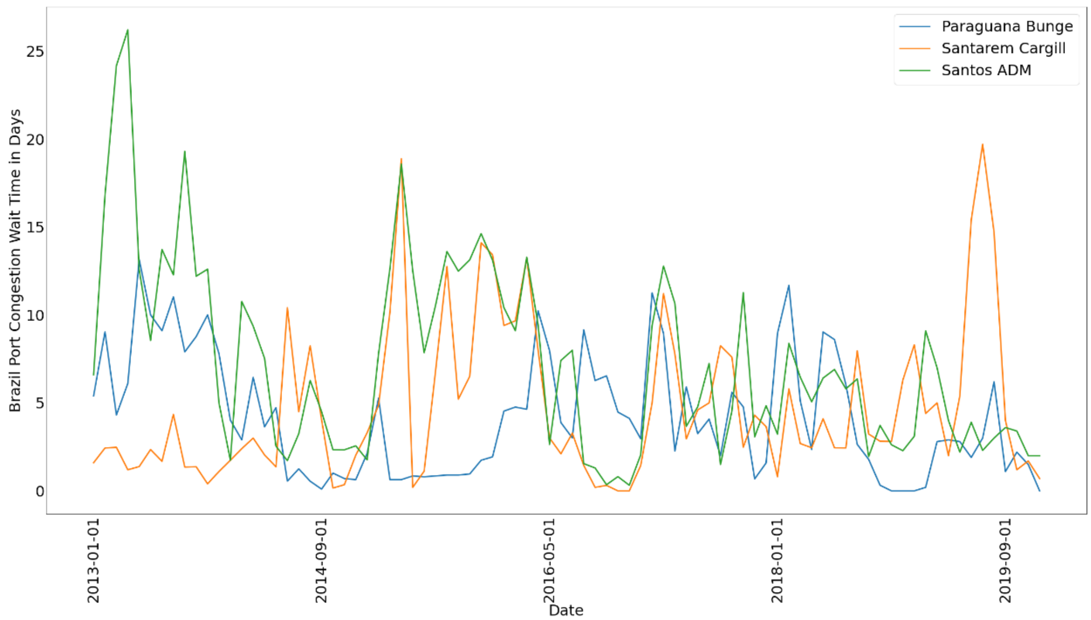


Figure 4.6: Wait times in Brazil from 2013 to 2019 for Paranaguá, Santarem, and Santos.

A distribution of wait times for the ports is derived for the simulation. If actual wait time is equal to or less than the expected wait time value, demurrage costs are nil since exporters and importers would take an expected wait time into account. If actual wait time is greater than the expected value, demurrage costs are equal to days waiting in excess of expected value multiplied by the demurrage rate. Equation 4.5 shows demurrage cost as an IF function with IF(logical test, value_if_true, value_if_false).

$$DemurrageCost = IF(WaitTime > ExpectedWaitTime, WaitDays * DemurrageRate, 0) \tag{4.5}$$

4.3.4. Ocean Shipping Cost

Ocean transportation rates are sourced from the USDA AMS. The ocean rates from USG to China and PNW to China are varying, so a time series distribution was fitted to each variable.

Ocean rates represent the final part of the transportation route from the United States and Brazil to China. The ocean rates are shown in Figure 4.7 below.

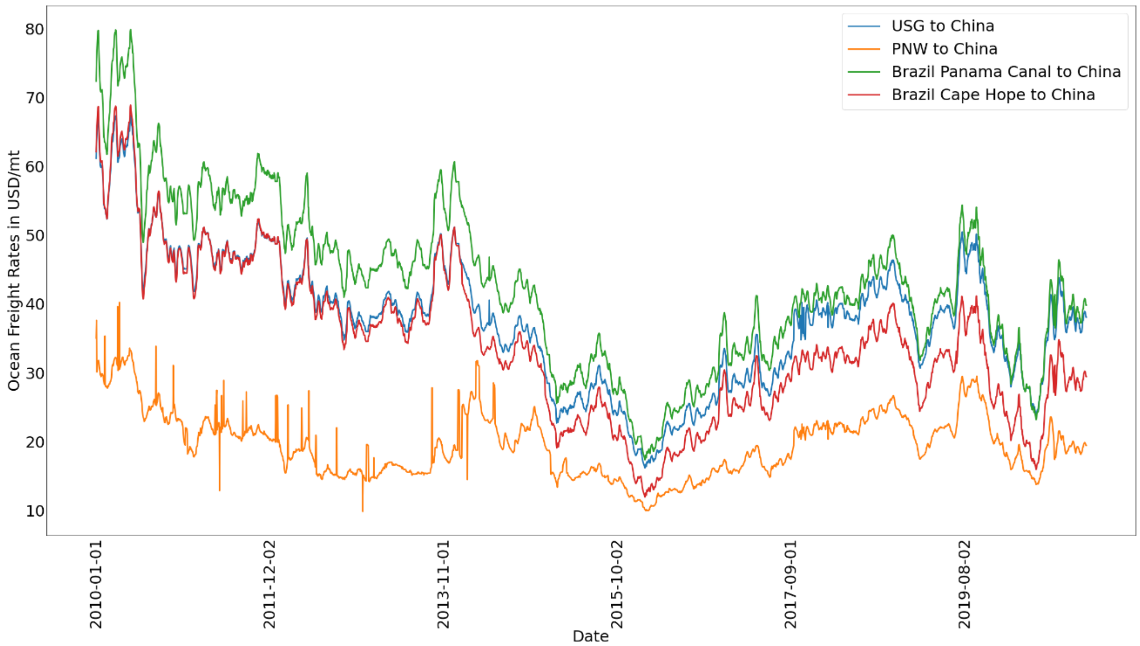


Figure 4.7: Ocean freight rates for USG through Panama Canal, PNW, Brazil through Panama Canal, and Brazil around Cape Hope from 2010 to 2019.

4.4. Data Types, Sources, Conversions, and Distributions

Input parameters fall into two groups, random and non-random. The random inputs are linked values to their @Risk distributions that change with each iteration of the simulation. The non-random inputs are static and do not change unless they are a non-random user input, which can be altered to perform sensitivity analysis.

4.4.1. Random Inputs

The data behind the distributions made for the model's random inputs was collected for the years of 2013 to 2019. The data was converted into USD per bushel from the original units for each respective variable except the exchange rate and waiting time days. The frequency for the included variables was collected in the most frequent form available for each variable; the most common frequencies were daily and weekly data. The data was converted to monthly averages from which the time series distributions were built to forecast the random values. Random inputs for the U.S. portion of the model are summarized in Table 4.1, and those for Brazil are summarized in Table 4.2.

Table 4.1: Random inputs for U.S. side of the model.

Model Input	**Mean Value**	**Original Units**	**Converted Units**	**Source**
Basis: Ayr, ND	-0.9815	USD/Bushel	Basis in USD/bushel	DTN *ProphetX*
Basis: Alberta, MN	-0.7061	USD/Bushel	Basis in USD/bushel	DTN *ProphetX*
Basis: Jasper, MN	-0.6598	USD/Bushel	Basis in USD/bushel	DTN *ProphetX*
Basis: Ida Grove, IA	-0.5404	USD/Bushel	Basis in USD/bushel	DTN *ProphetX*
Basis: St. Joseph, MO	-0.3113	USD/Bushel	Basis in USD/bushel	DTN *ProphetX*
Ocean: USG to China via Panamá Canal	0.9940	USD/mT	USD/bushel	Thomson Reuters Eikon
Ocean: PNW to China	0.4831	USD/mT	USD/bushel	Thomson Reuters Eikon
Port Basis: USG	0.7356	USD/mT	USD/bushel	Thomson Reuters Eikon
Port Basis: PNW	1.0003	USD/mT	USD/bushel	Thomson Reuters Eikon
Barge: Twin Cities	0.8426	USD/bu	USD/bu	USDA GTRTable9
Barge: Mid-Mississippi	0.6710	USD/bu	USD/bu	USDA GTRTable9
Barge: Lower Illinois River	0.5668	USD/bu	USD/bu	USDA GTRTable9
Barge: St. Louis	0.3862	USD/bu	USD/bu	USDA GTRTable9
Barge: Cincinnati	0.4942	USD/bu	USD/bu	USDA GTRTable9
Barge: Lower Ohio	0.4243	USD/bu	USD/bu	USDA GTRTable9
Barge: Cairo-Memphis	0.2691	USD/bu	USD/bu	USDA GTRTable9
Daily Car Value	0.1345	USD/bu	USD/car	Thomson Reuters Eikon

Table 4.2: Random inputs for Brazil side of the model.

Model Input	Mean Value	Original Units	Converted Units	Source
Basis: Barreiras	-0.8344	Real/60kg bag	Basis in USD/bushel	Thomson Reuters Eikon
Basis: Sorriso	-1.7205	Real/60kg bag	Basis in USD/bushel	Thomson Reuters Eikon
Basis: Rio Verde	-0.7332	Real/60kg bag	Basis in USD/bushel	Thomson Reuters Eikon
Basis: Ponta Grossa	0.06589	Real/60kg bag	Basis in USD/bushel	Thomson Reuters Eikon
Basis: Rondonópolis	-0.9361	Real/60kg bag	Basis in USD/bushel	Thomson Reuters Eikon
Ocean: Brazil to China via Cape Hope	0.82213	USD/mT	USD/bushel	Thomson Reuters Eikon
Ocean: Brazil to China via Panamá Canal	1.0512	USD/mT	USD/bushel	Thomson Reuters Eikon
Port: Santos	0.6967	USD/mT	USD/bushel	Thomson Reuters Eikon
Port: Paranaguá	0.7670	USD/mT	USD/bushel	Thomson Reuters Eikon
Port: North (Pecém)	1.4559	USD/mT	USD/bushel	Thomson Reuters Eikon
Exchange Rate	3.1081	USD/BRL	USD/BRL	Thomson Reuters Eikon
Waiting Time: Paranaguá	4.1204	Days	Days	Agencia Maritima Cargonave Ltda
Waiting Time: North (Santarem)	4.7112	Days	Days	Agencia Maritima Cargonave Ltda
Waiting Time: Santos	7.1053	Days	Days	Agencia Maritima Cargonave Ltda

4.4.2. BestFit Distributions

The random inputs were evaluated and made random using BestFit @Risk technology done in batches. The batches were formed out of like variables to capture their correlations. To demonstrate, this section shows a few of the thirty distributions.

The best-fitting time series distribution for each value is chosen based on Akaike information criterion (AIC). BestFit @Risk chooses from a variety of models including: Geometric Brownian Motion (GBM), Brownian Motion with Mean Reversion (BBRM), autoregressive and moving average each with one and two lags, and combined autoregressive-moving average. Graphical analysis indicates that series are stationary and homoscedastic; therefore, no differencing was performed, and wide-tailed distributions such as auto regressive conditional heteroscedasticity (ARCH), generalized ARCH (GARCH), and any jump diffusion processes were excluded from the BestFit application. A complete list of time series functions and their parameters is in Appendix A. Trends and seasonality are detected by BestFit to find the proper distribution for each variable dataset. The @Risk model is set and then predicts a forecast length or interval that the user specifies (Palisade Technology).

The originating basis values for the elevators in the United States and Brazil were split into two separate batches because the AIC fit criteria were stronger when the origins were split by country. Figure 4.8 shows the basis over time for the originating elevators in both countries. The Brazilian prices have far greater range of movement compared to their U.S. counterparts.

Figure 4.8. Origin basis (Thomson Reuters Eikon, DTN *ProphetX*).

The first BestFit batch consisted of the Brazil origins, ports, wait days, and Real/USD exchange rate. Tables 4.3 describes the time series functions and AIC scores for Brazil's random variables, and Table 4.4 describes their correlations using Spearman rank-order correlation coefficients. The origin basis values are highly and positively correlated and are also positively correlated with the port basis values. The basis values are negatively correlated with the waiting time in days.

Table 4.3: Brazil time series functions (@Risk).

Input	Distribution	Function	AIC Score
		Origin Basis	
Barreiras	Auto Regressive at 2 lags	RiskAR2(-0.83444, 0.35496, 1.4072, -0.6479, -0.071974, -0.43158)	74.7700
Sorriso	Auto Regressive at 2 lags	RiskAR2(-1.7205, 0.43962, 1.379, -0.56428, -0.61355, -0.74158)	110.5810
Rio Verde	Auto Regressive at 2 lags	RiskAR2(-0.73321, 0.44162, 1.297, -0.5317, 0.089079, -0.23579)	111.0001
Ponta Grossa	Auto Regressive at 2 lags	RiskAR2(0.065888, 0.35269, 1.2789, -0.56045, 0.18329, 0.19053)	73.1642
Rondonópolis	Auto Regressive at 2 lags	RiskAR2(-0.93606, 0.40221, 1.3859, -0.59527, -0.11618, -0.29)	95.6490
		Terminal Basis	
FOB Paranaguá	Auto Regressive at 2 lags	RiskAR2(0.76698, 0.39797, 1.0692, -0.42009, 0.91649, 0.969)	92.8161
FOB Santos	Auto Regressive at 2 lags	RiskAR2(0.69671, 0.38706, 1.1318, -0.37254, 0.78322, 0.95649)	88.3606
North Port	Auto Regressive at 2 lags	RiskAR2(1.4559, 0.38676, 0.37397, 0.19005, 1.5922, 0.19995)	87.1041
		Exchange Rate	
BRL = USD	Auto Regressive Moving Average at 1 lag	RiskARMA11(3.1081, 0.11518, 0.97797, 0.4527, 4.1067, -0.075594)	-112.6163
		Wait Days	
Paranaguá	Brownian Motion Mean Reversion	RiskBMMR(4.1204, 3.3148, 0.47819, 0)	409.2072
North Port	Moving Average at 2 lags	RiskMA2(4.7112, 3.6215, 0.65843, 0.2089, -2.8983, -1.2654)	463.0178
Santos	Auto Regressive Moving Average at 1 lag	RiskARMA11(7.1053, 3.7666, 0.56966, 0.25471, 2, -1.5283)	469.9090

Table 4.4: Brazil random inputs Spearman rank-order correlation matrix (@Risk).

Correlation	Barreiras	Sorriso	Rio Verde	Ponta Grossa	Rondo-nopolis	FOB Paranaguá	FOB Santos	North Port	Exchange Rate	Wait Paranaguá	Wait North	Wait Santos
Barreiras	1.000											
Sorriso	0.861	1.000										
Rio Verde	0.879	0.949	1.000									
Ponta Grossa	0.837	0.902	0.916	1.000								
Rondonópolis	0.870	0.966	0.956	0.920	1.000							
FOB Paranaguá	0.683	0.775	0.761	0.857	0.798	1.000						
FOB Santos	0.522	0.572	0.579	0.601	0.577	0.581	1.000					
North Port	0.309	0.354	0.408	0.498	0.430	0.449	0.380	1.000				
Exchange Rate	0.424	0.511	0.387	0.331	0.417	0.310	0.415	-0.046	1.000			
Wait Paranaguá	-0.263	-0.277	-0.308	-0.165	-0.243	-0.179	-0.201	-0.214	-0.294	1.000		
Wait North	-0.062	-0.123	-0.138	-0.127	-0.118	-0.072	-0.035	-0.069	0.329	-0.231	1.000	
Wait Santos	-0.333	-0.428	-0.419	-0.377	-0.374	-0.332	-0.417	-0.068	-0.254	0.226	0.249	1.000

The U.S. BestFit batch consisted of the five originating basis values, the two port basis variables, and the daily car value. The @Risk BestFit distribution functions are described in Table 4.5, and their correlation matrix is shown in Table 4.6. Origin and port basis values are positively correlated. DCV is mostly negatively correlated with the origin basis values, so as DCV rises, basis prices are driven downward. DCV and port basis are positively correlated.

Table 4.5: U.S. time series functions (@Risk).

Input	**Distribution**	**Function**	**AIC Score**
		Origin Basis	
Ayr, ND	Auto Regressive at 2 lags	RiskAR2(-0.98153, 0.1633, 0.80525, -0.17759, -1.0254, -0.95913)	-57.3657
Alberta, MN	Auto Regressive Moving Average at 1 lag	RiskARMA11(-0.70606, 0.17866, 0.91854, -0.49883, -0.72155, 0.10113)	-42.0456
Jasper, MN	Auto Regressive at 1 lag	RiskAR1(-0.6598, 0.15724, 0.83034, -0.57107)	-65.2476
Ida Grove, IA	Auto Regressive at 1 lag	RiskAR1(-0.54036, 0.10968, 0.88397, -0.58298)	-125.4100
St. Joseph, MO	Brownian Motion Mean Reversion	RiskBMMR(-0.31129, 0.22809, 0.29044, -0.34488)	-26.3282
		Terminal Basis	
FOB USG	Moving Average at 2 lags	RiskMA2(0.7356, 0.22766, 0.97761, 0.537, -0.049773, -0.091109)	-1.0405
FOB PNW	Brownian Motion Mean Reversion	RiskBMMR(1.0003, 0.16523, 0.14053, 0.82563)	-68.2104
		Transportation	
Daily Car Value	Auto Regressive Moving Average at 1 lag	RiskARMA11(0.1345, 0.19585, 0.45076, 0.44104, -0.16964, -0.19321)	-26.7174

Table 4.6: U.S. random inputs Spearman rank-order correlation matrix (@Risk).

Correlation	**Ayr, ND**	**Alberta, MN**	**Jasper, MN**	**Ida Grove, IA**	**St. Joseph, MO**	**FOB USG**	**FOB PNW**	**DCV**
Ayr, ND	1							
Alberta, MN	0.554	1						
Jasper, MN	0.388	0.904	1					
Ida Grove, IA	0.32	0.858	0.938	1				
St. Joseph MO	0.331	0.775	0.775	0.816	1			
FOB USG	0.429	0.553	0.515	0.595	0.467	1		
FOB PNW	0.481	0.762	0.752	0.766	0.619	0.74	1	
DCV	-0.179	-0.083	-0.079	0.006	-0.118	0.37	0.362	1

DCV correlation with other variables is of great significance. The negative correlation with most origin basis values represents the effects of secondary market volatility on the price producers receive, due to transportation and export entities incurring DCV volatility risk. DCV is shown as positively correlated with both FOB USG and FOB PNW basis.

Origin and destination basis are shown to be positively correlated in concurrence with Lakkakula and Wilson (2021), as they are determined simultaneously by adding shipping costs to the origin basis to determine the export basis and subtracting shipping costs from the export basis to find the origin basis. Changes in shipping costs will affect both basis prices, and therefore in this analysis uses only the origin basis in the cost equation and the export basis in tandem in other analyses.

Figures 4.9 through 4.13 display @Risk times series forecasts for a Brazil origin basis, Ponta Grossa, a Brazilian FOB basis, Santos, the Paranaguá Wait Days, a U.S. origin basis, Ayr, and the U.S. Daily Car Value. These graphs provide a sample of how the random variables are forecasted, and the remaining time series forecasts are in Appendix B. The X-axis shows both historical and predictive data. The historical data is shown in the negative X-axis values, and the forecasted basis price is located to the right of 0. The mean forecasted basis is the dark line. The shaded areas represent confidence intervals for 5%, 25%, 75%, and 95%. The red line shows a sample predicted path.

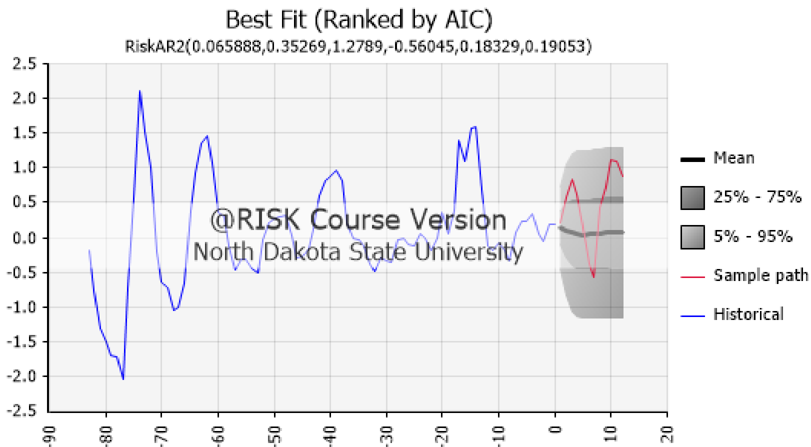


Figure 4.9: Time series forecast of Ponta Grossa, basis (@Risk).

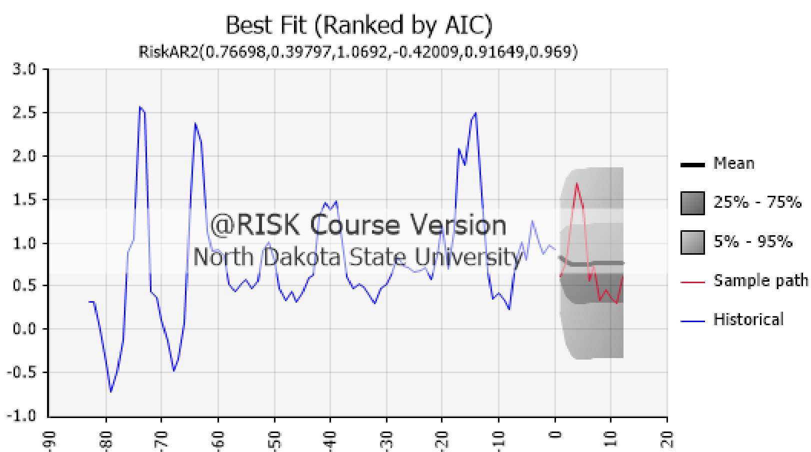


Figure 4.10: Time series forecast of FOB Paranaguá basis (@Risk).

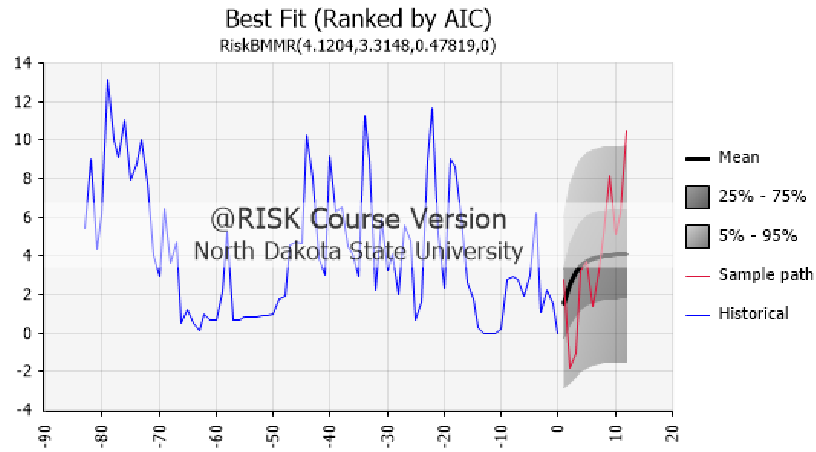


Figure 4.11: Time series forecast of Paranaguá Wait Days (@Risk).

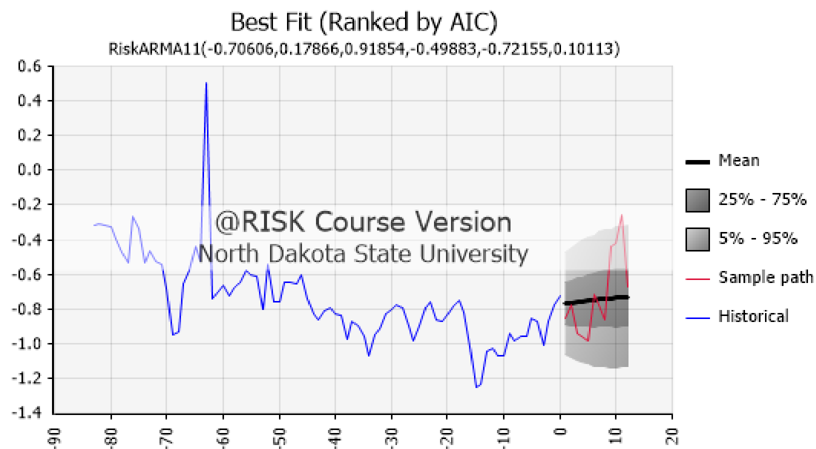


Figure 4.12: Time series forecast of Alberta, MN basis (@Risk).

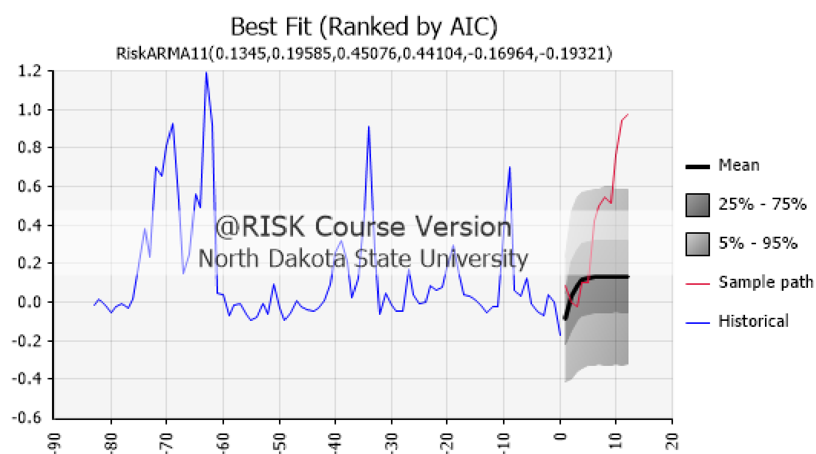


Figure 4.13: Time series forecast of DCV (@Risk).

4.4.3. Non-Random Inputs

The non-random inputs include variables in both the U.S. and Brazilian sides of the model. U.S. trucking costs from the five originating elevators to six barge locations. The USD per mile rate is multiplied by the miles from origin to barge destination. In the model, these values do not vary across months but are rather one static value for each origin to barge route. The U.S. rail tariff is a single reported value for each shuttle-loading originating location from BNSF Ag Price Documents that does not change within the period of the model.

The interior Brazil transportation variables are non-random inputs. The data was collected from years 2017 to 2019, due to limited data availability. These variables are also the only variables not reported at a frequency that makes possible a time series distribution, so they are static averages, either monthly averages for three years or plain three-year averages, that resemble a more recent weighted value than that of data collected more for more previous year, to reflect the rates going forward. Due to data availability, if interior transportation data could not be obtained for the exact origin to port route needed for the model, the most similar origin to port value that could be found is used. Non-random inputs for the United States are summarized in Table 4.4, and those for the Brazil side are in Table 4.5.

Table 4.7: Non-random inputs for U.S. side of the model.

Model Input	Mean	Original Units	Converted Units	Source
US: Origins Truck Cost to 6 Barge Locations	$1.56	USD/mile	USD/mile x number of miles traveled	USDA AMS
Rail Tariff: Ayr	$1.09	USD/car	USD/bushel	BNSF Ag Price Documents
Rail Tariff: Alberta	$1.10	USD/car	USD/bushel	BNSF Ag Price Documents
Rail Tariff: Jasper	$1.11	USD/car	USD/bushel	BNSF Ag Price Documents
Rail Tariff: Ida Grove	$1.18	USD/car	USD/bushel	BNSF Ag Price Documents
Rail Tariff: St. Joseph	$1.10	USD/car	USD/bushel	BNSF Ag Price Documents

Table 4.8: Non-random inputs for Brazil side of the model.

Model Input	Mean	Original Units	Converted Units	Source
Barreiras to Santos	$1.97	Real/mT	USD/bu	Thomson Reuters Eikon (Canarana to Santos)
Sorriso to Santos	$2.22	Real/mT	USD/bu three-year monthly average	CONAB
Rio Verde to Santos	$1.39	Real/mT	USD/bu three-year average	USDA AMS
Rondonópolis to Santos	$1.65	Real/mT	USD/bu three-year monthly average	CONAB
Sorriso to Paranaguá	$1.97	Real/mT	USD/bu three-year monthly average	CONAB
Rio Verde to Paranaguá	$1.44	Real/mT	USD/bu three-year average	USDA AMS
Ponta Gross to Paranaguá	$0.74	Real/mT	USD/bu three-year monthly average	Thomson Reuters Eikon (Campo Murao to Paranaguá)
Rondonópolis to Paranaguá	$1.47	Real/mT	USD/bu three-year monthly average	CONAB

There are also user inputs that take non-random values in the base case. The required monthly shipment of soybean to China is one million metric tons and is represented in bushels in the model. The base case also contains a quality discount for soybeans shipped through both U.S. ports. Research indicates that soybean buyers discount the USG soybeans by ten cents a bushel, relative to Brazilian soybeans, due to a perceived quality disparity in the protein levels (Wilson 2016, Thomson Reuters 2018). Similarly, soybeans moving through the PNW are subject to a ten to fifteen cent per bushel discount relative to the USG, also for a protein discount. The model uses 25 cents for the PNW discount to demonstrate the total discount relative to Brazil, which for the PNW is the aggregate of both discounts. Demurrage cost per day of vessel wait time in Brazil in the base case is set to zero dollars. Table 4.6 summarizes the user inputs that are present in the base case.

Table 4.9: Base case user model inputs.

Model Input	Base Case Value	Original Units	Converted Units	Source
Required Monthly Shipment	36,743,700	1 MMT	Bushels	User Model Input
USG Discount to Brazil	$0.10	USD/bushel	USD/bushel	User Model Input
PNW Discount to USG	$0.25	USD/bushel	USD/bushel	User Model Input
Rail Unload Incentives	$0.00	USD/car	USD/bushel	User Model Input
Demurrage	$0.00	USD/day	USD/bushel*days	User Model Input

4.5. Base Case Definition

4.5.1. Base Case Definition

The base case consists of the variables and settings used in the initial model simulation that are designed to model the current or representative state of nature. The five locations in each country cover appropriate geographic areas from which to source basis prices. The U. S. locations are Ayr, ND, Alberta, MN, Jasper, MN, Ida Grove, IA, and St. Joseph, MO. Each of these locations are a BNSF shuttle facility, so they are all able to ship grain via rail car to the PNW. In the model, they are also plausible to ship grain to the nearest barge-loading location which would transport the soybeans to the USG port.

The Brazil origin locations are Barreiras, BA, Sorriso, MT, Rondonópolis, MT, Rio Verde, GO, and Ponta Grossa, PR. The Brazil interior transportation costs are non-random inputs. In Brazil, it is not plausible for all locations to truck soybeans to the northern port, so only Barreiras and Sorriso have transportation routes to the North port. All of the Brazil origins except Ponta Grossa are plausible to transport soybeans to the Santos port because soybeans leaving Ponta Grossa would need to drive past the Paranaguá port to reach the Santos port. Likewise, all Brazil origins except Barreiras can realistically truck soybeans to the Paranaguá port. Soybeans leaving Barreiras would need to be driven past the Santos port to reach the

Paranaguá port. While an argument may exist that the excluded routes would be realistic in a case of arbitrage, the data for interior transportation costs for Brazil does not include scenarios for the unincluded routes. Altogether, the ten origins and five ports, with their realistic interior transportation routes, make up 20 possible routes than soybeans in the model can take from originating location to China.

To form the routes, origin basis, interior costs, and ocean freight are considered. The basis distribution functions aggregate with their respective transportation costs according to the equations established in Section 4.3: Detailed Data Specification/Empirical Model. The U.S. transportation costs for soybeans procured through the PNW are aggregated using Equation 4.2, minimized transportation cost to the USG for any origin is described in Equation 4.3 as the minimum trucking and barge cost from the barge locations each month according to Equation 4.3, both previously introduced. Using these transportation costs, in Equation 4.6 below, the total cost of importing beans from Ayr through the PNW to China for the month of January is described as an example of the procurement costs for each origin and month.

$$AyrthroughPNW_{Jan} = AyrBasis_{Jan} + AyrTransCost_{PNW} + AyrOcean_{fromPNW} \quad (4.6)$$

Equation 4.6 was applied to each origin, month, and realistic port by using the basis, minimized transportation cost, and ocean freight charge that corresponds. This concept finds a total cost for soybean procurement *through* the port, rather than stopping at the exporting location. Once the model has calculated the cost for the twenty routes, it compares the least-cost option that sources from Brazil and the least-cost option that sources from the United States. So, the model does not compare two different origins and routes within the same country, but rather once it has compiled the various routes, it looks at the two countries as the competing origins for China's purchase of 1 MMT per month. The model elects which country is the optimum choice to purchase the required monthly quantity from January through December, and according to the optimized Monte Carlo simulation settings, repeats the procedure to form the distribution of outcomes.

In practice this model can be intuitively explained. The trader sells or plans to sell 1 million metric ton per month to China. These tons can be originated from any of 5 origins in the United States and any of 5 origins in Brazil. Soybeans would be bought at the origin at basis values, and shipments from origin to port would occur using rail, truck/barge in the United States and truck in Brazil. Ocean shipping costs would then be accrued. The trade chooses the least-cost origin/route in each country to each port, PNW and USG in the United States and Paranaguá, Santos, and the northern ports represented by one “North” in Brazil. These route costs are added to the ocean shipping costs. The random variables are viewed as risky and would be managed as appropriate by the trader. At the time of sale, or shipment planning, the trade does not know the value of the random or risky variables. These are taken from distributions, and many of these variables are correlated. For each distribution, values are determined for each variable and an optimal solution is derived. This is repeated, and the optimal solutions are summarized in a distribution which can be used to determine the least-cost strategy and the distribution about these costs.

4.6. Sensitivities Definition

Sensitivity analysis will be performed to show how the quantity of soybeans shipped from each country changes relative to the established base case. Types of sensitivity studies will include changing the model to establish the effects of trade policy, shipping variables, distribution changes, and structural variables.

4.6.1. Trade Policy Sensitivity

Trade policy changes can be demonstrated in the model by first assuming a base case of 0 percent tariff on U.S. soybeans. This will demonstrate the value and importance of diversification for soybean buyers. Then, enacting a 25 percent import duty on U.S. soybeans through the model will show the implications that such a trade policy, which could be due to various macropolitical events, will have on U.S. soybean exports to China.

4.6.2. Shipping Variable Sensitivities

Shipping variables are another sensitivity variable to be studied. DCV in the United States will be studied to find the tipping point that shifts demand for U.S. soybeans to demand for Brazilian soybeans. This will be a random simulation of DCV from 0 to 5000 dollars per car, in increments of 500 to find where the share of the required monthly quantity shipped tilts in favor of Brazil.

In Brazil, demurrage represents an important random shipping cost that can cause a severe drop in the share of soybeans coming from Brazil. As discussed previously in Equation 4.5, the demurrage cost is incurred if the simulated wait time days is greater than the average expected wait days. Average expected wait days are simply the historical average. A trader takes this into account when planning shipments. However, for days waiting in the port that exceed the average, a demurrage cost is usually incurred. Demurrage cost is incurred each day over the expected wait days until the vessel is stalled no longer, and the soybeans leave the country, no longer incurring a demurrage cost. The demurrage rate in the base case is 0, whereas in the sensitivity analysis the value will resemble current market demurrage costs in Brazil. In the months where extended wait time occurs, it is expected that the Brazilian share of China’s soybean imports will fall due to charges incurred while waiting for soybean load out.

4.6.3. Distribution Sensitivities

The @Risk BestFit distribution functions are fit according to the previous values and their discovered correlations with one another. One of these distributions stands out. Daily Car Value is notoriously unpredictable in the United States. U.S. market initiatives to mitigate the risk found in the volatility of the DCV can be simulated by normalizing the distribution to find the effects of a less volatile secondary car market.

4.6.4. Structural Variable Sensitivities

There exist many structural variables that are expected to influence the market shares as they are distributed between the two countries. Unload incentives in the United States were set to zero in the base case but for sensitivity analysis are simulated from 0 to 1000 in intervals of 200. The incentive represents a payment from the rail company to an exporter for filling or completing a shipment early (RJO'Brien, 2021).

The interior shipping costs in Brazil in the base case model are static values due to inadequate data to form time series distributions. It can be assumed that interior transportation costs are changing in Brazil as investments in infrastructure are made and demand for Brazilian soybeans grows. Performing a sensitivity analysis on changing shipping costs within Brazil is expected to increase competition for the United States. Similarly, reducing wait time as the industry develops will increase Brazilian competitiveness. A reduction in wait time and therefore demurrage costs incurred represents another sensitivity measure.

There exists a residual in the model between the stochastically simulated port basis and the calculated port basis from origin basis and transportation costs to port. This residual is represented by Equation 4.7, and it can be described as an arbitrage surplus that soybean buyers are collecting when shipping from markets that have a discrepancy between the export basis price and the realized cost to the port. Capturing the residual for each of the five ports in the base case will demonstrate by what degree arbitrage exists.

4.7. Risk-Optimization Procedures

4.7.1. Simulation Settings and Procedures

Within the @Risk software, the model uses the built-in simulation feature to create an *optimized Monte Carlo simulation* where the decision maker knows the randomly generated value at each iteration before making the optimization decision. To conduct the optimization, the simulation executes a macro that runs a built-in Excel Solver model at each iteration following the realization of the random variable values. This differs from the more common procedure known as *Monte Carlo optimization* that utilizes the built-in *RiskOptimizer* feature of @Risk to derive optimal values of the decision variables based on the simulated statistical properties (i.e., moments) of the Monte Carlo simulation. Under optimized Monte Carlo simulation, for each iteration run of the Solver macro, the solutions to the deterministic optimization problem are stored into a data register at each iteration. The collection of optimal solution values in the data register form a sample distribution that can be subjected to further statistical or sensitivity analysis. The Solver macro uses the LP Simplex method because the cost minimization equation can be solved linearly. Table 4.7 summarizes the @Risk settings employed in the model.

Table 4.10: Model @Risk settings.

@Risk Specification	**@Risk Setting**
Sampling Type	Latin Hypercube
Generator	Mersenne Twister
Initial Seed	6152021
Multiple Simulations	All Use Same Seed
Macros	Excel Tool: Solver
Solver Specification	LP Simplex

Since the model is a LP cost minimization model using Simplex, the model is likely to find corner solutions. Therefore, it will choose the lowest cost location first and try to fill the entire monthly demand from that location. If the location constraint is reached, then the solver will go to the next lowest cost location and fill as much as it can of the remainder and so forth until it has reached the minimum monthly shipment. and the mean quantity for each origin is calculated applying the @Risk *RiskMean* simulation statistics function to each cell. The mean quantities across the five locations in Brazil are aggregated over the total quantity shipped each month to form Brazil's market share of sales. The same is done for the United States. The mean quantity shipped for any origin location for any given month over the monthly requirement can be interpreted as the probability that origin will be the least-cost origin of procurement in that month.

Convergence testing was performed for 1 percent and 3 percent tolerance at a 95 percent confidence level. The model converges when the mean is not changing by greater than the tolerance level over the course of the previous 100 iterations. For both one and three percent, convergence is assumed at 200 iterations. The model simulation uses 500 iterations to increase convergence confidence.

4.8. Conclusion

Chapter 4 describes the empirical model for Chinese sourcing of soybeans from Brazil and the United States. First, the most common paths for which soybeans are shipped from the United States and Brazil to China are established. Then, a mathematical specification of the model is formulated with the objective of minimizing the total delivered soybean cost by allocating a fixed demand across the model trade flows. This information is then used to establish the U.S. and Brazil market shares on a monthly basis. The model is an application of optimized Monte Carlo simulation where the optimization occurs (using Excel's built-in Solver application with the Simplex option) at each iteration based upon the iteration's randomly generated values. The approach assumes that the optimization occurs with perfect knowledge of the random variables; therefore, the decision is made in the absence of risk.

The data used in the model includes basis, interior transportation costs, cost of waiting, and ocean shipping costs are all converted to a common unit of U.S. dollars per bushel. The variables are split into non-random and random categories according to their purpose in the model. The statistical distributions that generate the random variables were estimated using the BestFit feature of the Palisade @Risk Monte Carlo simulation add-in to Microsoft Excel. The random variables were fit using time series projections if data was available from the course of the study's time period, 2013-2019, and a non-random average was used in the case where data availability was too limited to employ proper time series analysis

The model base case was defined through specifying the state of nature that will establish the base case market shares for each country. The @Risk simulation settings and procedure for simulation was specified. This chapter establishes the scenario under which the U.S. and Brazilian shares of China's soybean imports can be studied at length.

5. RESULTS

5.1. Introduction

This chapter discusses the results derived from the optimized Monte Carlo model simulation model described in the previous chapter. First, the base case model results are presented to provide a foundation for comparison. Next, the results from the sensitivity analyses are presented to demonstrate the effects that potential market and policy changes can have upon the crop year market shares for the United States and Brazil and the delivered prices from each country. The sensitivities performed are grouped into distinct categories that include: trade policy and competition, shipping variables, and structural variables. The results for the sensitivities are displayed in tabular and/or graphical form and then discussed further in each category of analysis.

5.2. Base Case

5.2.1. Base Case Definition and Assumptions

The base case is defined to reflect market conditions that exist in the competition for China's soybean imports. Five origins in each country are chosen to represent the originating basis across the different geographic regions that grow soybeans in the United States and Brazil. Transportation costs via truck, rail, and barge where most appropriate are aggregated as discussed in equations given in Chapter 4 to represent the real cost of transporting soybeans to the export locations. Two ports in the United States and three in Brazil are employed as exporting locations. Ocean freight from these exporting locations represents additional transportation cost. Using the time series distributions presented in the previous chapter for the random variables: originating basis, DCV, ocean freight, barge rates, and wait days, and the non-random variables previously presented: rail tariff, Brazil interior transportation, and U.S. truck rates, the optimized Monte Carlo simulation forms a distribution of outcomes. These outcomes display the decisions of a modeled trader buying and shipping soybeans to meet Chinese demand.

There are various trade, shipping, and structural assumptions made to form a cohesive model. It is assumed that there is no discrimination between origins. No origin takes a discount compared to another origin of the same country or the opposing country; only basis price separates them in value to the decision maker. There is however a 10 cent per bushel (c/bu) discount applied to the USG port under Brazil, and the PNW port is discounted 15c/bu under the USG according to perceived quality differences in the marketplace (RJO'Brien, 2017, Hertsgaard et. al, 2018).

The base case assumes 0% tariff to begin to demonstrate the value of diversification. In a fair-trade scenario, 0% would be preferred as this signifies optimal trade relations between all parties. A 25% import duty on importing U.S. soybeans into China represents the 2018-2019 trade tensions between the United States in China (Carter and Steinbach 2020, Adjemian et al., 2019).

Another assumption made in the base case is that the demurrage rate in Brazil is 0. Demurrage is analyzed as a sensitivity, rather than being present in the base case. Unload incentives, or discounts given from the rail tariff, are assumed to be 0 in the base case and studied later as a sensitivity parameter.

In the model, the trader is assumed to be perfectly hedged and can provide shipments from either of the ports and origins. The trader is also assumed to originate the soybeans at the interior origin, accrues the costs related to the origin basis, and all logistics costs to China. These include from the United States, interior truck, rail, and barge in addition to secondary rail car values and ocean shipping. From Brazil, these include origin basis, interior truck cost, and demurrage as accrued (in the sensitivities), and ocean shipping. Finally, the trader is assumed 100% hedged in the futures market.

As discussed in Chapter 4, the base case assumes that the decision maker knows the simulated values before choosing the optimal source for soybeans. This is the main tenant of the optimized Monte Carlo simulation. This assumption carries through every sensitivity analysis.

5.2.2. Base Case Results

The base case contains many important outputs that show the most common optimal shipping months for soybeans moving to China. The monthly results can be interpreted as the predicted market share by origin, and they can also be interpreted as the probability that an origin is the least-cost origin. For example, an average market share of 80% for Brazil in September can be interpreted as there is an 80% probability that buying beans out of Brazil would be the least-cost option for China in that month. All values are the average for that specified data point over the 500 iterations. Figure 5.1 below shows the graphic illustration of each countries' market share throughout the U.S. crop year September to August.

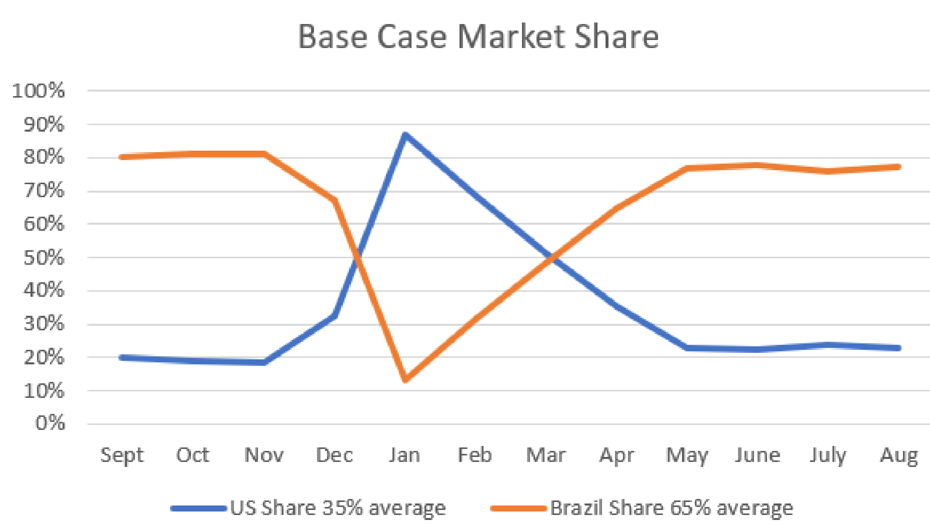


Figure 5.1: Base case market share illustration.

December and between March and April are the most competitive months. In December the U.S. soybean crop is beginning to dominate the exports, but already in March and April, the Brazilian harvest begins and takes over the market. On average, the U.S. share for the crop year in the base case is 35% of China's imports whereas Brazil captures 65%. This base case prediction is based off the time series forecasts from historical data and the assumptions discussed previously. Analyzing how these shares change in the off months for the United States shows how changes in the marketplace can raise or lower exports to China.

Delivered price is another valuable output. The price reported is the average aggregated price from the iterations of the optimized Monte Carlo simulation. Figure 5.2 displays the model's output average cost delivered over time. This graph is not the single optimal cost for each month that the model chooses, but rather the averages over all origins for each shipping month. This graph acts inversely to the market share, as the lower-cost country wins more market share.

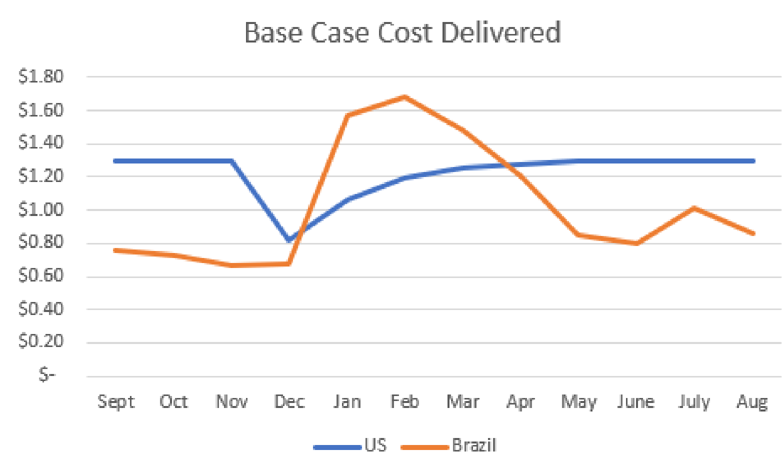


Figure 5.2: Base case cost delivered displayed graphically over the crop year.

The distributions of delivered price show a measure of risk by how wide the distribution appears on an overlay graph. The values shown are averages across all origins and months for each specified market: USG, PNW, and Brazil. This width is a graphical representation of standard deviation. Figure 5.3 displays the distribution comparisons for delivered cost from Brazil, USG, and PNW. Brazil has the lowest average cost, but the widest distribution by far displaying its risk relative to U.S. markets.

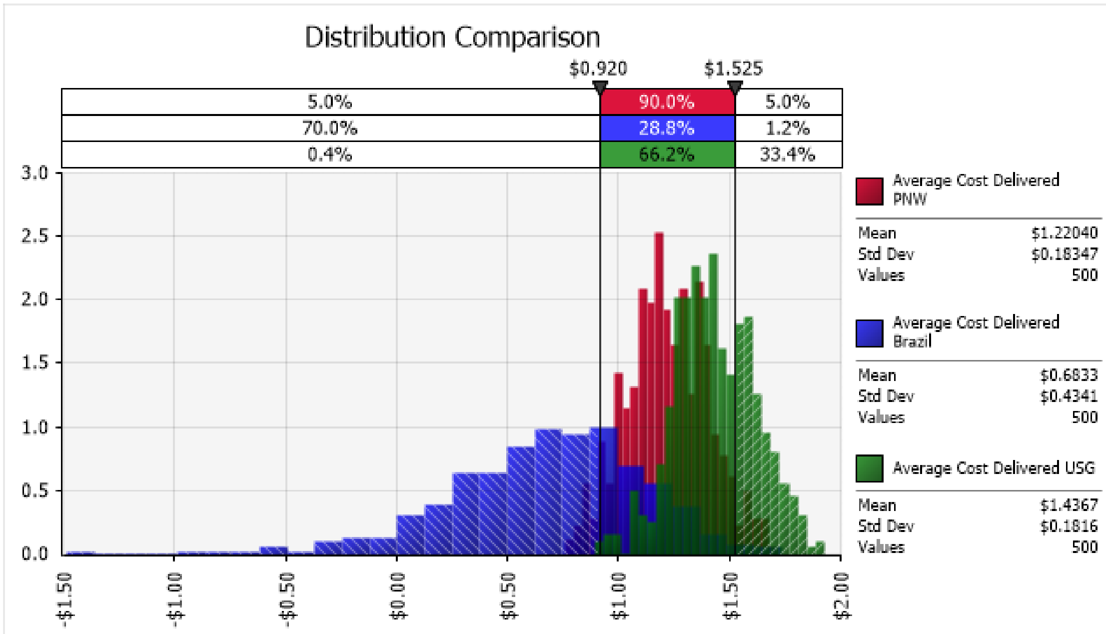


Figure 5.3: Distribution overlay of cost delivered to China from Brazil, USG, and PNW.

Figure 5.4 below shows the composition of these prices across the variables of the model. These values do not represent any single optimized iteration, rather they are the averages across all optimized iterations for all months for all origins. Originating basis appears to be competitive despite the volatility present in Brazil's basis data. Interior transportation captures the bulk of the cost.

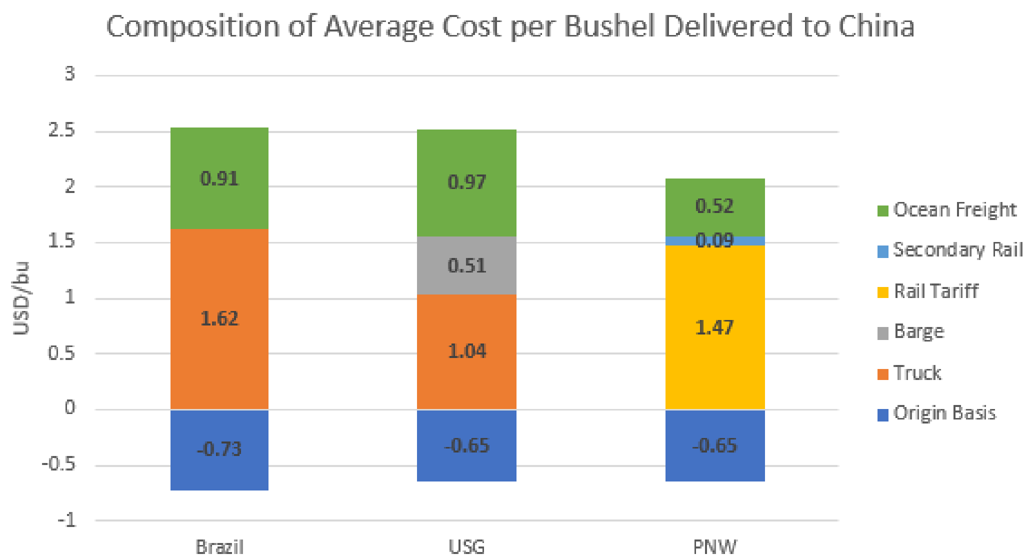


Figure 5.4: Composition of cost per bushel delivered to China.

An intuitive way to analyze output distributions is through tornado input graphs generated across the simulation. A tornado graph ranks random inputs according to how much they affect the specified output cell. Figure 5.5 shows the tornado graph for cost delivered in China from Brazil in January, and Figure 5.6 represents that cost for April. For Brazil in January, the origin basis for all origins is highly important. Also included as important are waiting time in port and ocean freight through Cape Hope and the Panama Canal. No new variables enter the tornado graph rankings in April compared to January. The origin prices remain most important towards the top of the tornado, and the waiting time and ocean freight move rankings in some cases but stay in the lower half of the tornado graph.

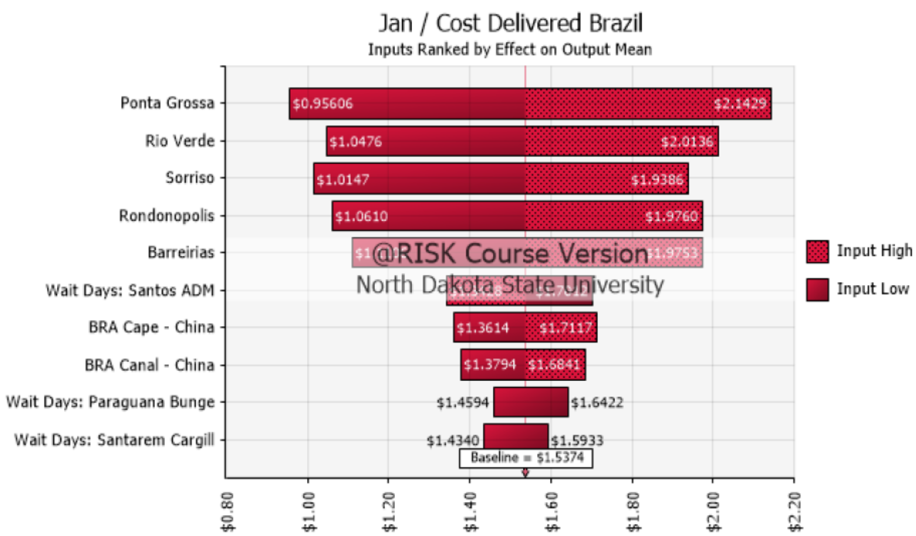


Figure 5.5: Tornado graph: January cost delivered to China from Brazil.

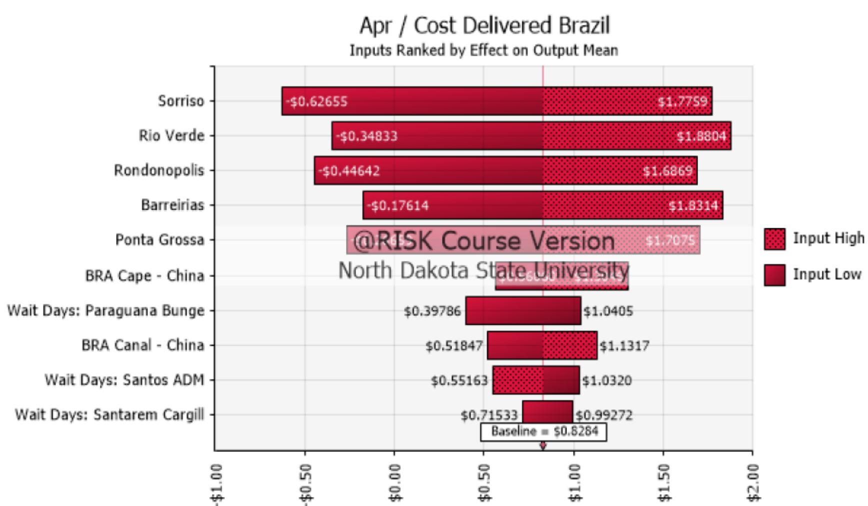


Figure 5.6: Tornado graph: April cost delivered to China from Brazil.

The USG experiences similar input significances. Figure 5.7 and Figure 5.8 below show the USG tornado graphs for January and April, respectively. Origin prices and port basis offerings have importance in each month. The USG is distinct compared to the other ports because its transportation variables include barge rates. A few barge rates are important in January, but in April various barge rates make up over half of the very significant inputs.

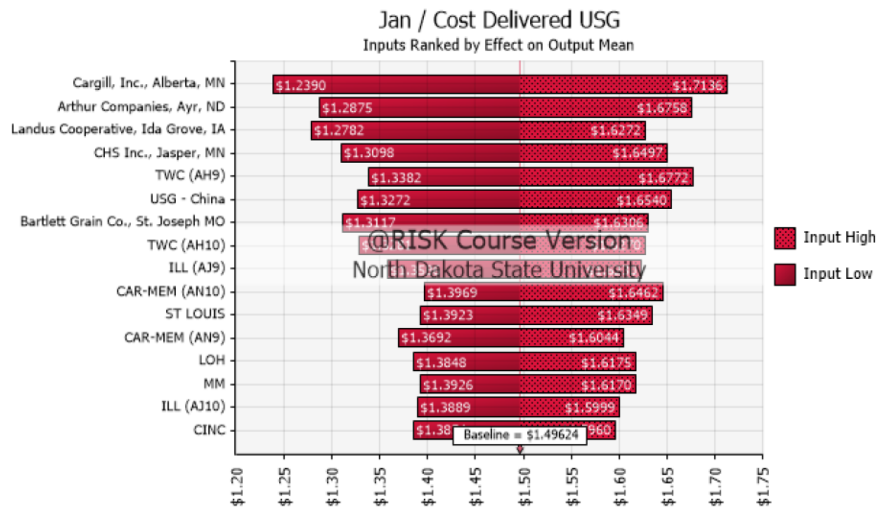


Figure 5.7: Tornado graph: January cost delivered to China from USG.

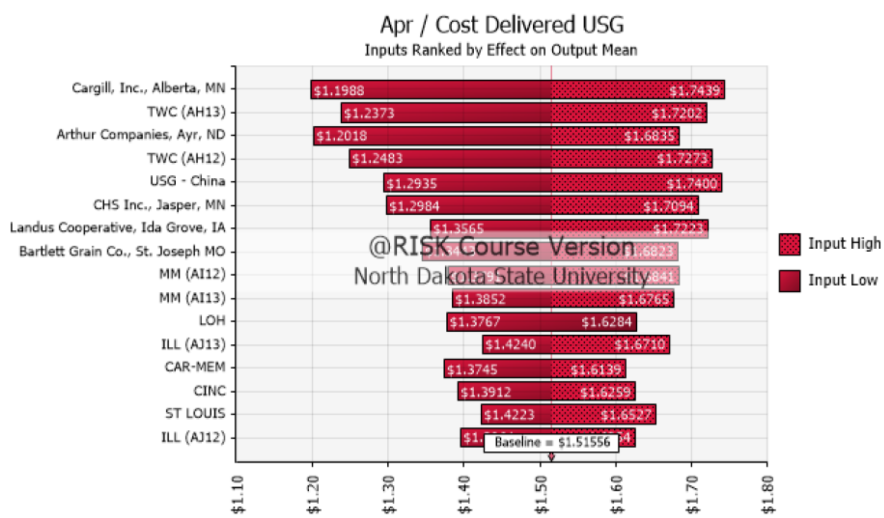


Figure 5.8: Tornado graph: April cost delivered to China from USG.

The PNW tornado graphs are shown in Figure 5.9 for January and Figure 5.10 for April. The secondary rail market is the single highest-ranked input in each month, followed by the northern-most origin Ayr, North Dakota and the ocean freight rate from the PNW to China. This reinforces what much of the literature states about the importance of DCV volatility as well as rural basis offerings.

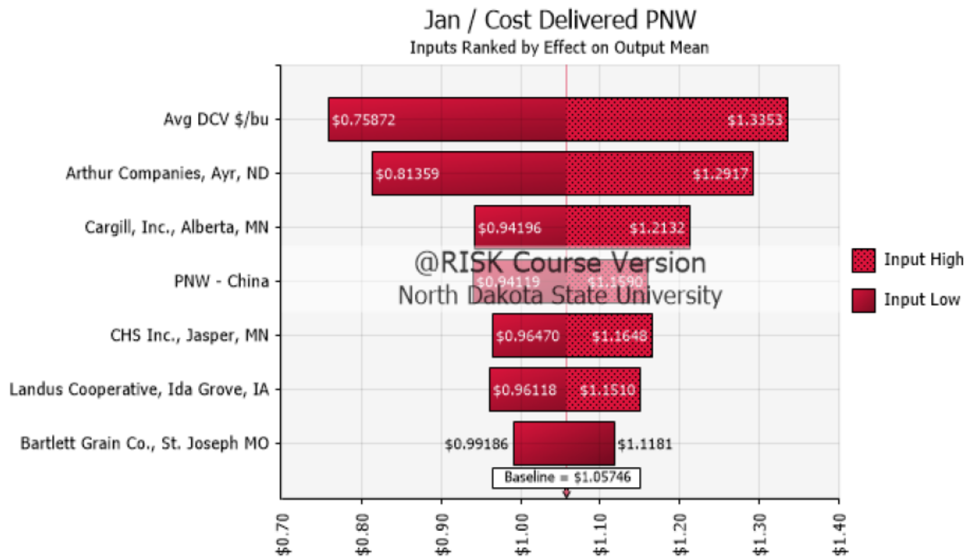


Figure 5.9: Tornado graph: January cost delivered to China from PNW.

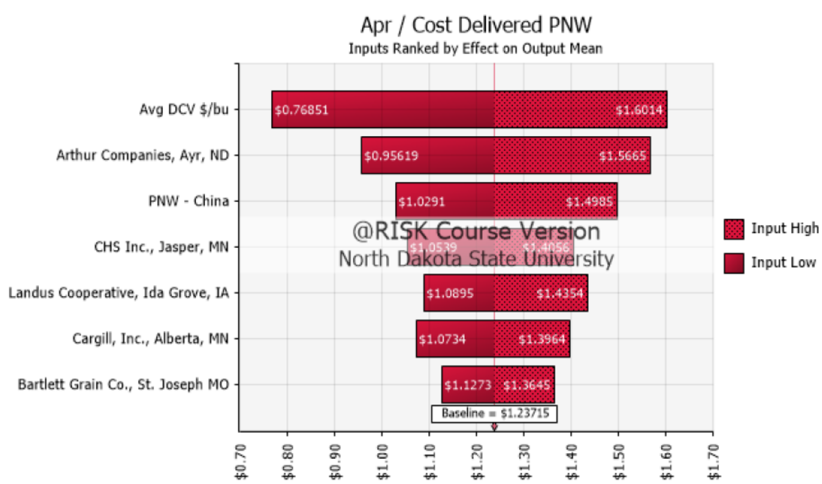


Figure 5.10: Tornado graph: April cost delivered to China from PNW.

Total cost over an average of the simulation has a right-skewed distribution as shown in Figure 5.11. This is logical, as it is expected that the cost would be greater than 0 in almost all cases. Only a few special cases where the simulation found extremely negative origin basis values as well as negative costs like a DCV of -$1000 USD/car creates those scenarios of an overall negative cost to the trader for shipping soybeans to China. The values shown are an average of the total cost calculation from all optimized simulations concerning all origins and all months.

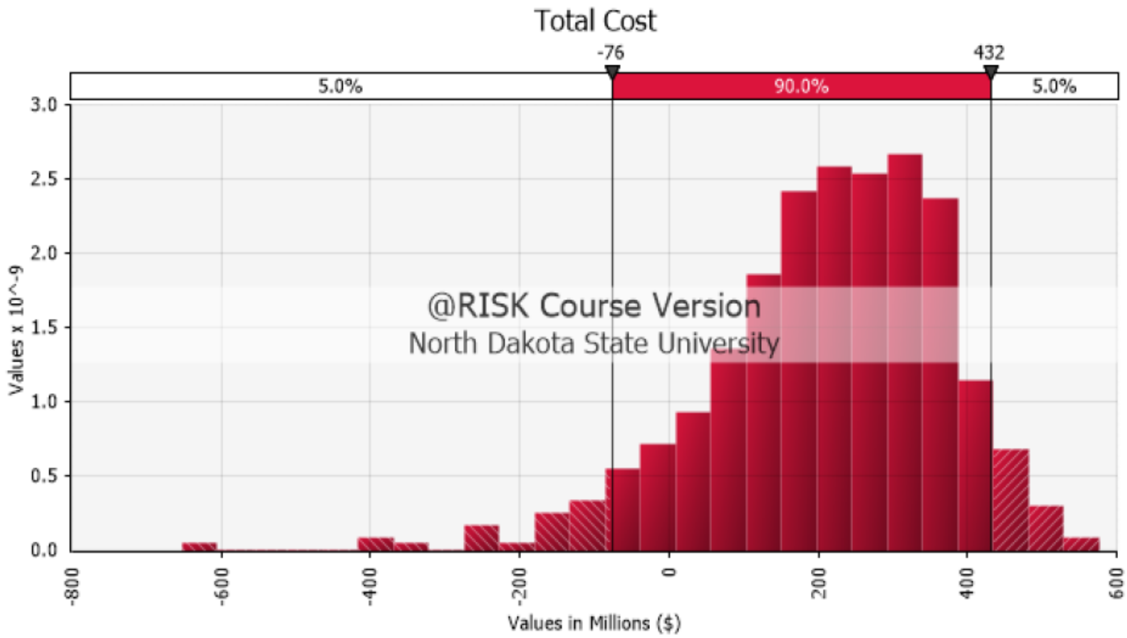


Figure 5.11: Tornado graph: total cost delivered to China.

5.3. Sensitivity Analysis

This section conducts four sets of sensitivity analysis: trade competition, shipping variables, structural variables, and supply chain interruptions. Table 5.2 summarizes the results from all sensitivity analyses for comparison purposes across the study. All results are summarized in their respective type of sensitivity section. Values are averages across all optimized iterations; they are not representative of a single most optimal shipping scenario. Rather, the values represent a crop-year average across all origins and months. Where not displayed, a graphic interpretation of market share over the course of all months for any given sensitivity is located in Appendix D.

Table 5.1: All sensitivity results as averages across all origins and months.

Model Scenario	Crop Year Share		Cost Delivered to China		
	U.S.	Brazil	From Brazil	From USG	From PNW
Base Case	35%	65%	$1.02	$1.55	$1.26
25% Import Duty on US	25%	75%	$1.02	$1.93	$1.58
No US Discount	44%	56%	$1.02	$1.45	$1.01
$10,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
$20,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
$30,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
$40,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
DCV ($1000)	47%	53%	$1.02	$1.55	$0.90
DCV ($500)	42%	58%	$1.02	$1.55	$1.03
DCV $0	37%	63%	$1.02	$1.55	$1.17
DCV $500	32%	68%	$.102	$1.55	$1.30
DCV $1000	29%	71%	$1.02	$1.55	$1.43
DCV $1500	26%	74%	$1.02	$1.55	$1.57
DCV $2500	24%	76%	$1.02	$1.55	$1.83
DCV $3000	24%	76%	$1.02	$1.55	$1.97
DCV $3500	24%	76%	$1.02	$1.55	$2.10
DCV $4000	24%	76%	$1.02	$1.55	$2.23
DCV $4500	24%	76%	$1.02	$1.55	$2.37
DCV $5000	24%	76%	$1.02	$1.55	$2.50
Brazil Interior Trans down 20%	25%	75%	$0.72	$1.55	$1.26
Brazil Interior Trans up 20%	46%	54%	$1.31	$1.55	$1.26
Unload Incentive ($200)	37%	63%	$1.02	$1.55	$1.21
Unload Incentive ($400)	38%	62%	$1.02	$1.55	$1.16
Unload Incentive ($600)	40%	60%	$1.02	$1.55	$1.10
Unload Incentive ($800)	42%	58%	$1.02	$1.55	$1.05
Unload Incentive ($1000)	44%	56%	$1.02	$1.55	$1.00
Ocean Freight Increase 25%	38%	62%	$1.26	$1.79	$1.39
Ocean Freight Increase 50%	40%	60%	$1.50	$2.03	$1.52
Ocean Freight Increase 75%	42%	58%	$1.72	$2.26	$1.65
Ocean Freight Increase 100%	45%	55%	$1.92	$2.50	$1.78
Exclude 2013-2014 (Volatility)	48%	52%	$1.26	$1.45	$1.19
Supply Chain Shock with discounts	42%	58%	$2.62	$3.48	$2.55
Supply Chain Shock without discounts	46%	54%	$2.23	$2.90	$2.03

5.3.1. Trade Policy/Competition Sensitivity

The base case assumes no presence of an import tariff on U.S. soybeans. However the United States and China experience many macro-political and economic events that directly impact the ag industry. Modeling a 25% import duty on U.S. soybeans demonstrates the effects of the recent 2018-2019 trade tensions that took place between U.S. leaders and China's government (Adjemian et. al, 2019). A 25% tariff lowers U.S. market share by 10% on average. Both U.S. ports experience over 30 c/bu increase in cost to deliver to China. Table 5.2 and Figure 5.12 summarize the trade policy sensitivity.

Table 5.2: Trade policy and competition sensitivity results.

Model Scenario	**Crop Year Share**		**Cost Delivered to China**		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
25% Import Duty on US	25%	75%	$1.02	$1.93	$1.58

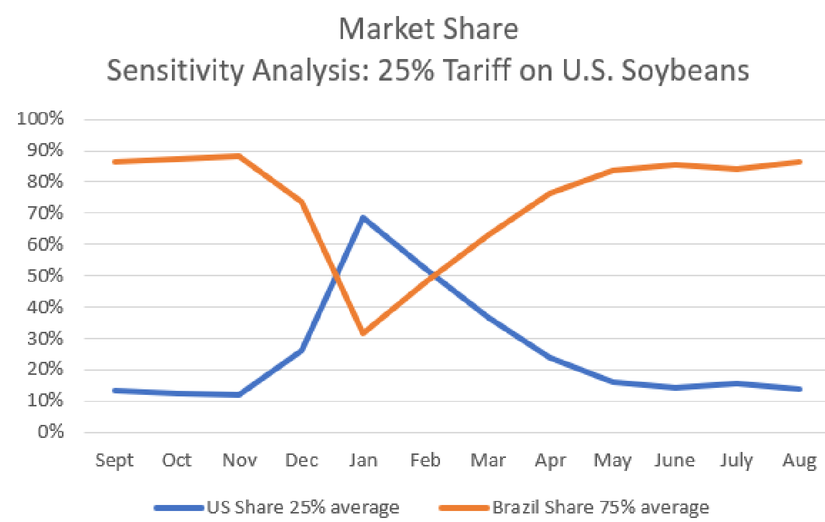


Figure 5.12: Monthly market share results from 25% tariff on U.S. soybeans sensitivity.

An important goal for buyers or traders in international commodity trading is diversification. This would be relevant both for the individual trading company, or for the importing country, in this case China. This involves allocating shares of purchases across origins and through time for purposes of reducing costs and risks. The model used sought to define a solution that minimizes costs. The results, through simulation can be used to derive the standard deviation which is a traditional measure of risk. The model was simulated to illustrate the implications of alternative diversification or restricted solutions, and the mean cost and risk (standard deviation) were derived.

The results are illustrated in Table 5.3 and are very clear. The lowest cost, and risk solution is that of the base case. The effect of a 25% import tariff on US origin soybean is to raise cost and raise risk. The reason for the former is obvious. The reason for the latter is that Brazil is a riskier origin (i.e., greater volatility in relevant cost parameters) than is the US. Thus, as more purchases are concentrated at Brazil, the overall level of procurement risk increases.

The model was also simulated in two extreme cases where 100% of shipments were constrained to originate from only Brazil, or only the United States. If imports were forced to be undiversified and forced to be exclusively from Brazil, costs and risks would increase relative to the base case. The results are slightly different if imports were from only the United States. In that case, average costs would increase substantially due to the United States being a higher cost supplier for most months. Risk would be lowered, due to the United States being a lower risk supplier. These results are somewhat instructive and illustrate that in reality, China (or, suppliers to China) should/would rationally pursue strategies of spatial and temporal diversification, similar to the base case results.

Table 5.3: Demonstrating risk mitigation through diversification.

Model Scenario	**Simulation Mean**	**St. Dev. (Risk)**	**US Share**	**Brazil Share**
Base Case	$211,848,219	$161,369,438	35%	65%
25% Tariff on U.S. soybeans	$245,659,731	$172,325,758	25%	75%
100% from Brazil	$341,243,451	$161,417,977	0%	100%
100% from United States	$503,117,345	$70,975,165	100%	0%

5.3.2. Shipping Variables

As shown in the composition of delivered costs, shipping variables including Daily Car Value (DCV) and ocean freight prices represent a significant amount of cost. The study departs from the base case time series forecasted distribution for DCV, where the mean value for the distribution is near $500 per car, or 13 c/bu. In the sensitivity analysis, DCV is simulated at static values from ($1000) to $5000 per car, or -26 c/bu to 133 c/bu, each in its own simulation. The results are tabulated in Table 5.4 and demonstrated graphically in Figure 5.13. DCV affects the PNW delivered price only, as that is the port that has rail freight in its cost equation.

Table 5.4: DCV sensitivity results.

Model Scenario	**Crop Year Share**		**Cost Delivered to China**		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
DCV ($1000)	47%	53%	$1.02	$1.55	$0.90
DCV ($500)	42%	58%	$1.02	$1.55	$1.03
DCV $0	37%	63%	$1.02	$1.55	$1.17
DCV $500	32%	68%	$.102	$1.55	$1.30
DCV $1000	29%	71%	$1.02	$1.55	$1.43
DCV $1500	26%	74%	$1.02	$1.55	$1.57
DCV $2500	24%	76%	$1.02	$1.55	$1.83
DCV $3000	24%	76%	$1.02	$1.55	$1.97
DCV $3500	24%	76%	$1.02	$1.55	$2.10
DCV $4000	24%	76%	$1.02	$1.55	$2.23
DCV $4500	24%	76%	$1.02	$1.55	$2.37
DCV $5000	24%	76%	$1.02	$1.55	$2.50

U.S. market share drops steeply, and after about $1500 per car, the U.S. market share is at maintenance levels and does not drop below 24% average over the crop year. This is likely due to temporal and spatial capacity constraints in Brazil, where given the season it is not feasible to service the entirety of China’s demand. A DCV of 0, representing the lack of a secondary car market, moves 2% of the market share.

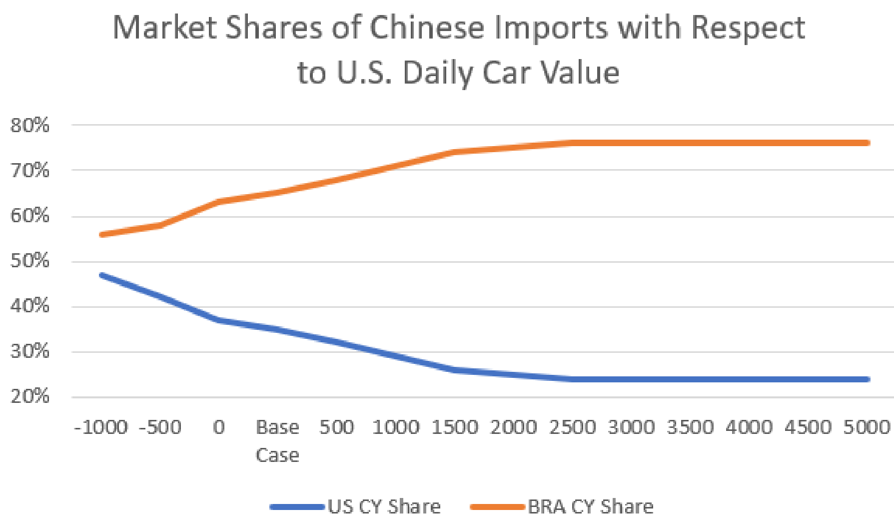


Figure 5.13: Graphic representation of U.S. and Brazil market share as DCV changes.

Ocean freight from the United States and Brazil ports is another shipping variable that affects marketplace competition. Ocean freight is increased from the base case in intervals of 25%, up to 100% increase. Table 5.5 contains the results of each simulation communicated as averages across all optimal solutions. Ocean freight rate increases are in favor of the United States and disfavor Brazil. Brazilian ports and the USG experience 20 c/bu or more increases in delivered cost with each ocean freight increase, but the PNW experiences less. Therefore, when ocean freight increases, China sources soybeans through the U.S. PNW port which has the shortest and least-cost ocean route.

Table 5.5: Ocean freight sensitivity results.

Model Scenario	Crop Year Share		Cost Delivered to China		
	U.S.	Brazil	From Brazil	From USG	From PNW
Base Case	35%	65%	$1.02	$1.55	$1.26
Ocean Freight Increase 25%	38%	62%	$1.26	$1.79	$1.39
Ocean Freight Increase 50%	40%	60%	$1.50	$2.03	$1.52
Ocean Freight Increase 75%	42%	58%	$1.72	$2.26	$1.65
Ocean Freight Increase 100%	45%	55%	$1.92	$2.50	$1.78

5.3.3. Structural Variables

Similar to shipping variables, there exist structural variables that pertain to the dynamics of the marketplace and the way players interact. In the United States, it has become not uncommon for the rail companies to offer unload incentives to shippers for targeted export quantities. These incentives are designed to make the U.S. supply chain more competitive in the global marketplace and come to fruition via requests from sellers and shippers involved in the supply chain. Unload incentives are added into the model as a negative cost for the decision maker, each value with its own simulation. The results are tabulated in Table 5.6 as averages across the optimal decisions from each iteration. A $200 increase in unload incentive causes a 2% increase in U.S. market share on average. Similar to DCV and consistent with the cost equation, this variable only affects the PNW port delivered price.

Table 5.6: Unload incentive sensitivity results.

Model Scenario	**Crop Year Share**		**Cost Delivered to China**		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
Unload Incentive ($200)	37%	63%	$1.02	$1.55	$1.21
Unload Incentive ($400)	38%	62%	$1.02	$1.55	$1.16
Unload Incentive ($600)	40%	60%	$1.02	$1.55	$1.10
Unload Incentive ($800)	42%	58%	$1.02	$1.55	$1.05
Unload Incentive ($1000)	44%	56%	$1.02	$1.55	$1.00

Figure 5.14 displays the effects of unload incentives in the United States. With the exception of increasing from $200 to $400, each increase narrows the gap in market share by 2%.

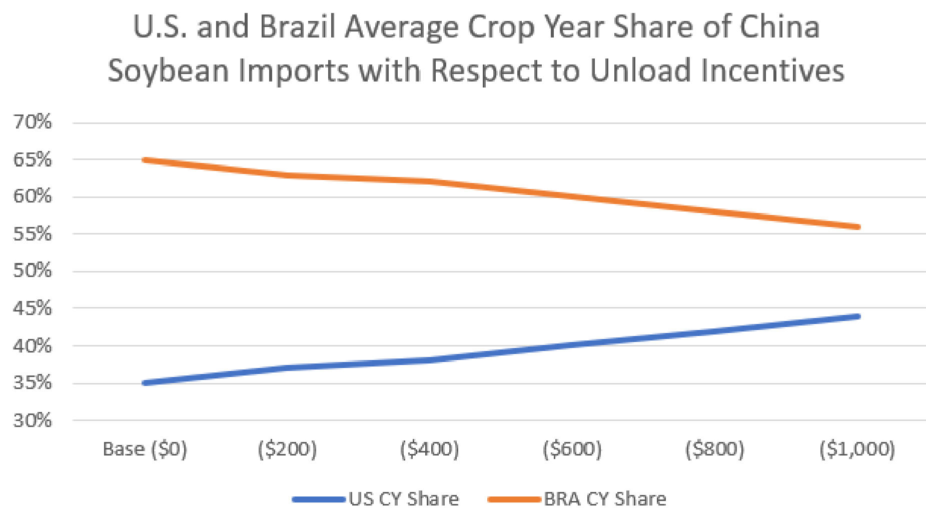


Figure 5.14: Graphic representation of unload incentive sensitivity.

Determining an optimal unload incentive scenario is derived by using the bushels of soybeans traveling through the PNW alongside the decreasing rail tariff. In practice, these incentives are targeted, but this analysis shows what the change is when implemented over all. Table 5.7 shows the calculations and the clear result that an unload incentive of $800 as a discount to the rail tariff would increase average U.S. market share enough to raise revenue the most compared to the other tested unload incentives, including the offering of no unload incentive.

Table 5.7: Railroad revenue as unload incentive increase.

Model Scenario	US Share	PNW Quantity mt	PNW Quantity bu	Average Rail Tariff USD/car	Average Rail Tariff USD/bushel	Rail Revenue
Base Case	35%	3,838,387	141,022,321	$5,317	$1.42	$ 199,965,890
Unload Incentive ($200)	37%	4,094,412	150,428,708	$5,117	$1.36	$ 205,281,031
Unload Incentive ($400)	38%	4,280,431	157,263,036	$4,917	$1.31	$ 206,220,067
Unload Incentive ($600)	40%	4,498,453	165,273,163	$4,717	$1.26	$ 207,909,231
Unload Incentive ($800)	42%	4,728,476	173,724,214	$4,517	$1.20	$ 209,275,136
Unload Incentive ($1000)	44%	4,928,496	181,072,954	$4,317	$1.15	$ 208,470,498

Graphically, it is shown in Figure 5.15 that as U.S. market share grows, it compensates for more than the loss the railroad might expect from offering an unload incentive. However, at

1000 USD per car unload incentive, the market share increase is not enough, and therefore 800 would be the optimal unload incentive in terms of revenue.

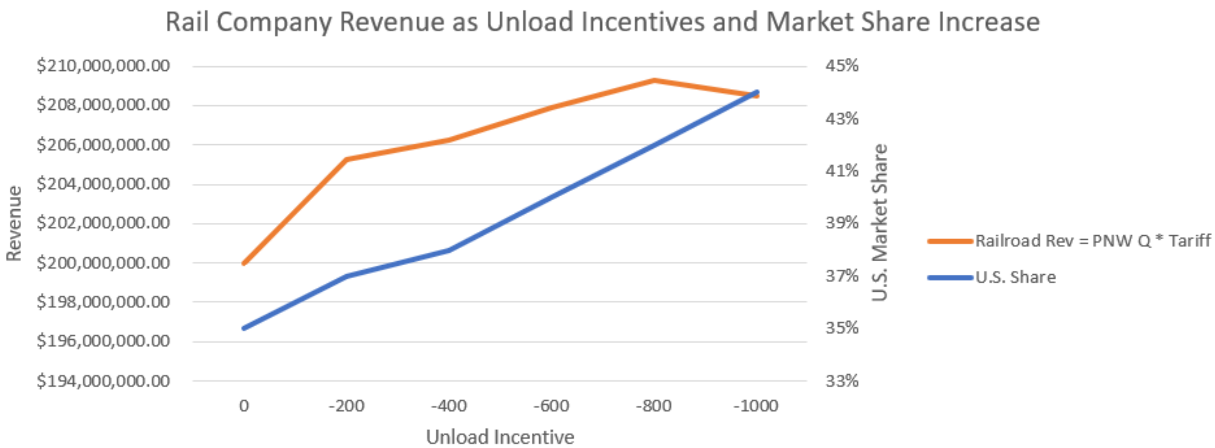


Figure 5.15: Rail company revenue as unload incentives and U.S. market share increase together.

As discussed in the background section of Chapter 2, advancements in infrastructure in Brazil are underway and are expected to improve the overall efficiency of the originating portion of Brazil's supply chain. However, macropolitical events and economic instability cause volatile physical and social conditions in the country, especially within logistics where road conditions are poor and worker strikes are frequent. The sensitivity analysis demonstrates this in two ways. First, implementing demurrage rates according to commonly charged per day waiting time costs of vessels at port shows how Brazil's underdeveloped road systems can shrink Brazilian market share as shippers incur large fees waiting for grain. Implementation of demurrage at $10,000 intervals increases the average delivered price for Brazil consistently but does not let the Brazilian market share fall below 64%. Table 5.8 displays the demurrage results as well as the interior transportation sensitivity results as averages across the optimized iterations of the simulation.

Recalling Chapter 4, Brazil's interior transportation data is not available in quantities large enough to form time series distributions that re-populate with each iteration, so the

Brazilian interior transportation is non-random. To capture some idea of the effects of a changing cost, the costs for interior routes are raised and lowered 20%. Lowering transportation cost in Brazil is expected to garner three-quarters of China's soybean purchases on average, and rising transportation costs will move over 10% of China's demand from Brazil to the U.S.

Table 5.8: Brazilian demurrage and interior transportation sensitivity results.

Model Scenario	Crop Year Share		Cost Delivered to China		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
$10,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
$20,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
$30,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
$40,000 Demurrage Brazil	36%	64%	$1.03	$1.55	$1.26
Brazil Interior Trans down 20%	25%	75%	$0.72	$1.55	$1.26
Brazil Interior Trans up 20%	46%	54%	$1.31	$1.55	$1.26

Another structural variable implemented is a perception of U.S. soybeans as lower quality in protein and amino acids that leads to a real discount in the marketplace (RJO'Brien, 2017, Hertsgaard et. al, 2018). The base case scenario treats the USG as having a 10 c/bu discount relative to the Brazilian ports and the PNW as having a 15 c/bu discount relative to the USG. Removing these discounts demonstrates the market share the U.S. soybean industry stands to gain if it can improve quality and perception of quality to the extent that U.S. soybeans are treated as equal in content to those grown in Brazil. Table 5.9 displays the results of removing the discounts. Without a discount, the PNW delivered cost would be on average within a cent per bushel of the Brazilian ports. This change shifts China's purchases 9% on average to the United States.

Table 5.9: No U.S. discount sensitivity results.

Model Scenario	Crop Year Share		Cost Delivered to China		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
No US Discount	44%	56%	$1.02	$1.45	$1.01

Figure 5.16 graphically displays the results of removing discounts across all months. Even in off months where Brazil is generally capturing near 80% of China's purchases, no quality discounts would pull 10% back to the United States.

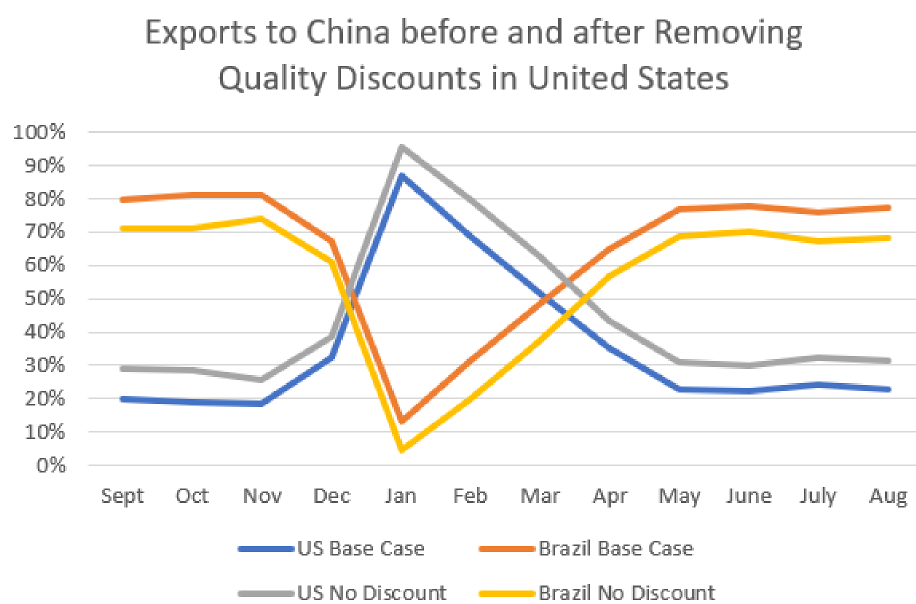


Figure 5.16: Graphic representation of the presence and absence of quality discounts.

In Chapter 4 where the origin basis prices were displayed from 2013-2019 as shown below in Figure 5.17, a break in volatility is present near the end of 2014. The time series distributions are formed from the entirety of the 2013-2019 data, so an appropriate sensitivity is to re-form the distributions based off of data from 2015 onward to demonstrate how decreasing volatility in Brazilian basis prices affects who from and when China buys soybeans. Around the start of 2015, the Brazil basis increases on average and the volatility decreases, causing a change in the distribution properties.

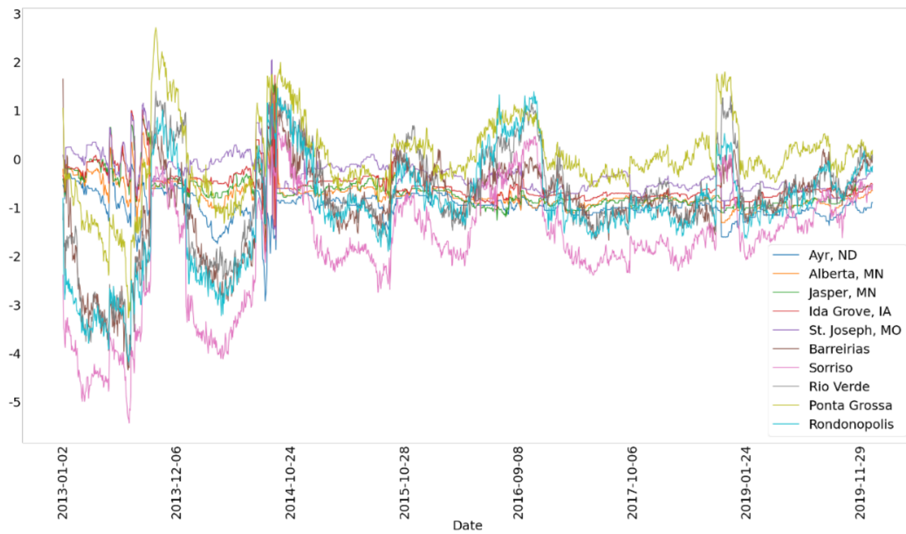


Figure 5.17: Origin basis prices over time.

Specifying each random variable in the model to only use data from January of 2015 creates the results displayed in Table 5.10. Delivered prices on average for Brazil gained 24 c/bu from the origin basis not experiencing such lows. In this case, the PNW is extremely competitive to Brazil and on average has lower delivered costs to China. Brazil captures just over half of the market share demonstrating that as time has progressed and efficiencies have increased in the marketplace, the competition between United States and Brazil has become tighter.

Table 5.10: Decrease volatility sensitivity results.

Model Scenario	**Crop Year Share**		**Cost Delivered to China**		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
Exclude 2013 and 2014 data	48%	52%	$1.26	$1.45	$1.19

Figure 5.18 displays the average market share per month for each country. In the base case, there were two months of neck-and-neck contention: December and March. In this scenario, the March contention has moved closer to April, and July has become a month of heavy competition as well.

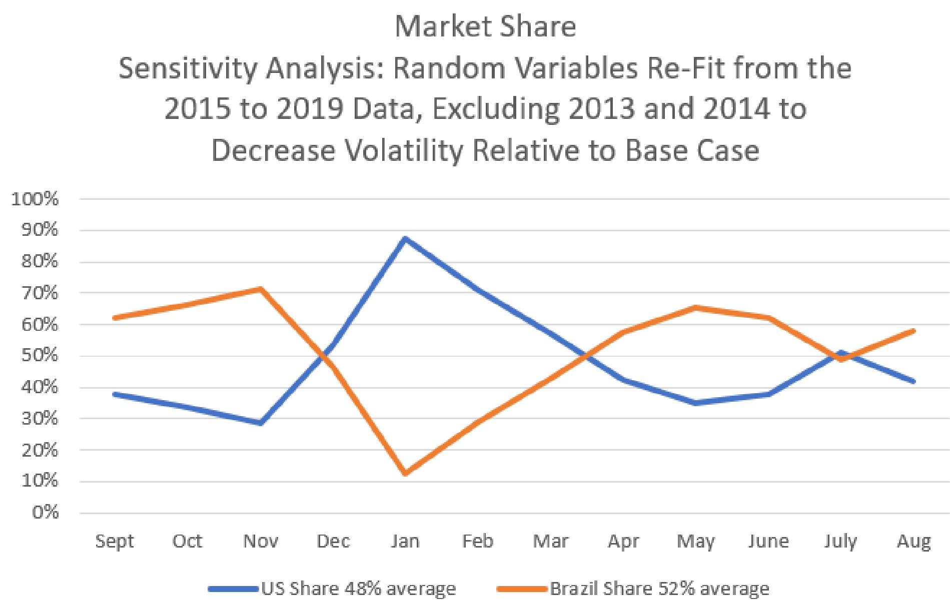


Figure 5.18: Sensitivity results random variables re-fit excluding 2013 and 2014.

5.3.4. Supply Chain Shock

Supply chain shocks can exist for a variety of reasons including natural disasters, droughts, war, extreme trade policies, natural resource shortages, and more. During this study the world experienced the COVID-19 pandemic which caused shocks in many supply chains. Agriculture is widely considered an essential industry, but restricted movement, labor shortages, and perceived and true resource shortages caused costs to rise in many sectors. To illustrate this supply chain shock, each variable is adjusted to represent the way it behaved. This sensitivity increases commodity basis prices by 50 c/bu in the United States and 25 c/bu in Brazil, ocean freight prices by 250%, demurrage up to $40,000, and wait time increases up an average of 4 days.

For the first analysis, discounts on the USG and PNW remain. Results are tabulated in Table 5.11. The delivered costs experience an increase as expected. Brazil's cost delivered to China on average is extremely high, but this includes averages across the monthly simulation, not necessarily the optimal choice. A shock to the supply chain causes China to shift purchases from Brazil in large part due to the sharp increase in ocean rates, which drives preference toward purchases through the PNW. The reason for the U.S. market share increasing among others, is that it has a lower ocean shipping cost; PNW to China is typically the least-cost ocean route, which becomes especially true with the percentage-based freight increase. Similarly, the reason for the loss from Brazil is due mostly to the higher ocean shipping costs from that origin, which is exacerbated under the supply chain disruptions sensitivity. Greater ocean shipping costs increase demurrage costs, and increased wait times and demurrage also have a significant impact on Brazil's cost delivered to China and loss of market share. During the spring of 2021, there were significant switching of soybean sales from Brazil to U.S. origins which are likely partly due to these effects.

Table 5.11: Supply chain shock sensitivity results.

Model Scenario	**Crop Year Share**		**Cost Delivered to China**		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
Base Case	35%	65%	$1.02	$1.55	$1.26
Supply Chain Shock with discounts	42%	58%	$2.62	$3.48	$2.55
Supply Chain Shock without discounts	46%	54%	$2.23	$2.90	$2.03

Figure 5.19 displays the results graphically over time. The highly competitive months move from December and March in the base case to now March through May and August. Whereas Brazil's share usually floats above 50%, this graph is a stark contrast with Brazil hardly creeping above the previous U.S. market share average in the initial base case of 35%.

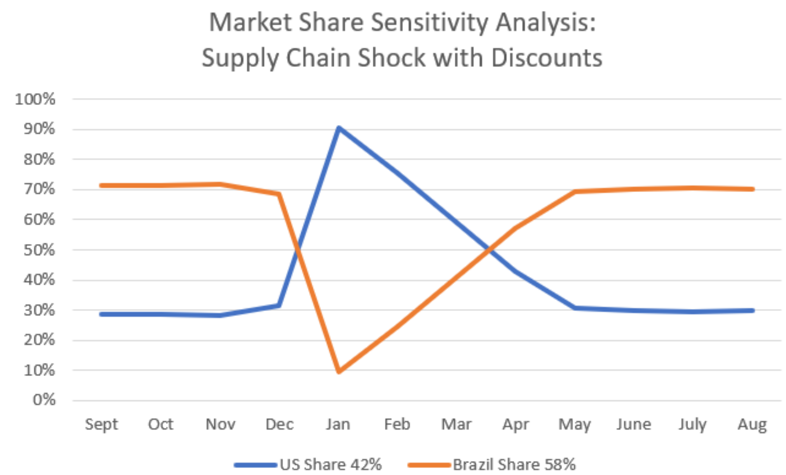


Figure 5.19: Supply chain shock sensitivity results with discounts.

If during this crisis/shock time Chinese buyers do not treat U.S. soybeans as discounted, then the competition is all but gone. Figure 5.20 displays the results of the exact same increases in prices and wait times as previously discussed, but with the 10 c/bu USG discount under Brazil and the 15 c/bu PNW discount under the USG. On average, during a supply chain shock of the magnitude such as modeled in this simulation, Brazil's share of China's purchases drops below previously established maintenance levels on the U.S. side, reaching below 20 and 10%.

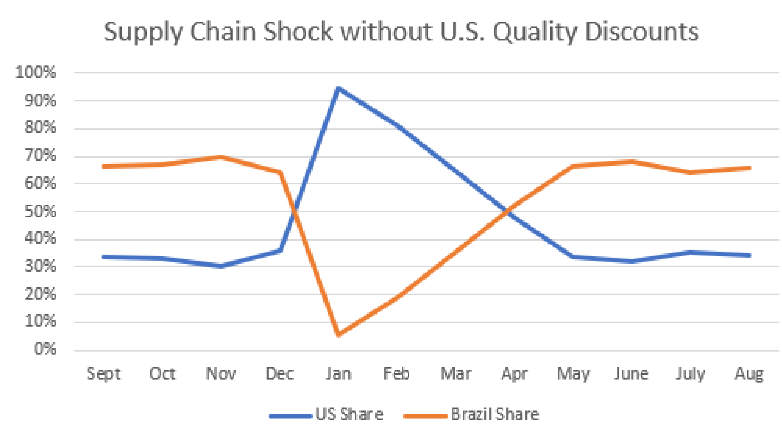


Figure 5.20: Supply chain shock without discounts.

5.3.5. Further Results: Alternative Objective Function/Residual

The analysis described above used observed interior shipping costs in the objective function. An alternative analytical approach, or assumption, would be to use FOB port values, which are published. In the base case, it is assumed the shipper accrues the cost of shipping from the interior origin to China. The alternative would be to assume the shipper buys FOB port and accrues these costs along with ocean shipping. In this case, there exists a residual that can be captured from the Brazilian ports that puts the United States at a disadvantage in many cases. A trader would want to be aware of this residual surplus in their strategy. This opportunity for arbitrage is demonstrated through calculating a residual between the reported export basis, which is fitted into a time series distribution, and the actual costs that are realized when originating and transporting soybeans to the ports. The difference between these two values is shown in Equation 5.1. The residual is the difference between the reported port basis and the actual cost, both realized via the base case simulation. This residual is calculated for each port.

$$Residual_i = \sum_i reported\_port\_basis - \sum_j cost\_to\_port \tag{5.1}$$

The residual from the base case for five ports is in Table 5.12 below. Santos reports a negative residual of 18 c/bu which signifies that the cost to originate and transport soybeans to Santos for export is greater than the exporting basis. Paranaguá reports a small, positive 10 c/bu. The North ports of Brazil report a 90 c/bu residual signifying that the export basis is over-estimating the cost to port by 90 cents. This is an opportunity for arbitrage for exporters that have positions in northern Brazil.

Table 5.12: Derived residual surpluses for five ports.

Port	Santos	Paranaguá	Brazil North	USG	PNW
Residual Surplus USD/bu	-0.18	0.10	0.91	0.01	0.06

Figure 5.21 below displays the average simulated port basis based off reported historical data that formed the time series distributions and the average cost to port derived from the originating and transportation data, the respective time series distributions, and the cost equation.

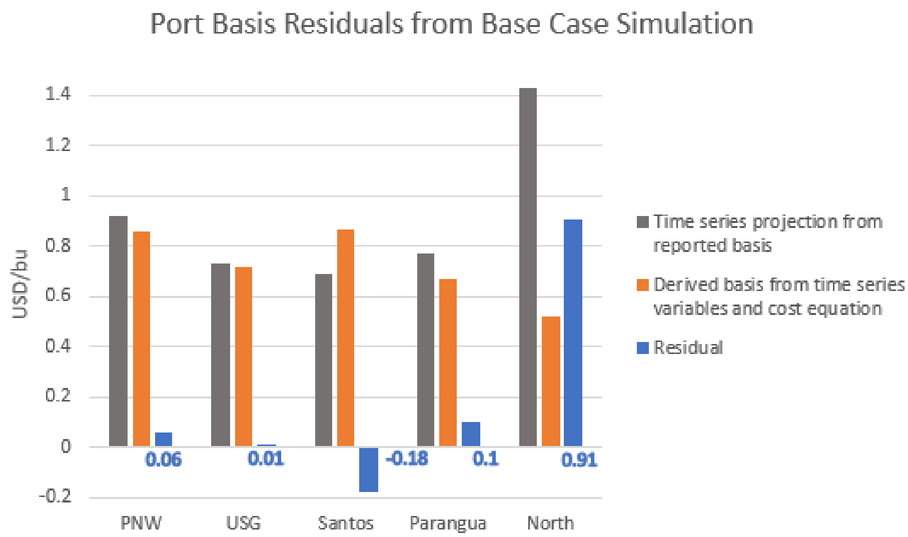


Figure 5.21: Port basis residuals from base case simulation.

5.4. Conclusion

The base case scenario establishes the average market share of China's soybean purchases for which the United States and Brazil compete. Over the course of the year, the U.S. market share is 35%, and Brazil's is 65%. Comparing market share as well as the delivered costs for Brazil, the USG, and the PNW to China demonstrates how changes in the marketplace affect who China will purchase from and in what months the competition is toughest.

Trade policies can have great, seemingly direct, influence on the share of soybeans sold to China. A 25% import duty on U.S. soybeans is shown to lose 10% of market share. Tensions between world leaders and their subsequent policies can be expected to have direct effects on the nation's agriculture industry.

Shipping variables are very important. DCV in the United States moves market share 5-7% on average between values of -$1000 and $1500. After $1500, China's demand for U.S.

soybeans is largely inelastic due to the need for diversity and the inability to only purchase soybeans from Brazil. Ocean freight price, which changes as fuel prices change, on average pulls market share away from Brazil. The PNW port has a strong distance and therefore price advantage to the USG and Brazil's ports, so as ocean freight increases, it is expected that China increases U.S. purchases and decreases those from Brazil.

Structural variables are factors within the marketplace that buyers and sellers create to increase efficiency and profits, which can lead to the industry being overall more or less competitive with the other country their trade partner buys from. The structural variable included for the United States is unload incentives which are discounts that the rail company offers off the rail tariff. Every $200 of rebate is shown to move 2% of China's purchases to the favor of the U.S., on average over the crop year.

Important structural variables in Brazil are demurrage and interior transportation dynamics. Demurrage in Brazil is important and imposes penalties on shippers if vessels cannot be loaded within a specific period. Demurrage is a per day charge, and a demurrage rate of even $20,000 per day over the average expected wait days will not cause Brazil's market share to fall below 50%. Brazil's interior transportation is also significant. If interior costs are decreased by 20%, Brazil garners three-quarters of China's purchases, and if interior costs are increased by 20%, Brazil is expected to still win over half of China's purchases on average throughout the crop year.

Another structural variable a quality discount for U.S. soybeans. It is common that the USG takes on a 10 c/bu, and the PNW takes on a 25 c/bu discount relative to Brazil. Removing these discounts to demonstrate an improvement in quality is shown to improve U.S. market share by 10%, even in less competitive months.

The time series distributions are re-configured to only look back as far as 2015, rather than 2013 as included in all base case and sensitivity analysis except the supply chain shock. Using the less volatile post-2014 data splits the average market share 48% for the United States and 52% for Brazil. The competitive months also change from December and March to December, April, and July showing that the competition between the two countries is tighter when volatility in the marketplace is reduced.

Finally, a supply chain shock such as the COVID-19 pandemic is demonstrated through increases ocean freight, local origin basis prices, wait time and demurrage costs in Brazil, and both maintaining and removing discounts. This analysis demonstrates that when a shock enters the marketplace, the most established market such as the United States is likely to win due to having long-standing systems in place that can keep grain moving.

6. CONCLUSION

Chapter 6 summarizes the thesis findings by reviewing the problem statement and objective of the analysis. The empirical model and its results are discussed with emphasis placed on the base case results and some of the more notable sensitivity results. The results of this thesis have implications in private and public spheres. The results also contain certain limitations that stem from the use of assumptions to create a model. This thesis contributes to knowledge through its use of an optimized Monte Carlo simulation that models one of the world's most concentrated agricultural trade sector. Suggestions for further research are made to further clarify the evolving soybean trade relationship between the United States, Brazil, and China.

6.1. Introduction

In recent years, China has imported 60% of the world's soybean imports on its own. The United States and Brazil are the two largest soybean producers in the world, and both countries are dependent on China for a majority of their soybean exports in most years. Many factors in this trade relationship are volatile such as basis values, transportation costs, and congestion delays. The three countries have notable elements to consider such as soybean quality, political wills, and rail freight pricing mechanisms.

6.2. Review of Problem Statement and Objective

The problem statement consists of a trader or shipping entity providing a set number of bushels, 1 MMT, per month to China while facing a scenario of costs. The trader has five originating locations in each country, the United States and Brazil, from which to source the entirety of the month's soybeans. The trader considers all the pertinent transportation costs and other important matters such as quality discounts. The objectives are to use the empirical model to determine the current U.S and Brazil market shares of China's soybean imports, as well as the average delivered price to China for the origins Brazil, the USG port, and the PNW port. Through the accomplishment of the objectives, the values for the base illustrate Brazil's market share advantage, the composition of delivered costs, and the changes that occur as important variables are adjusted.

6.3. Empirical Model and Results

The empirical model consists of random and nonrandom variables that are simulated and combined in a cost equation into an optimized Monte Carlo simulation. The originating basis, transportation costs to port, including truck, rail, barge, and delay costs, and ocean freight comprise the cost equation that determines the delivered price to China from each originating country. Most of the variables are random time series distributions based off of the historical data for each variable. They are simulated before each iteration, and the model chooses the least-cost origin at each iteration. The entire simulation forms a distribution of outcomes for the origin countries by quantifying the average bushels sourced from the United States and Brazil each month as the respective countries' average market share of China's soybeans for each month of the year. This market share can also be interpreted as the probability that that originating country will be the least-cost source of soybeans for China in that month.

The simulation also produces an average delivered cost over all months for Brazil's three ports all together, the USG port, and the PNW port. The average delivered cost for Brazil and the two U.S. ports shows the realization of the trader's decision-making, and the origin with the lowest average delivered cost location for the year has the greater market share percentage over the year as well. The average yearly market share and average yearly delivered cost are reported for the base case and each sensitivity.

6.3.1. Review of Base Case Results

The model determined the average U.S. market share over the crop year to be 35% in the base case scenario and Brazil's market share as 65%. This is in alignment with the research done by Salin and Somwaru (2020) that found the U.S. market share in 2019 to be 32%. Figure 6.1 illustrates again the average market share for the base case for each month. The most competitive months are December and March, when the difference between the delivered price from each origin to China is so slim that Chinese buyers split their purchases almost evenly. Recalling back to Figure 5.2 in Chapter 5, the cost delivered resembles a rough inverse of the market share graph. The country with the lower cost delivered in a certain month captures more market share in that month.

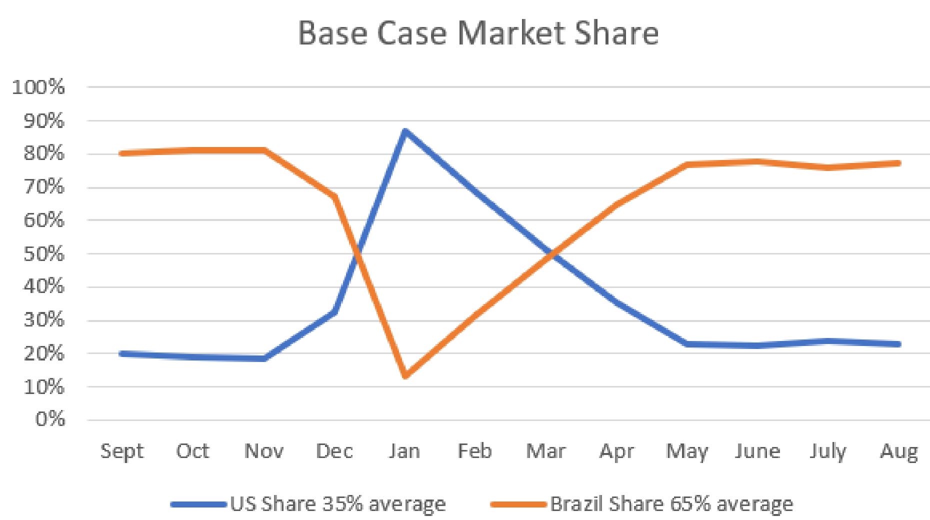


Figure 6.1: Base case market share illustration.

The average cost delivered is comprised of ocean freight, transportation, and origin basis. Transportation costs to the three sets of ports are different. The PNW costs include secondary rail market and rail tariff, the USG costs include barge and truck costs, and the Brazil port transportation costs includes only trucking costs in this analysis.

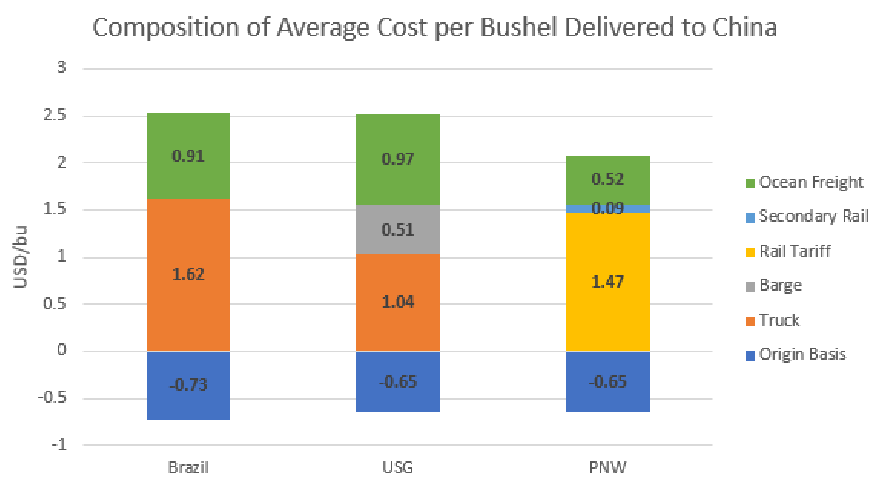


Figure 6.2: Composition of cost per bushel delivered to China.

The shortcomings of this graph are discussed in the limitations section of this chapter but understanding the composition of delivered costs is useful to predict how delivered costs and therefore the United States and Brazil market share change with respect to a sensitivity variable.

The last main point for the base case scenario the distribution plots for the average delivered costs illustrate how the U.S. ports each have higher delivered costs to China, but their distributions are much narrower compared to that of Brazil. The distribution is a graphical representation of Brazil's lower mean cost but larger standard deviation of delivered cost.

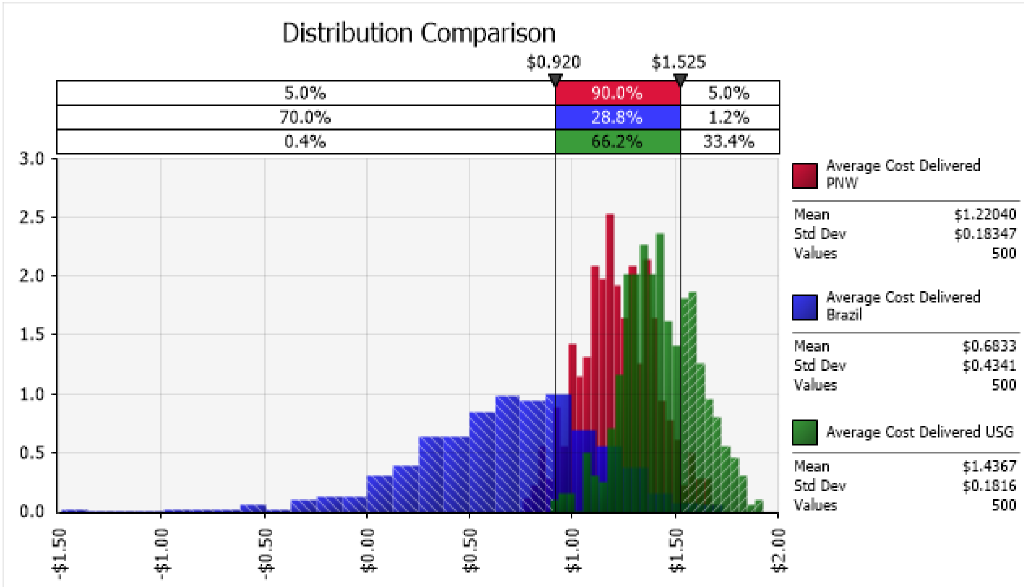


Figure 6.3: Distribution comparison of delivered costs for Brazil, USG, and PNW.

6.3.2. Notable Sensitivity Results

Many sensitivity analyses were performed in various areas of interest including: trade policy and competition, shipping and structural variables, and a supply chain shock. The most notable sensitivity results are listed in Table 6.1.

Table 6.1: Notable sensitivity results.

Model Scenario	Crop Year Share		Cost Delivered to China		
	U.S.	Brazil	From Brazil	From USG	From PNW
Base Case	35%	65%	$1.02	$1.55	$1.26
25% Import Duty on US	25%	75%	$1.02	$1.93	$1.58
Unload Incentive ($800)	42%	58%	$1.02	$1.55	$1.05
No US Quality Discount	44%	56%	$1.02	$1.45	$1.01
Exclude 2013 and 2014 data	48%	52%	$1.26	$1.45	$1.19
Supply Chain Shock with discounts	42%	58%	$2.62	$3.48	$2.55
Brazil Interior Trans down 20%	25%	75%	$0.72	$1.55	$1.26

Many of the sensitivities listed above contained interesting findings. The implementation of a 25% import duty on U.S. soybeans is shown to decrease U.S. average market share by 10%. In the model, the tariff was added simply as an extra cost, so the decrease of market share is from the added cost alone and does not include the further effects of tariff, such as declining basis prices and unpredictable transportation costs.

An unload incentive from U.S. rail companies of $800 per car was shown to increase railroad revenue due to causing the United States to capture almost 7% more market share on average over the crop year. In this case the delivered price in China from the PNW is within a couple cents of that from Brazil, and this shows how further increasing efficiency in the rail system can benefit U.S. soybean traders and shippers.

Removing the quality discount, 10 c/bu USG and 25 c/bu PNW under Brazil, increases average market share for the United States almost 10% and the increase is seen even in the off months that U.S. soybeans are usually not competitive in. Another sensitivity result that is shown to benefit U.S. market share is the exclusion of the 2013 and 2014 data wherein Brazil's origin basis was extremely volatile. U.S. market share reaches 48% on average in this case as traders are not able to benefit from very low Brazilian cash prices.

The supply chain shock is another noted sensitivity. The shock is intended to model when the supply chain suffers from an event such as the COVID-19 pandemic, where many abrupt changes happened to the prices of grain and costs of shipment. The supply chain shock included increasing wait times in Brazil, raising ocean freight rates, and strengthening the origin basis.

Decreasing Brazilian transportation cost by 20% is of importance. As Brazil continues to invest in infrastructure, it is likely that transportation costs will decrease. This sensitivity illustrates how those investments could capture more market share for Brazil.

6.4. Summary and Implications of Results

The results of this thesis have both private and public implications. Private implications include trading strategies based off where risk exists, the need for diversification, and the critical nature of the U.S. secondary car market and unload incentives. Public implications include concerns around quality, Brazil's interior infrastructure and wait times, the U.S. infrastructure, and trade policies.

Trading strategies are necessary for all parties involved in supplying soybeans to China. This thesis demonstrated the need for diversification as a trader and as China or a Chinese buyer. In reference to Table 5.4, sensitivity results show that China is open to more risk when it buys soybeans from only Brazil, as the standard deviation of costs is still large and the mean cost rises. Buying from Brazil has more risk overall than buying from the United States, since the standard deviation of cost when buying solely from the United States is much smaller. However, diversification of purchases for China allows for a lower cost on average even with more volatility and risk present in Brazil.

Diversification is essential as a soybean supplier as well. Under the base case conditions, there are months where there is almost an 80% probability that Brazil will be the least-cost origin such as June through November. A trader with a network of origins in both countries would be able to provide soybeans to China during all months, using the least-cost origin in those respective months. A trader with a position in only one country can plan to incur storage costs when China will not be buying from that origin country.

Another form of diversification that could benefit traders is access to originating locations that can use various ports within a country. For example, many sensitivity results pertaining to rail markets in the United States show that when favorable conditions arise in secondary market value or unload incentives, the PNW port becomes very competitive to Brazil. The alternative side is true; when no unload incentives exist or secondary market value is volatile and high, the PNW quickly becomes non-competitive. For these reasons, rail DCV and unload incentives are critical to U.S. market share and the strategies of U.S. traders.

A public implication is the discussion around quality of soybeans. Removing quality discounts on U.S. soybeans raises U.S. market share 10% even in the off/non-competitive months. An extra 10% market share over all months on average represents an important increase in purchases from the U.S. soybean industry. As outlined in Chapter 2, Hertsgaard et. al (2018) proposed different mechanisms to mitigate quality disparities such as improving protein quality, testing for buyer's quality preferences in soybean shipments to avoid rejection of shipments, and diversifying geographic placement of originating locations to have more control over the final shipment quality specifications sent to a buyer. This thesis reinforces the benefits that improving quality and providing proof of quality could have on U.S. market share.

Brazil interior transportation and wait times cause another key public implication that stems from this thesis. Lowering Brazil interior transportation costs captures another 10% market share for Brazil over the average crop year, and even with a $20,000 per day demurrage rate, Brazil's market share would not fall below 52%. The implications are that as Brazil's transportation methods continue to improve in efficiency and cost and as wait times decrease, Brazil will continue to become more competitive and capture more of the market share for China's soybean imports.

U.S. infrastructure provides a public implication as well. U.S. infrastructure is more stable than Brazil's, but transportation costs in the United States are frequently higher. This thesis demonstrates how any rise in transportation costs in the United States causes market share to quickly transfer to Brazil. Salin and Somwaru (2020) found that just a percentage point of market share lost is worth half of a billion U.S. dollars, so the importance of decreasing transportation costs to not lose market share is not understated.

Finally, there are public implications around trade policies. The 25% import tax on U.S. soybeans caused U.S. market share to fall 10% on average across the crop year based on simply the tax itself. Other factors that were adjacent to the tariff such as uncertainty among producers and sellers that the United States would have a market for its soybeans saw further effects outside of what the model can demonstrate. Open and good trade relations are critical when the United States exports well over half of its soybean to one country.

6.5. Research Limitations

Many of the assumptions made to create the model are limitations in the scope of the research. One assumption is that the trade is perfectly hedged in the futures market when buying at the origins, and this may not always be the case as traders may have different hedging strategies that expose them to more risk than a perfect hedge. The model also does not include a couple fixed costs such as handling costs or insurance, nor does it take into account the exchange rate between U.S. and Brazil currency.

Another limitation of the study is the use of only trucking costs for the interior Brazil transportation data. As discussed at length in Chapter 2, Brazil continues to make investments in rail and barge transportation for grains in order to diversify the transportation methods available to their industries. There are railways in operation already in the state of Mato Grosso, where two of the model's Brazil origins are located. Barge freight costs, especially those through the Amazon River that transport grain from interior Amazon River barge-loading locations to northeast Brazilian ocean ports, are another interior transportation limitation due to lack of data availability.

There are also limitations on the U.S. portion of the model. The ocean freight for the USG to China includes only the route through the Panama Canal, which is not always the least-cost choice for soybean shippers, as there are times that low fuel prices can cause the route around Cape Hope to be cheaper.

6.6. Contributions to Knowledge

This thesis contributes to knowledge by applying a somewhat novel approach to Monte Carlo minimization by performing the stochastic optimization when the values of the random variables are known. Wilson et. al (2020) provides the basis for this type of optimization, where each iteration itself minimizes cost based off already generated random variables, and the simulation forms a distribution of outcomes. Applying this type of optimized Monte Carlo simulation to a trade relationship that is at the forefront of agriculture studies and news in present times gives empirical context to the situations at hand. Minimizing cost from a network of origins and transportation routes can be applied to other competitive trade relationships.

Another contribution to knowledge is shown in the further results section of Chapter 5. The residual surplus found at many of the ports involved in this study suggests that traders are profiting by buying or selling soybeans from certain ports where the reported export/terminal basis and the calculated export basis are different. When it costs less than the reported basis to get soybeans to port, there is an opportunity for a trade to pocket the surplus. Recognizing where these residuals exist may explain why the northern arc of ports in Brazil has continued to experience growth, as traders have created demand for soybeans shipped through the northern ports, where the surplus in Brazil is largest. Even the modest 10 cent per bushel surplus derived for the Paranaguá port is significant multiplied over millions of bushels.

6.7. Suggestions for Further Research

As with any research project, there are refinements and extensions that would enhance the analytical model. However, it is unlikely they would impact the overall conclusions from this analysis. There are numerous additions that could be explored and are described below.

In the model there is no restriction on supply from any of the local origins in each country. More information on supply capacity could be applied to respect those real capacity and supply constraints. The buyer can currently supply the entire 1 MMT from a single origin location, i.e., originating town, in either country. This could be defended in the context of this model wish that of a grain buyer. However, it could be specified alternatively. This may not be representative of supply-side constraints, especially in less competitive months. Rather than fill the entire month's shipping requirement from one origin, the model would be forced to find the next cheapest origin for the rest of the bushels, whether it be in the same originating country or not.

Next, more detail on the supply chain from each origin could enhance the model. Transit time could be a large factor in providing shipments, even if demurrage cost is not incurred. An origin that is competitive price-wise may have transit time delays that make that option less attractive or feasible. This is also an area where quality discounts are applicable. Whole-region or whole-country discounts do not account for heterogeneity in quality across the region or country. More information on end-use traits of soybeans produced in different U.S. and Brazil states may allow to only apply quality discounts where they should actually be incurred in effort to show a scenario without blanket discounts.

An important suggestion for further research is the addition of forward contracts. Currently the shipper is buying spot shipments to supply soybean to China. The ability to forward contract for a month or more ahead exists in the market, as many purchases are based on forward basis, not spot basis. Having the ability to forward contract gives the shipper the opportunity to reduce risk in competitive months by locking in a basis price ahead of time. This would provide a more complex albeit realistic alternative to the current spot price method. This could be further extended by including the option to ‘switch’ origins or shipping periods which has become more common in recent years.

Finally, it is clear that while the United States and Brazil provide the majority of China’s soybean shipment, they do not provide all, and China does not import 100% of the world’s soybean exports. There remains many other medium and small surplus and deficit countries that could be added. Specifically, Argentina and Paraguay have become more prominent soybean suppliers in recent years, and the European Union imports the second-most soybeans by volume after China. Adding more demand regions and supply countries would strengthen the illustration of the soybean market on a world scale.

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APPENDIX A. TIME SERIES FUNCTIONS (@RISK)

Table A1: Time series functions in @Risk.

@Risk Time Series Distribution Function with Parameters	**Description in reference to parameters**
RiskAR1(mu, Sigma, A1, R0, StartValue, ReturnValue)	Computes a first-order autoregressive process
RiskAR2(mu, Sigma, A1, A2, R0, RNeg1, StartValue, ReturnValue)	Computes a second-order autoregressive process
RiskARCH1(mu, Omega, A, R0, StartValue, ReturnValue)	Computes a first-order autoregressive conditional heteroskedasticity process
RiskARMA11(mu, Sigma, A1, B1, R0, StartValue, ReturnValue)	Computes a first-order autoregressive moving average process
RiskBBMR(mu, Sigma, Alpha, R0, StartValue, ReturnValue)	Computes a Brownian motion with mean-reversion process
RiskBBMRJD(mu, Sigma, Alpha, R0, Lambda, JumpMu, JumpSigma, StartValue, ReturnValue)	Computes a Brownian motion process with mean reversion and jump diffusion
RiskEGARCH11(mu, Omega, Theta, Gamma, A, B, R0, Sigma0, StartValue, ReturnValue)	Computes an Exponential GARCH process
RiskGARCH11(mu, Omega, A, B, R0, Sigma0, StartValue, ReturnValue)	Computes a Generalized ARCH process
RiskGBM(mu, Sigma, StartValue, ReturnValue)	Computes a geometric Brownian motion process
RiskGBMJD(mu, Sigma, Lambda, JumpMu, JumpSigma, StartValue, ReturnValue)	Computes a geometric Brownian motion with jump diffusion process
RiskMA1(mu, Sigma, B1, StartValue, ReturnValue)	Computes a first-order moving average process
RiskMA2(mu, Sigma, B1, B2, StartValue, ReturnValue)	Computer a second-order moving average process

APPENDIX B. REMAINING TIME SERIES FORECASTS OF RANDOM VARIABLES

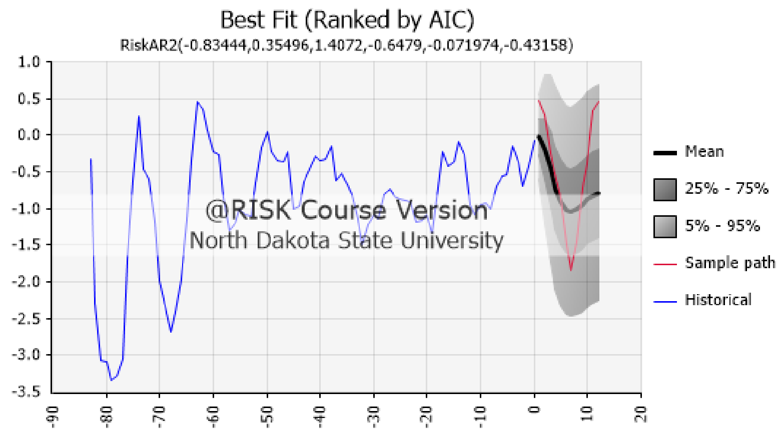

Figure B1: Time series forecast of Barreiras basis (@Risk).

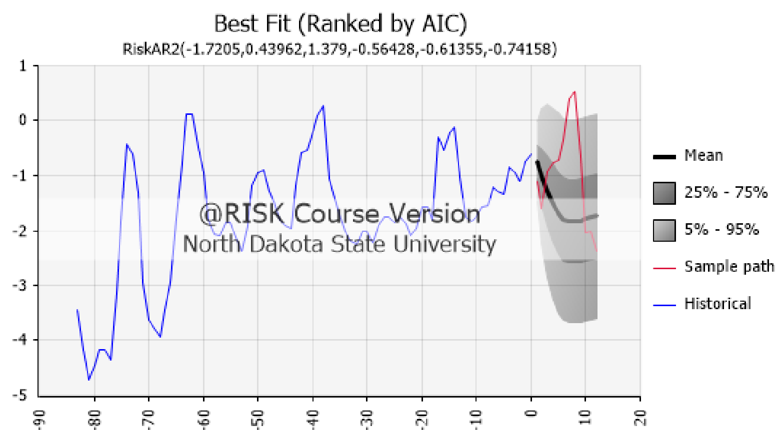

Figure B2: Time series forecast of Sorriso basis (@Risk).

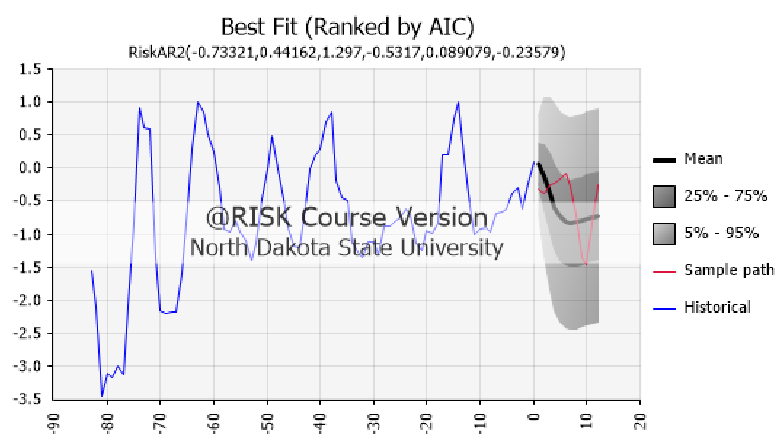

Figure B3: Time series forecast of Rio Verde basis (@Risk).

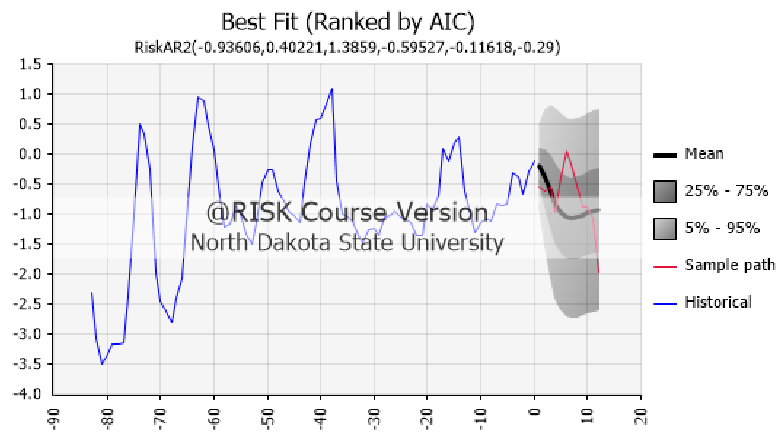

Figure B4: Time series forecast of Rondonópolis basis (@Risk).

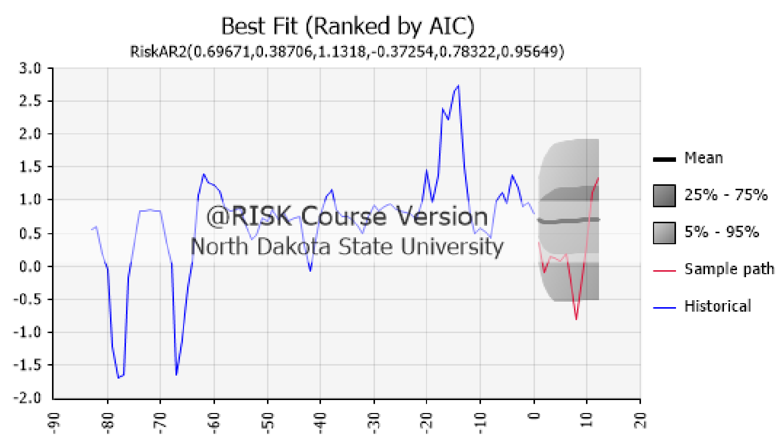

Figure B5: Time series forecast of FOB Santos basis (@Risk).

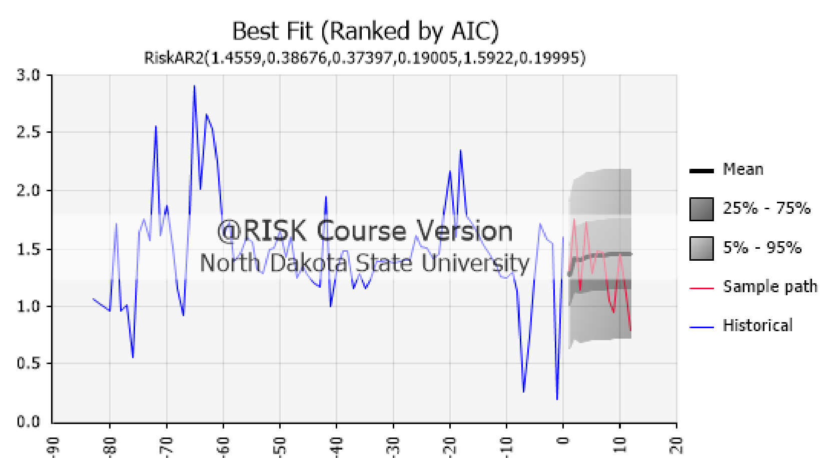

Figure B6: Time series forecast of CIF Pecém basis (@Risk).

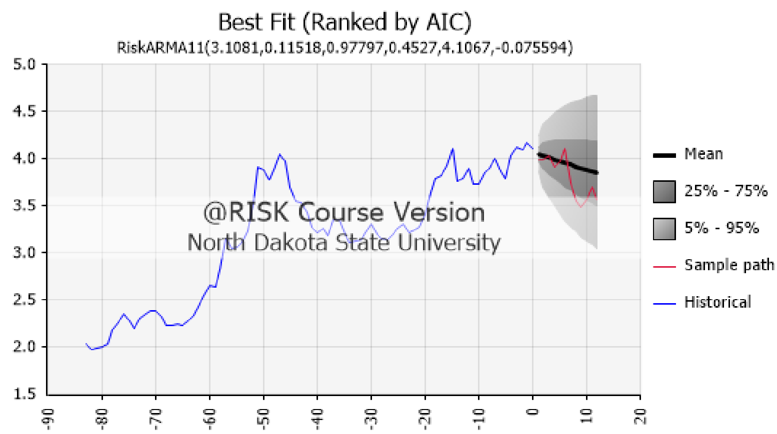

Figure B7: Time series forecast of BRA=USD Exchange rate (@Risk).

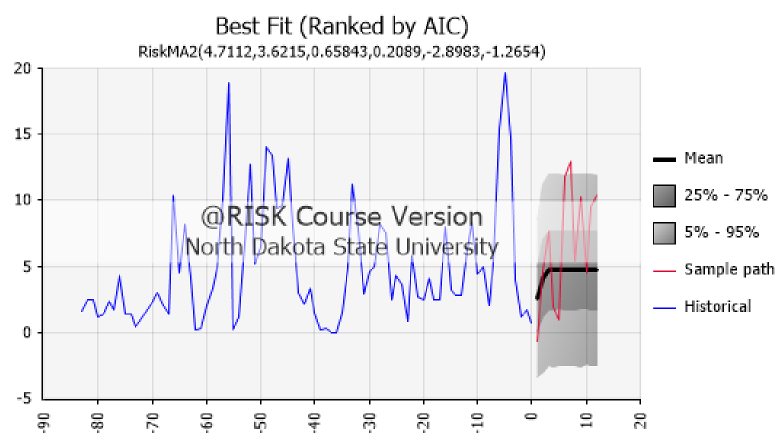

Figure B8: Time series forecast of North port wait days (@Risk).

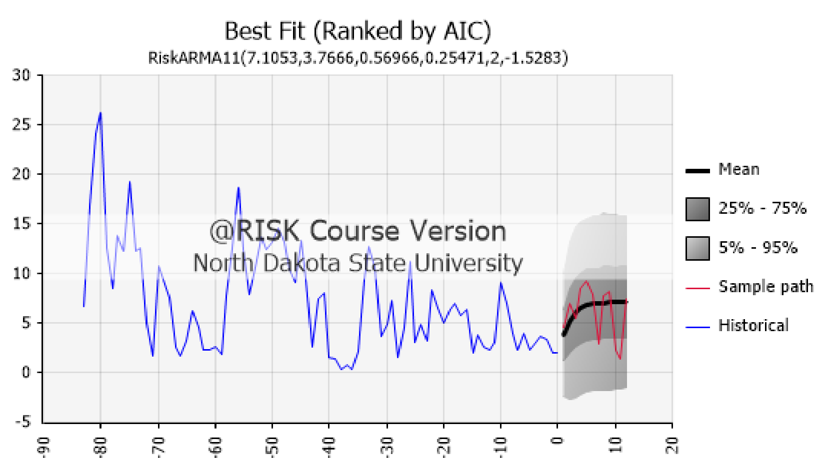

Figure B9: Time series forecast of Santos wait days (@Risk).

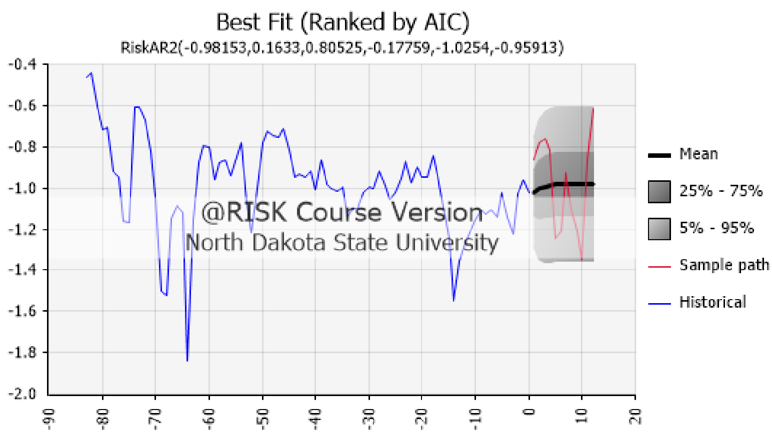

Figure B10: Time series forecast of Ayr, ND basis(@Risk).

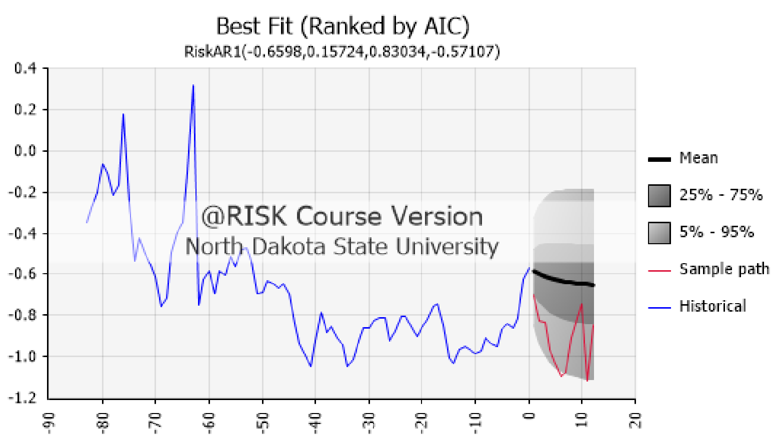

Figure B11: Time series forecast of Jasper, MN basis (@Risk).

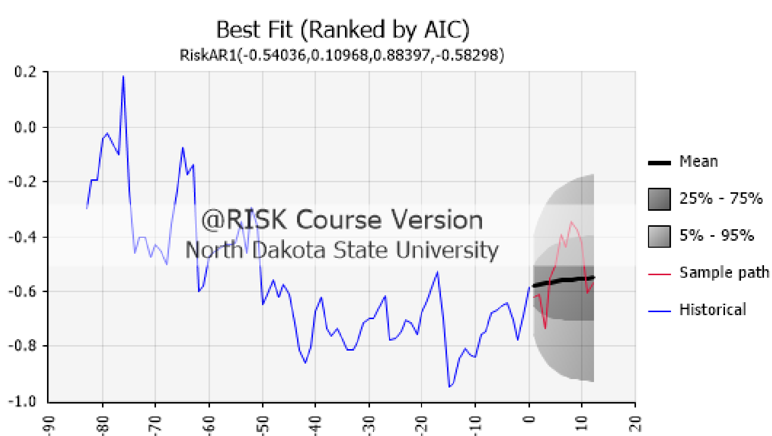

Figure B12: Time series forecast of Ida Grove, IA basis (@Risk).

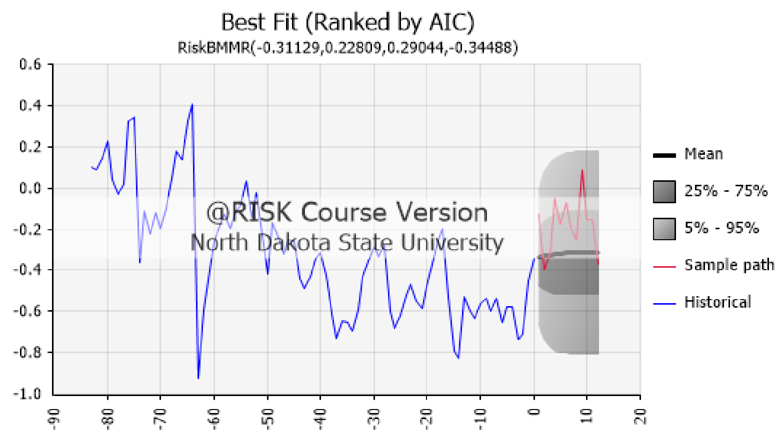

Figure B13: Time series forecast of St. Joseph, MO basis (@Risk).

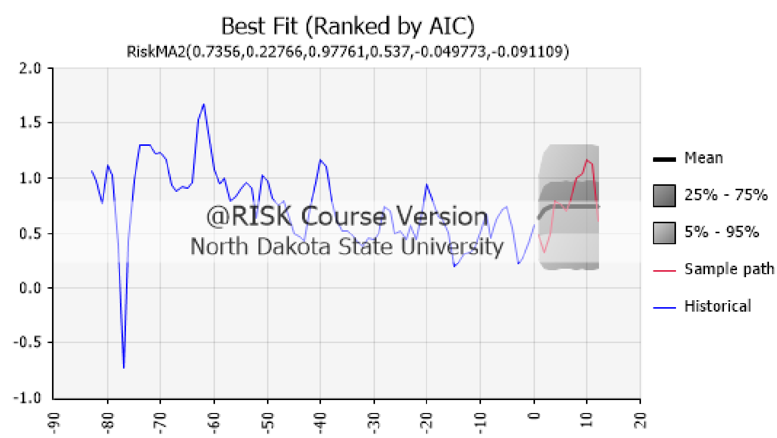

Figure B14: Time series forecast of FOB USG basis (@Risk).

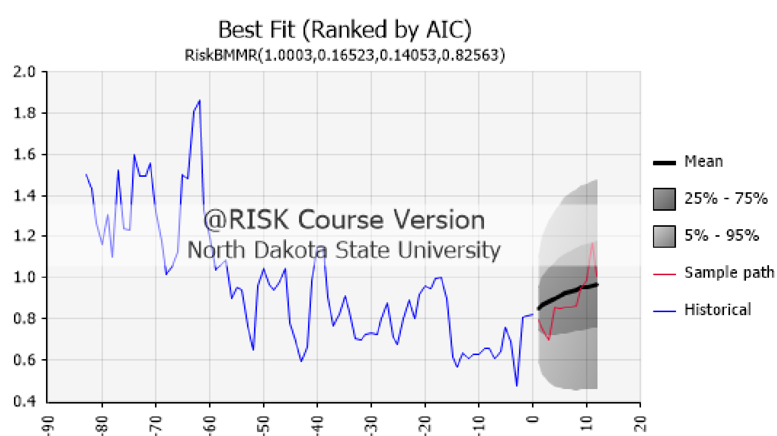

Figure B15: Time series forecast of FOB PNW basis (@Risk).

APPENDIX C. REMAINING GRAPHS OF BASE CASE OUTPUTS

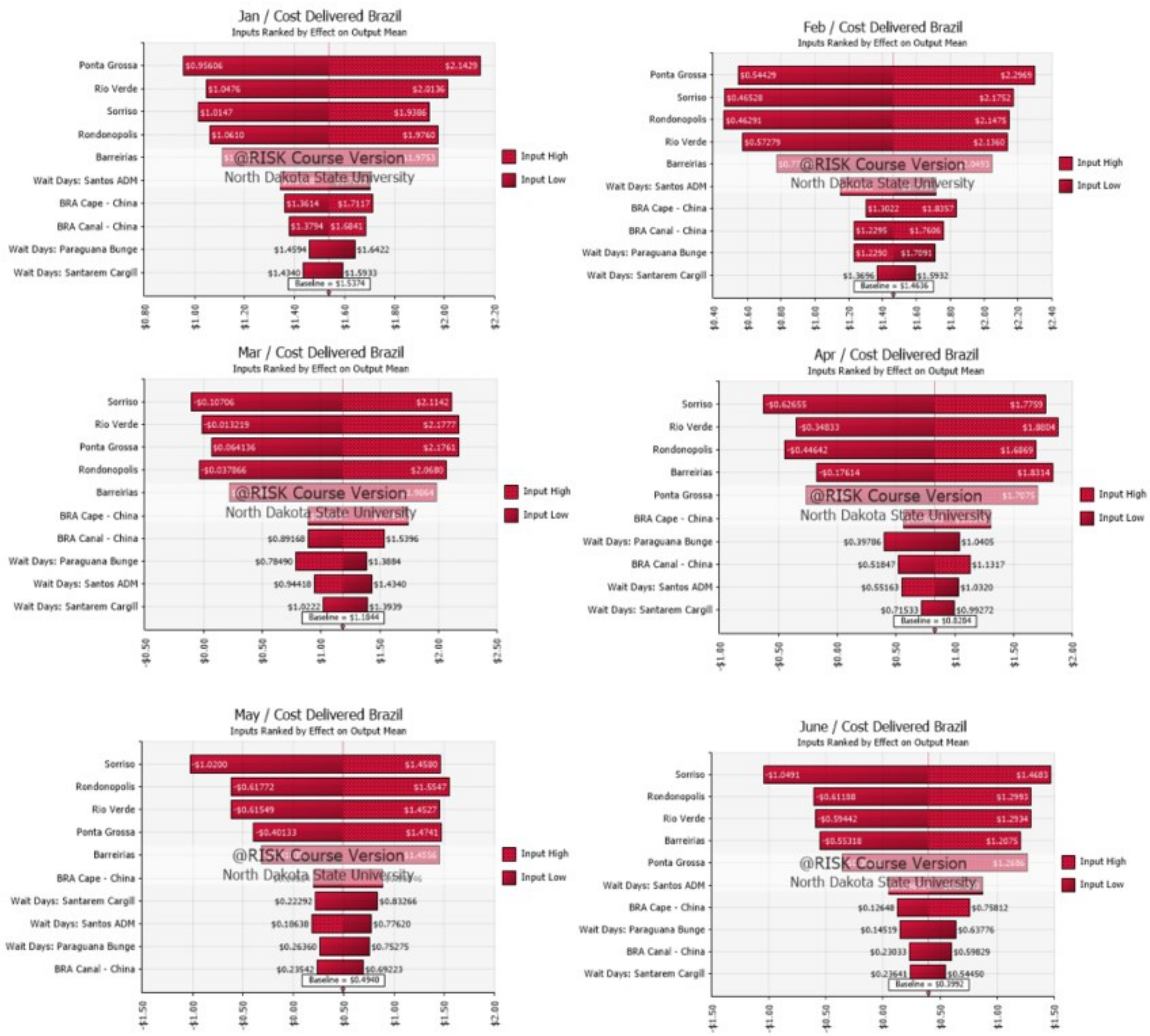

Figure C1: Base case cost delivered from Brazil tornado outputs January through June.

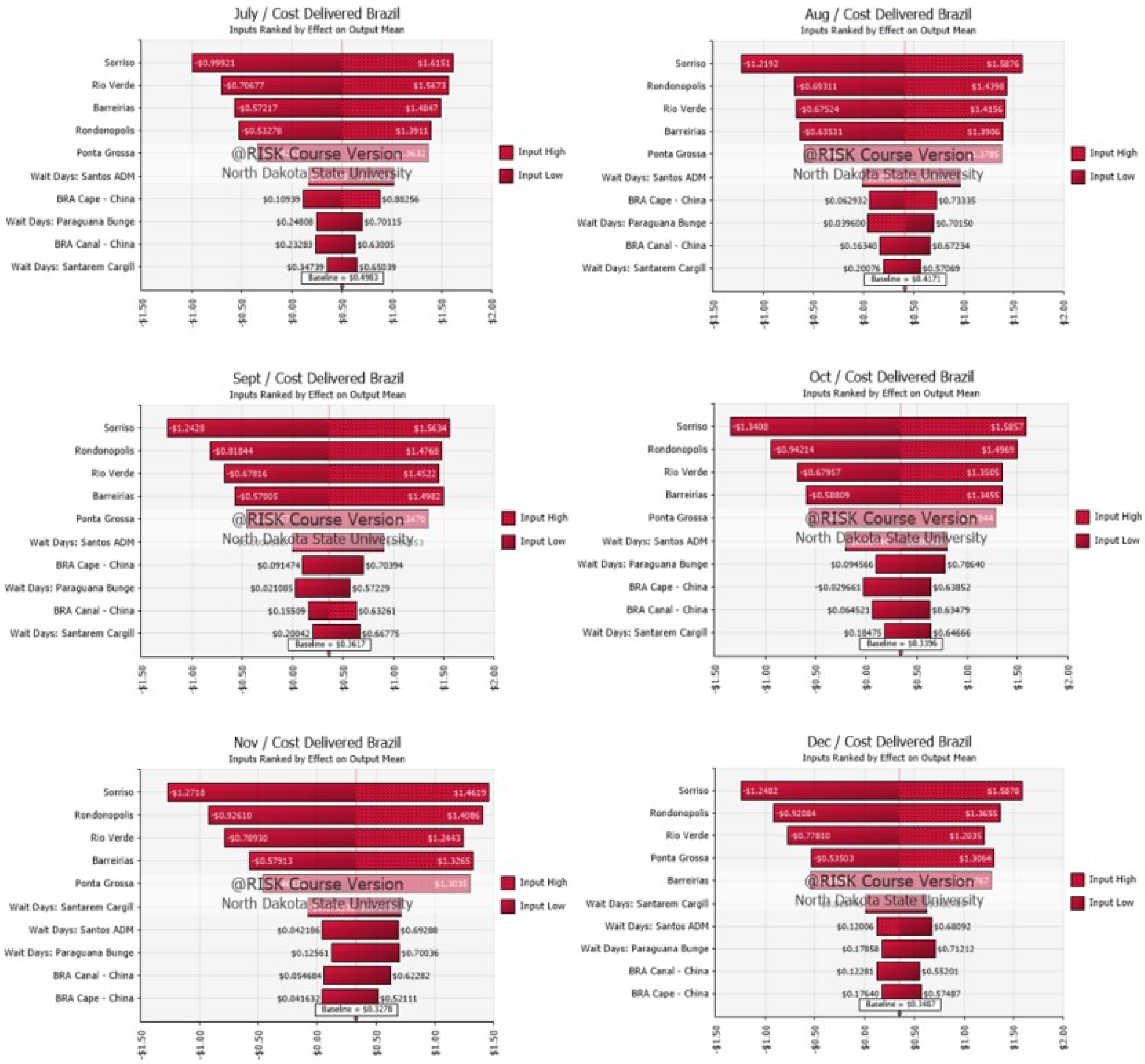

Figure C2: Base case cost delivered from Brazil tornado outputs July through December.

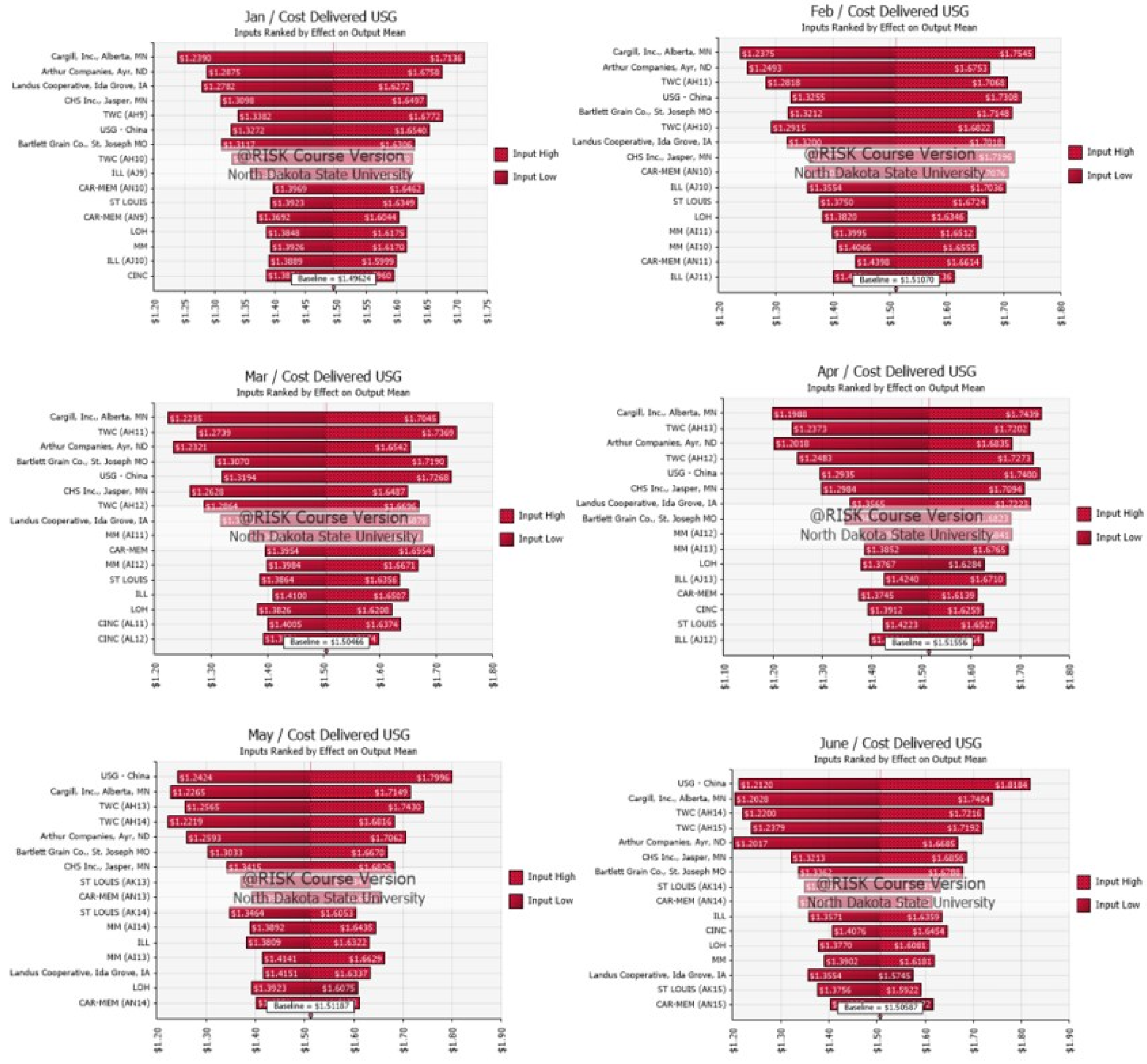

Figure C3: Base case cost delivered from USG tornado outputs January through June.

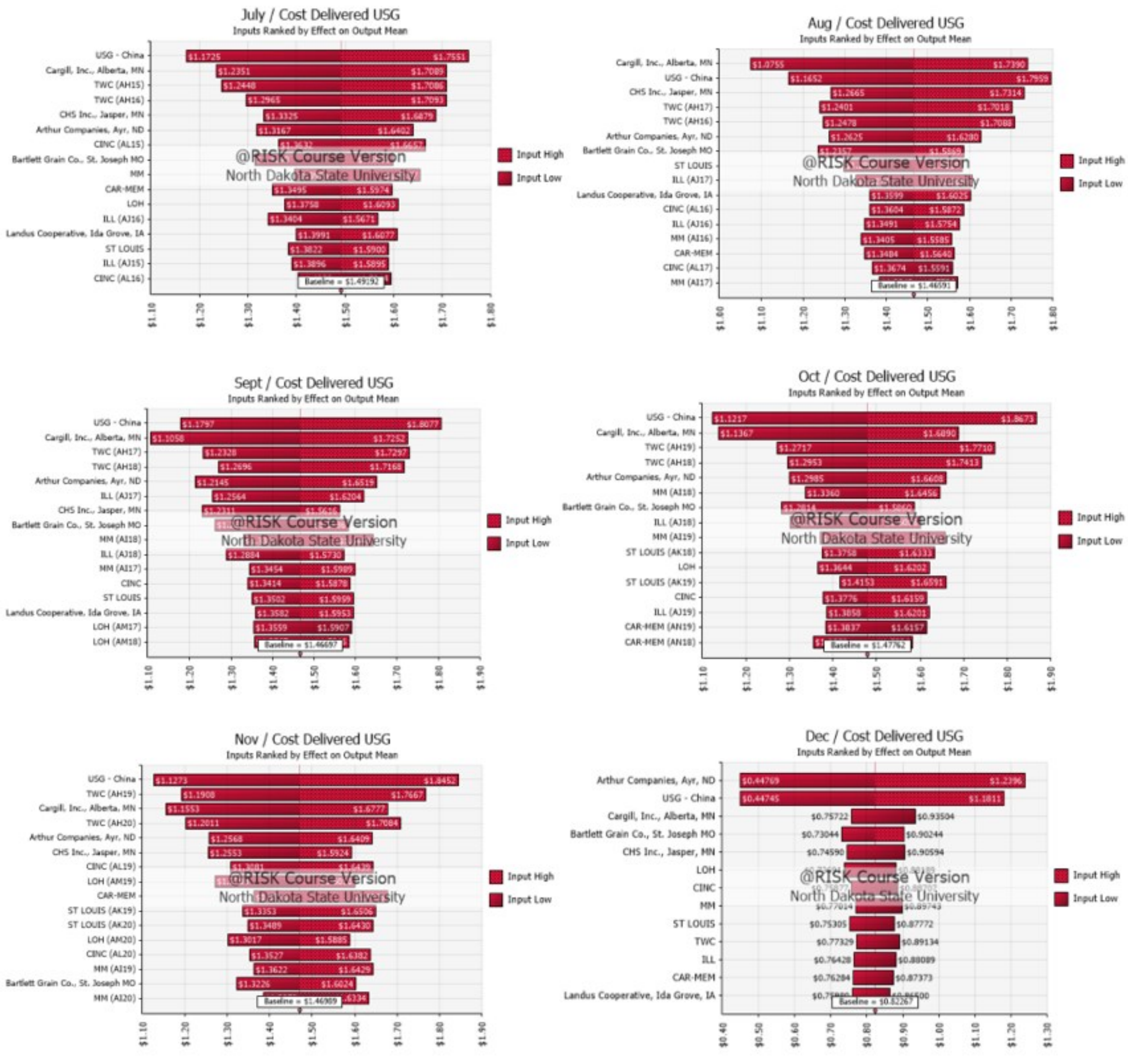

Figure C4: Base case cost delivered from USG tornado outputs July through December.

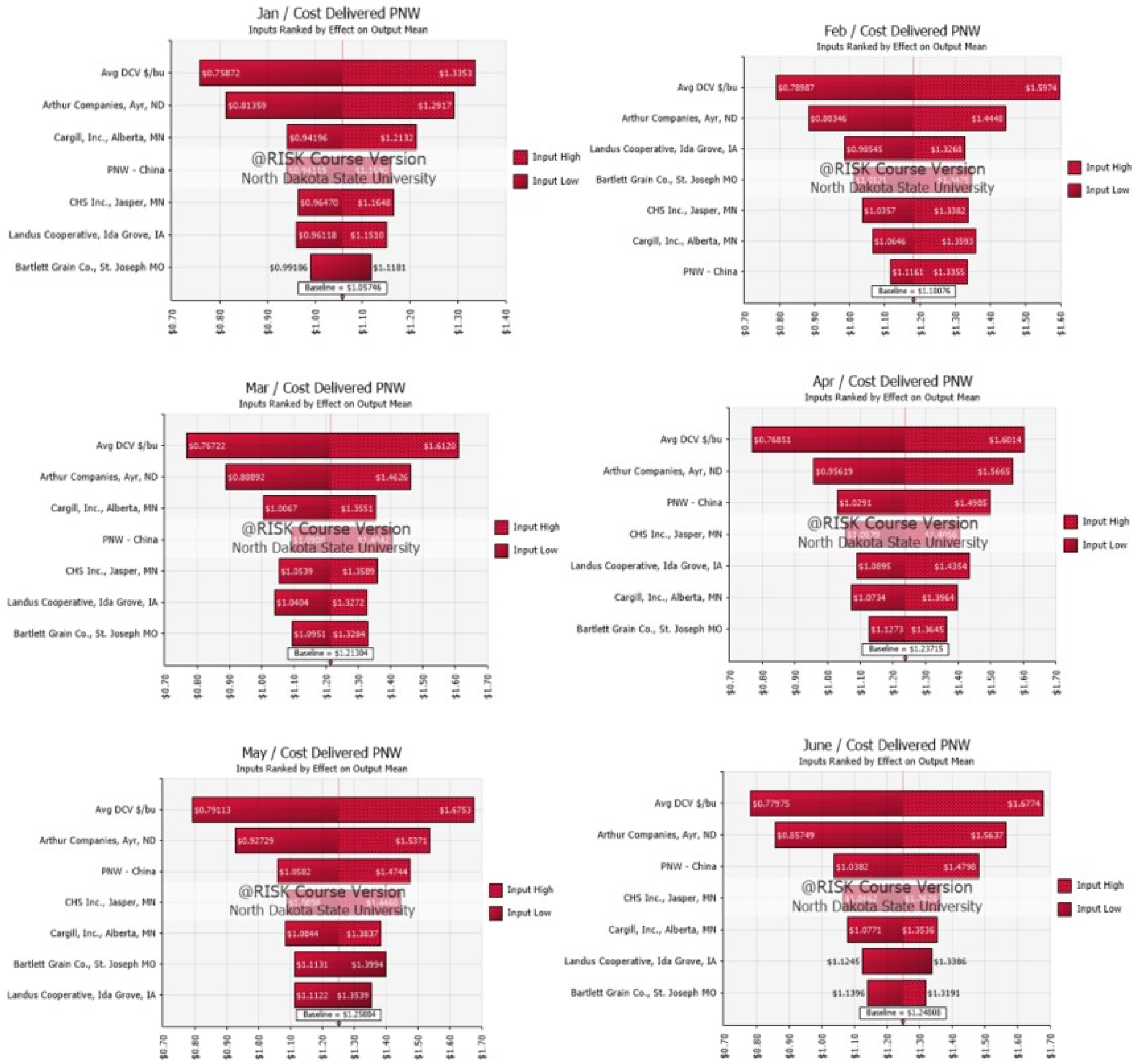

Figure C5: Base case cost delivered from PNW tornado outputs January through June.

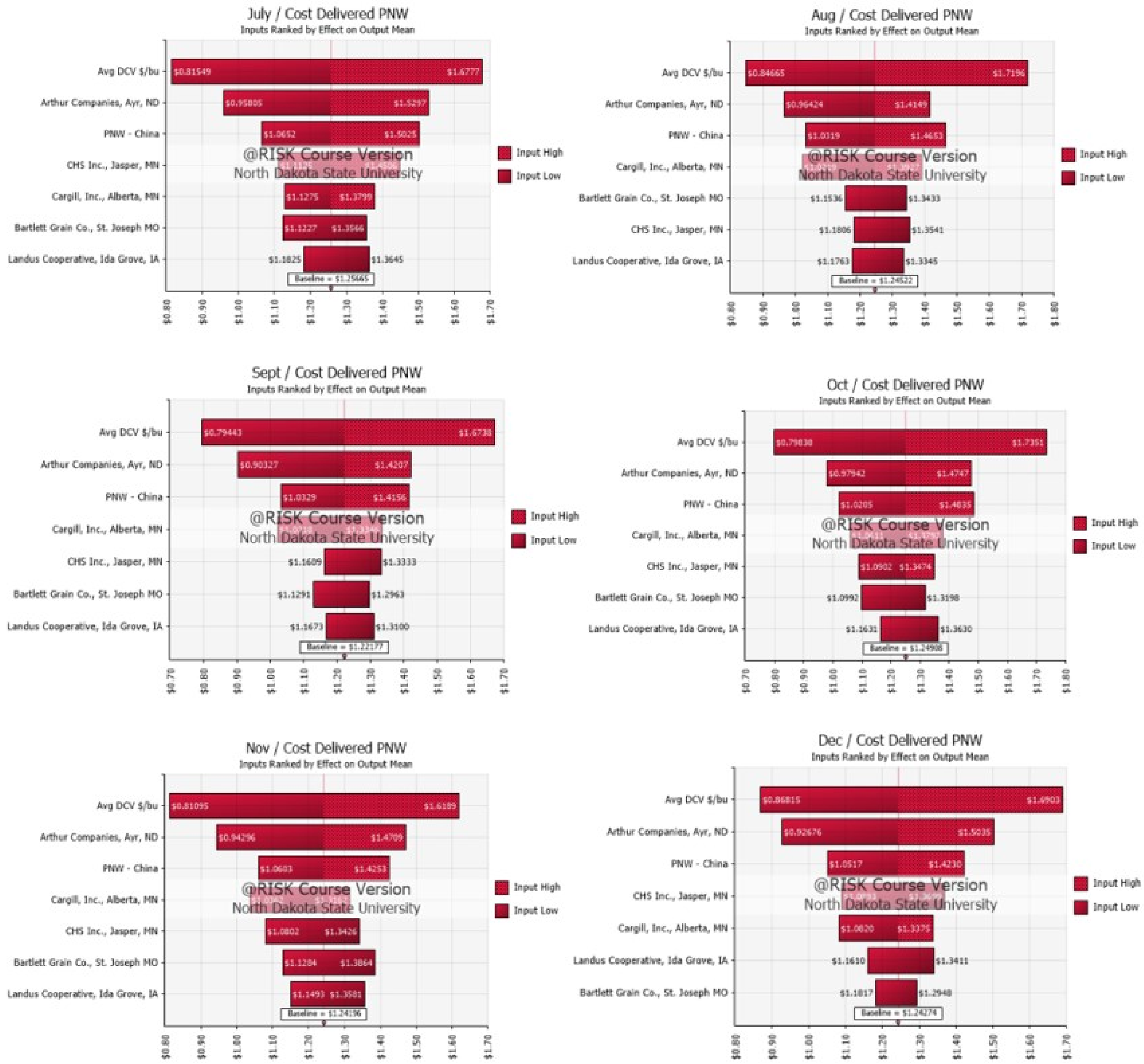

Figure C6: Base case cost delivered from PNW tornado outputs July through December.

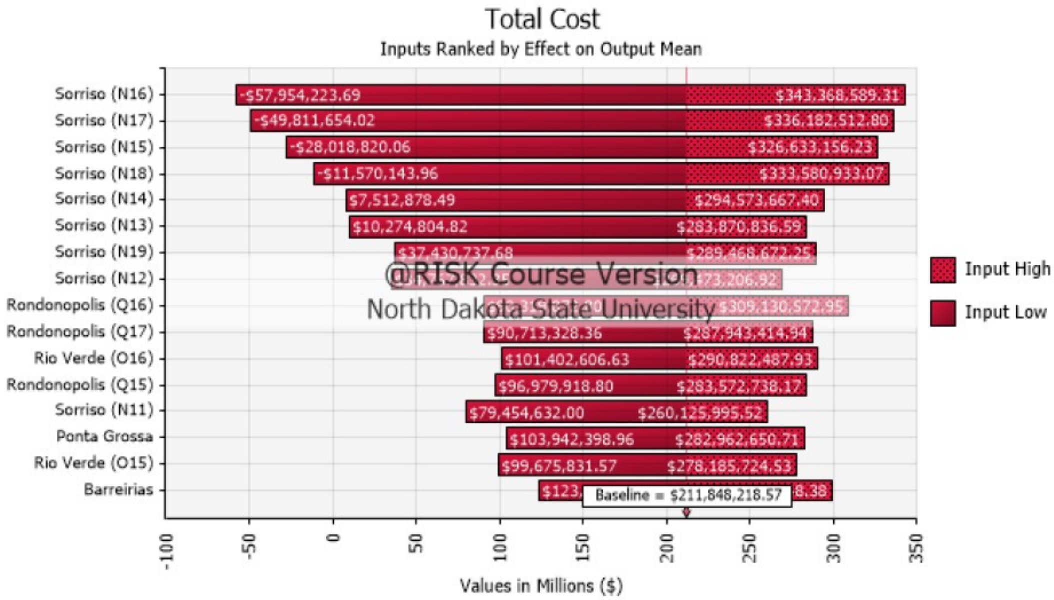

Figure C7: Total cost tornado graph for base case simulation.

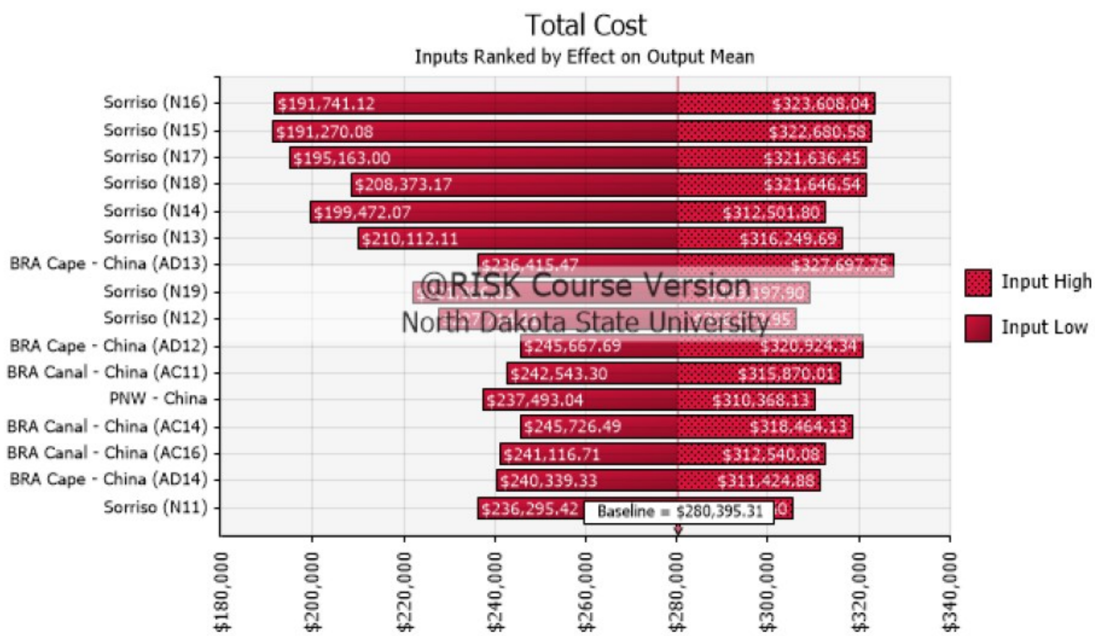

Figure C8: Total cost tornado graph for reduced volatility simulation excluding 2013 and 2014 data.

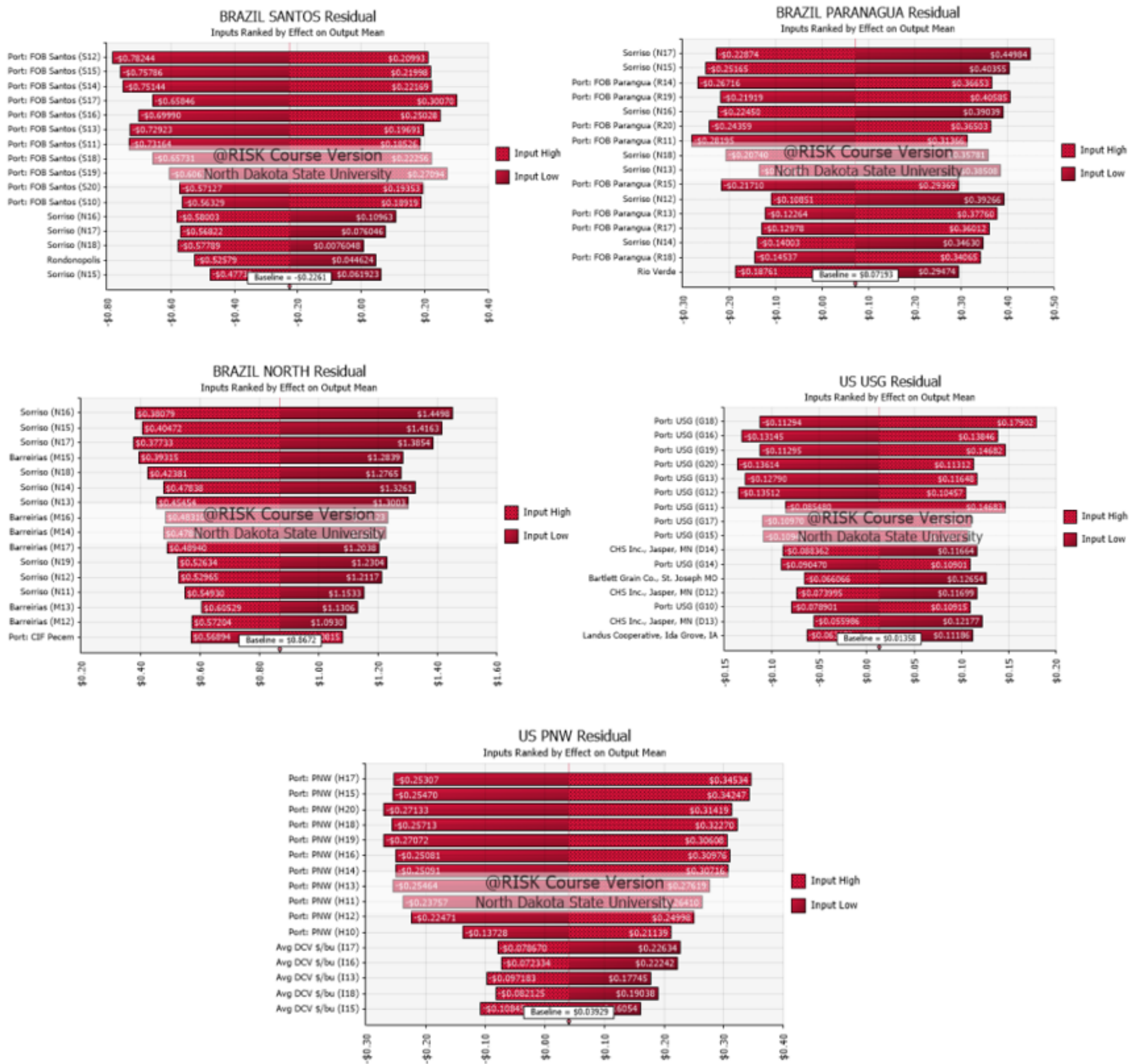

Figure C9: Base case port residual calculation tornado outputs for Santos, Paranaguá, North, USG, and PNW.

APPENDIX D. REMAINING GRAPHS OF SENSITIVITY RESULTS

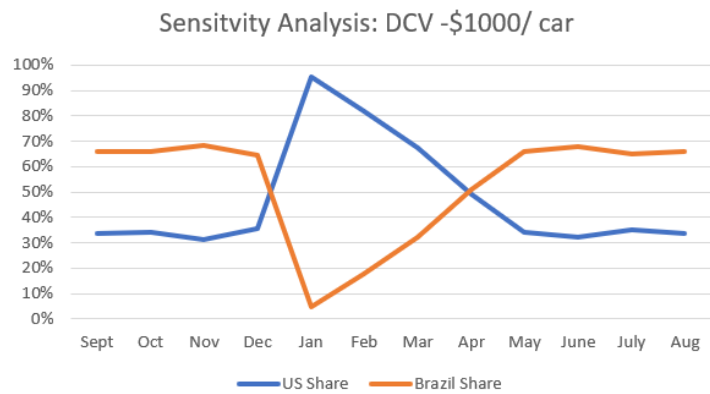

Figure D1: Sensitivity analysis: U.S. and Brazil market share when DCV is -$1000 per car.

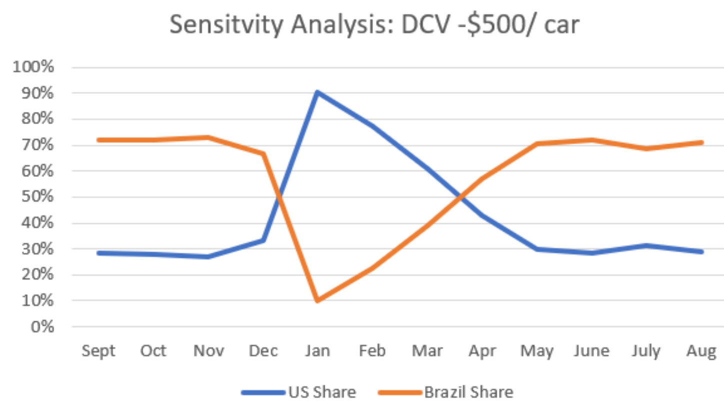

Figure D2: Sensitivity analysis: U.S. and Brazil market share when DCV is -$500 per car.

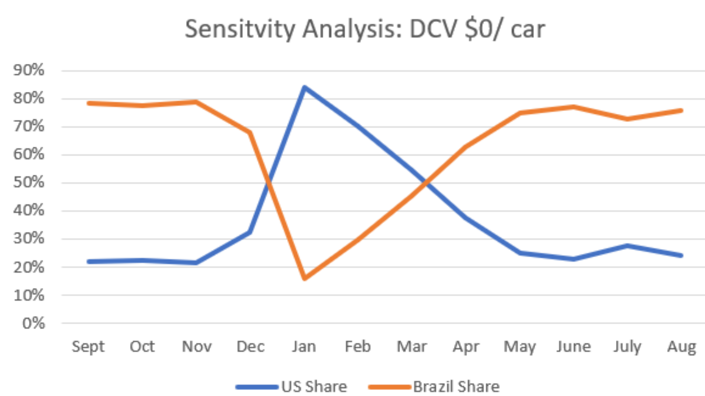

Figure D3: Sensitivity analysis: U.S. and Brazil market share when DCV is $0 per car.

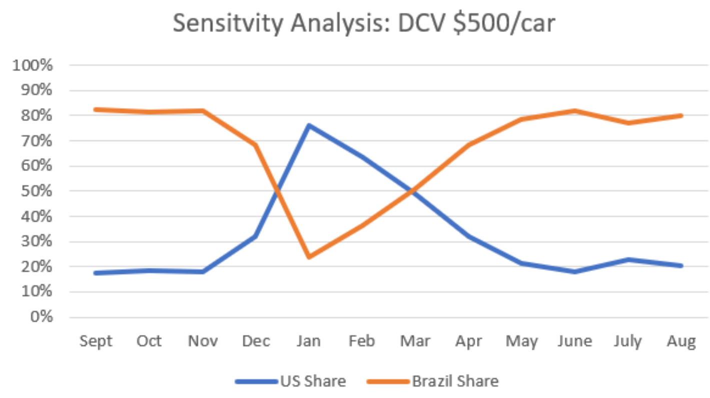

Figure D4: Sensitivity analysis: U.S. and Brazil market share when DCV is $500 per car.

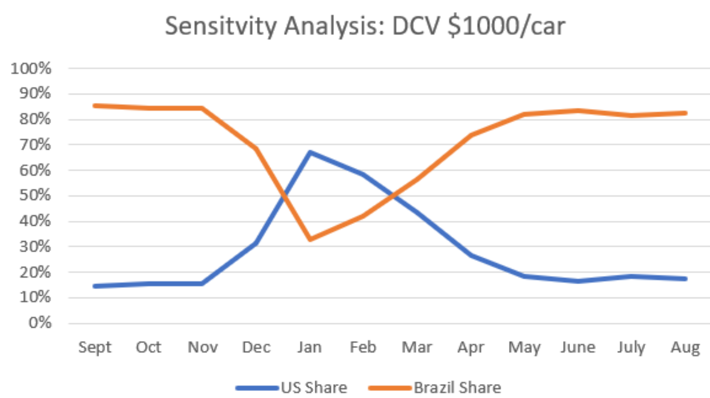

Figure D5: Sensitivity analysis: U.S. and Brazil market share when DCV is $1000 per car.

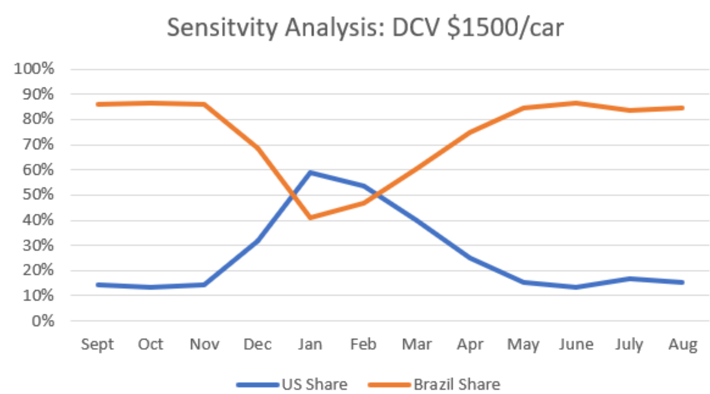

Figure D6: Sensitivity analysis: U.S. and Brazil market share when DCV is $1500 per car.

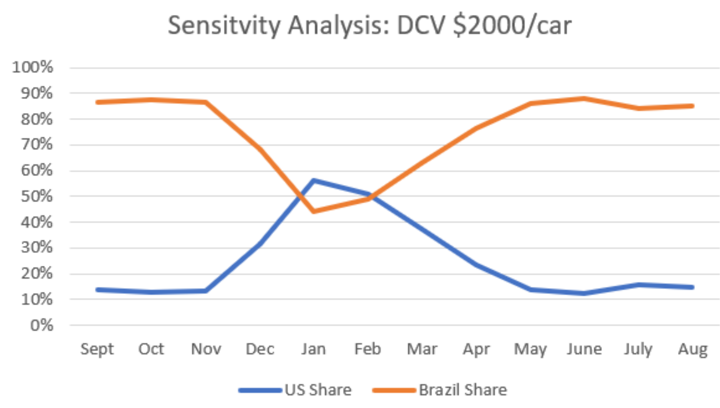

Figure D7: Sensitivity analysis: U.S. and Brazil market share when DCV is $2000 per car.

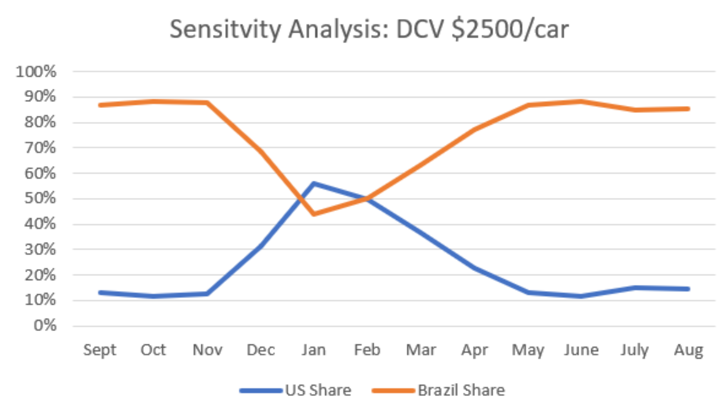

Figure D8: Sensitivity analysis: U.S. and Brazil market share when DCV is $2500 per car.

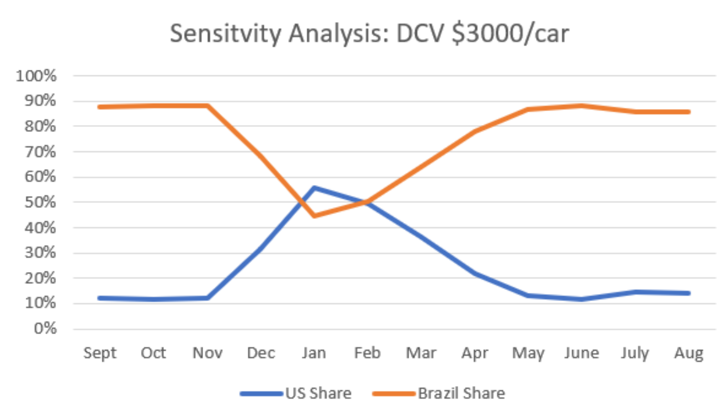

Figure D9: Sensitivity analysis: U.S. and Brazil market share when DCV is $3000 per car.

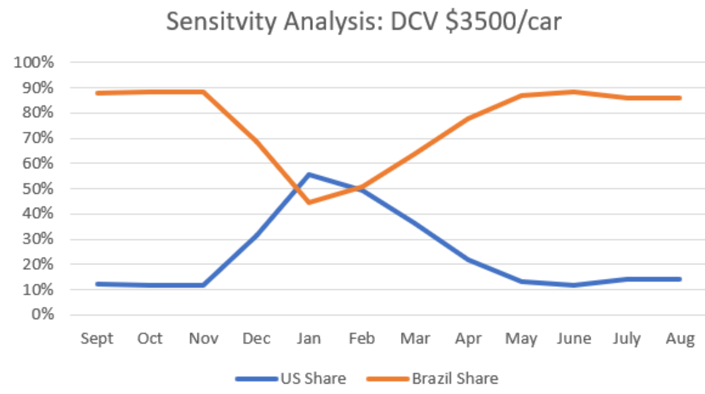

Figure D10: Sensitivity analysis: U.S. and Brazil market share when DCV is $3500 per car.

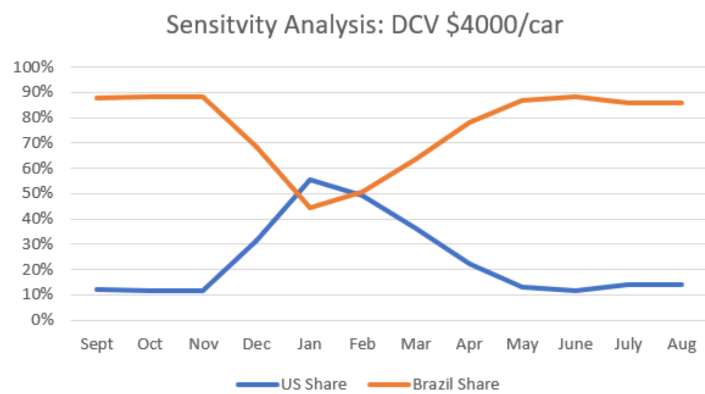

Figure D11: Sensitivity analysis: U.S. and Brazil market share when DCV is $4000 per car.

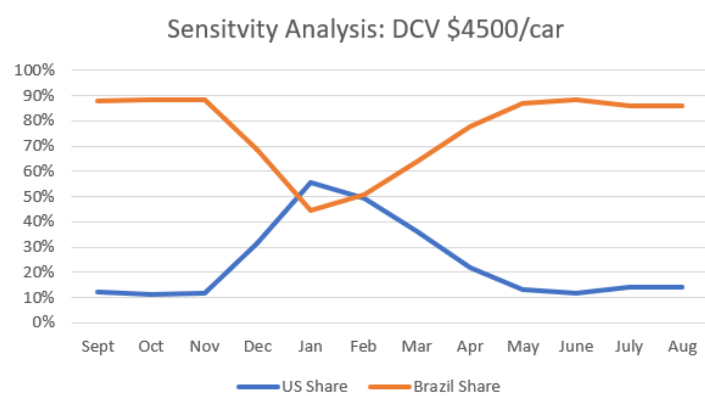

Figure D12: Sensitivity analysis: U.S. and Brazil market share when DCV is $4500 per car.

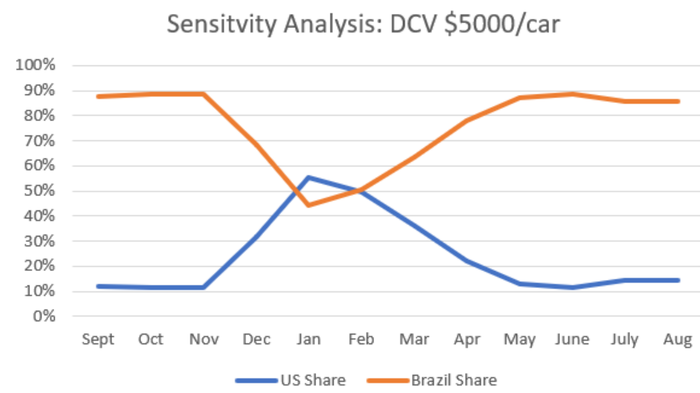

Figure D13: Sensitivity analysis: U.S. and Brazil market share when DCV is $5000 per car.

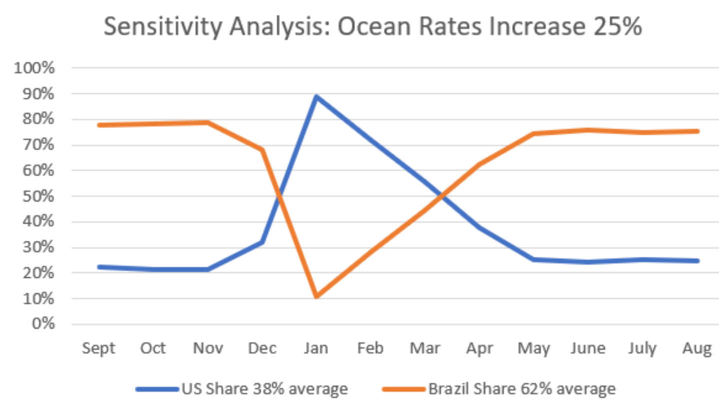

Figure D14: Sensitivity analysis: U.S. and Brazil market share when ocean rates increase 25%.

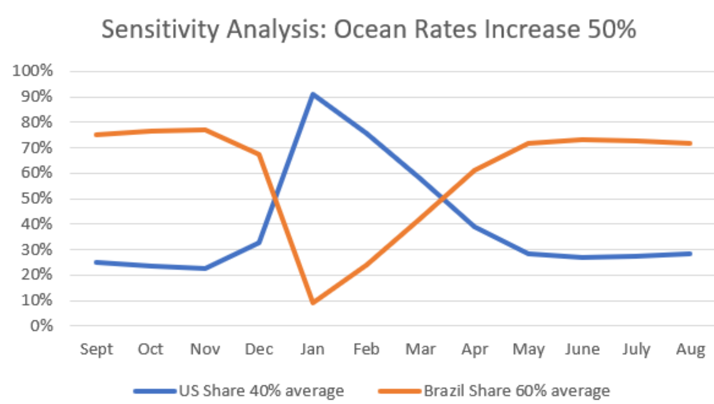

Figure D15: Sensitivity analysis: U.S. and Brazil market share when ocean rates increase 50%.

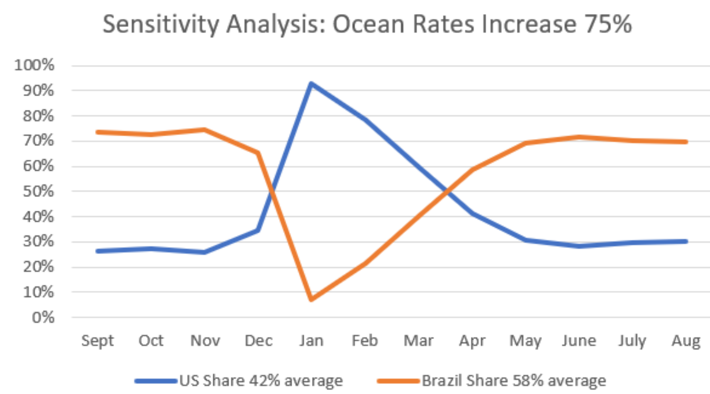

Figure D16: Sensitivity analysis: U.S. and Brazil market share when ocean rates increase 75%.

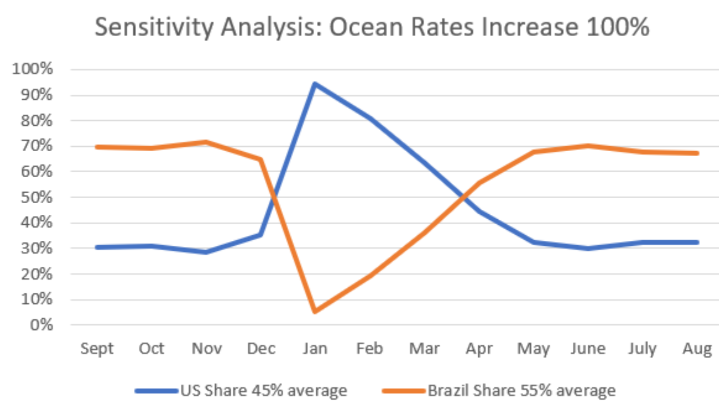

Figure D17: Sensitivity analysis: U.S. and Brazil market share when ocean rates increase 100%.

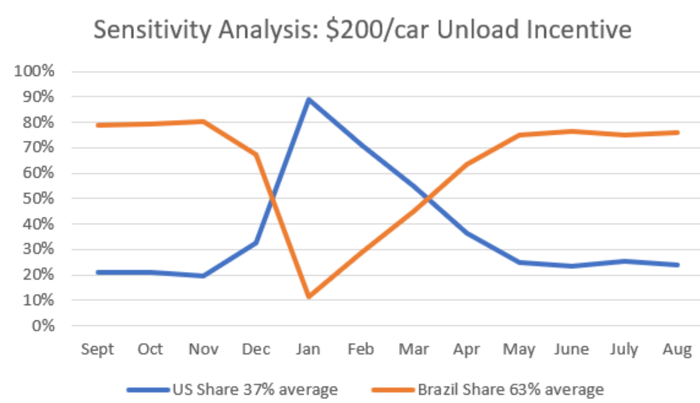

Figure D18: Sensitivity analysis: U.S. and Brazil market share when unload incentives are $200 per car.

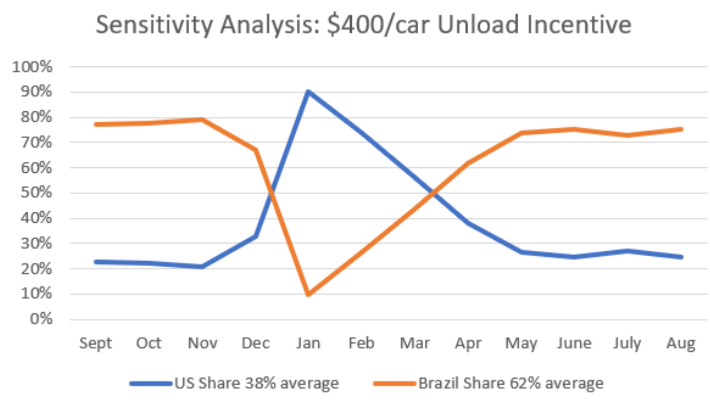

Figure D19: Sensitivity analysis: U.S. and Brazil market share when unload incentives are $400 per car.

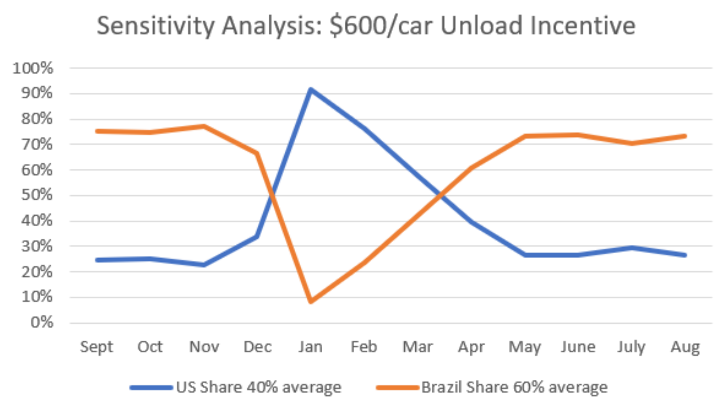

Figure D20: Sensitivity analysis: U.S. and Brazil market share when unload incentives are $600 per car.

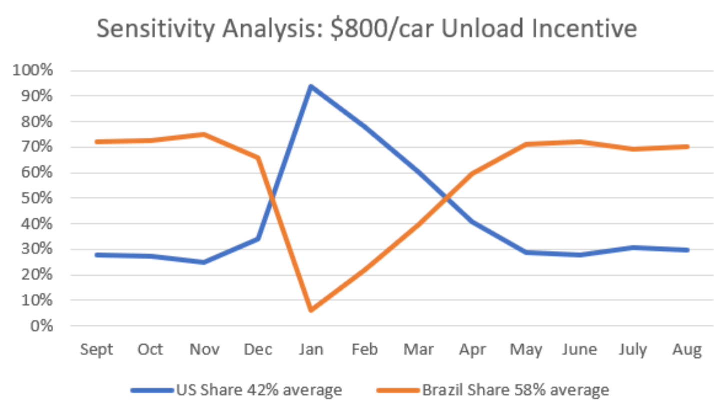

Figure D21: Sensitivity analysis: U.S. and Brazil market share when unload incentives are $800 per car.

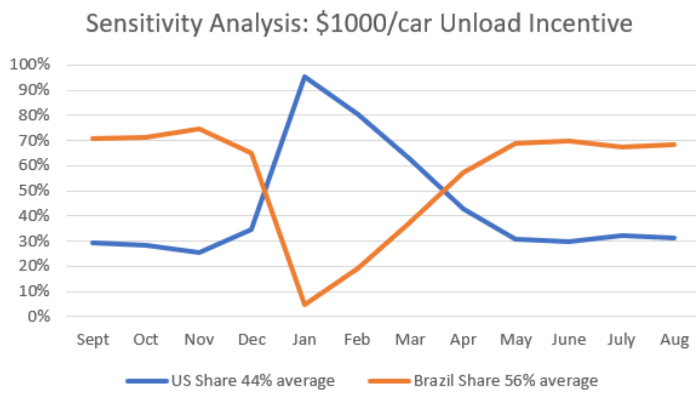

Figure D22: Sensitivity analysis: U.S. and Brazil market share when unload incentives are $1000 per car.

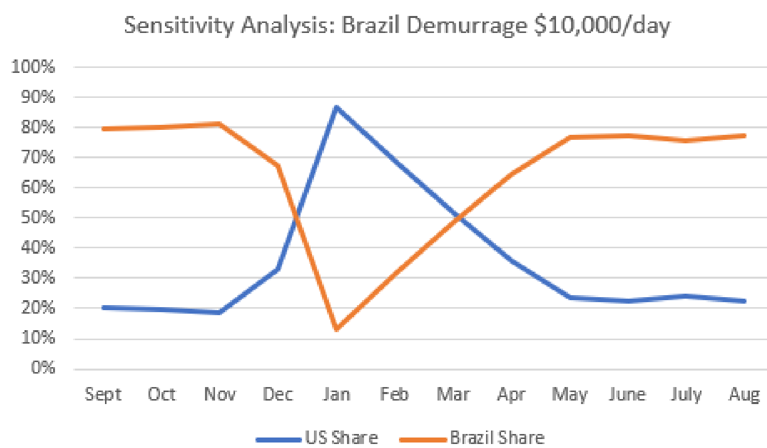

Figure D23: Sensitivity analysis: U.S. and Brazil market share when Brazil demurrage is $10,000 per day.

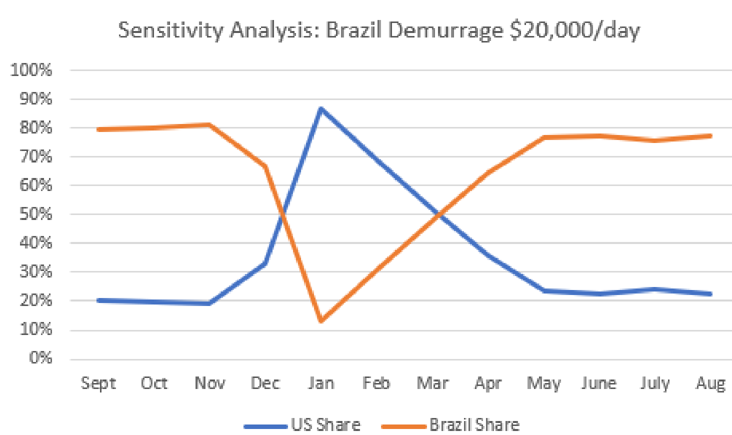

Figure D24: Sensitivity analysis: U.S. and Brazil market share when Brazil demurrage is $20,000 per day.

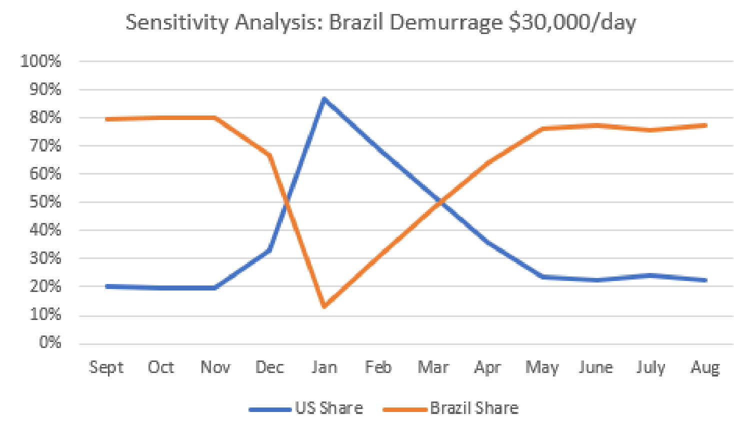

Figure D25: Sensitivity analysis: U.S. and Brazil market share when Brazil demurrage is $30,000 per day.

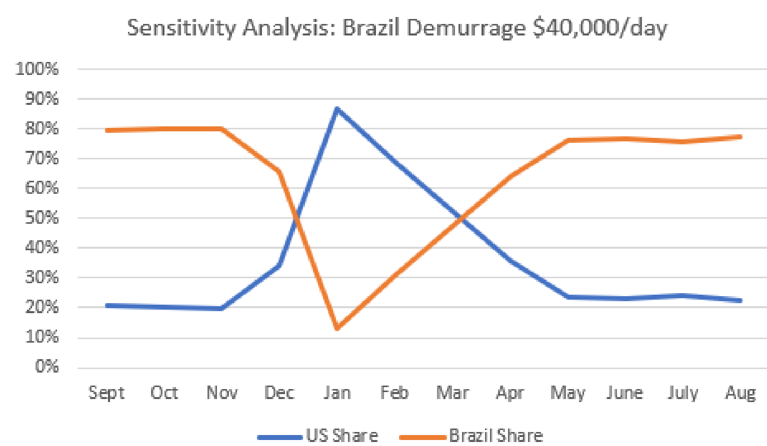

Figure D26: Sensitivity analysis: U.S. and Brazil market share when Brazil demurrage is $40,000 per day.

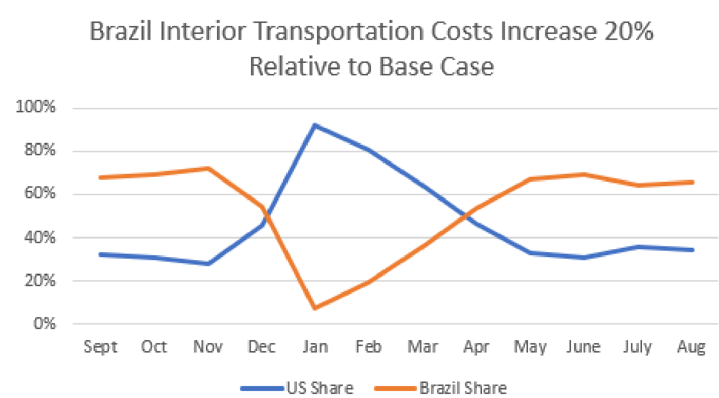

Figure D27: Sensitivity analysis: U.S. and Brazil market share when Brazil interior transportation costs increase 20% relative to base case.

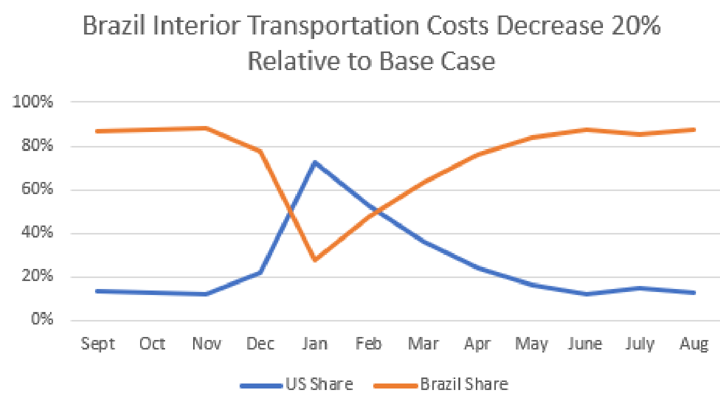

Figure D28: Sensitivity analysis: U.S. and Brazil market share when Brazil interior transportation costs decrease 20% relative to base case.