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SPATIAL AND LOGISTICAL COMPETITION FOR SHIPMENTS TO CHINA FROM THE UNITED STATES AND BRAZIL

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EXECUTIVE SUMMARY

A detailed analysis of the United States versus Brazil competitive share of soybean exports to China requires an optimized, stochastic approach. Using historical data from 2013 to 2019, this study analyzes the optimal share from each country under a variety of historically plausible scenarios for basis and logistics costs. The model includes five interior origins in each country with exports flowing through two ports in the United States (Pacific Northwest and Gulf of Mexico) and three ports in Brazil (Santos, Paranaguá, and the northern arc of ports) to a common destination in China. The model in this study employs a least cost Optimized Monte Carlo approach where a hypothetical exporting firm with operations in both the United States and Brazil faces a fixed export demand from China and chooses the optimal origin-port route combinations to minimize the total delivered cost based upon a Monte Carlo realization of the random origin basis and logistical cost variables that are observed by the decision-maker. The optimal choices are summarized across the total iterations of the model in terms of average monthly shares for each origin. The results from the model indicate that U.S. soybeans command a larger share in the December to March months while Brazil is favored in April through November. In the base case, Brazil captures an almost two-thirds share of the total export market. Additional sensitivity analyses related to the impact of trade disputes, quality discounts, infrastructure improvements, and congestion costs are also provided.

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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

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). Of the global soybean trade, China imports 60%. These three countries are highly interdependent in this trade relationship. Both originating countries have experienced decades of explosive soybean production. Numerous factors that are critically important to the movement of soybeans from the United States and Brazil to China such as internal logistics and quality in each exporting country, in addition to periodic trade interventions that impact these relationships.

Purpose and Scope:

The purpose of this study is to model the current soybean trade between the United States, Brazil, and China by incorporating impacts of transportation, logistics, and structural changes to this very large portion of the global soybean market. The study derives equilibrium crop year market share as a point of focus to demonstrate logistic competition between U.S. and Brazil origins in a spatial and temporal context. 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.

Empirical Model

The model is a least-cost stochastic optimization of soybean shipments from two origins to one destination. The model determines the least-cost origin for each month. Costs include origin basis at five interior locations in each country, interior transportation costs (for the United States, truck, barge, and rail costs, and for Brazil, truck costs), congestion/delay costs in Brazil, and ocean freight. The model contains addition information that allows it to reflect quality discrepancies and trade interventions. Many of the variables are random variables that represent the stochastic component of the model in addition to the risk that the variables pose in the marketplace. The empirical model is formed as an optimized Monte Carlo simulation (OMCS).

A base case scenario is formed by specifying the most appropriate variables and assumptions that model the current Within the sensitivity analysis, the market shares and delivered costs change as Brazil improves transportation efficiency, illustrating the predicted impacts on U.S. market share. An increase in uncertainty in the marketplace, such as a shock, favors U.S. market share.

Contributions

This study 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 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.

2. BACKGROUND AND PREVIOUS STUDIES

U.S. Soybean Production

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. U.S. soybean production was able to expand in output 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.

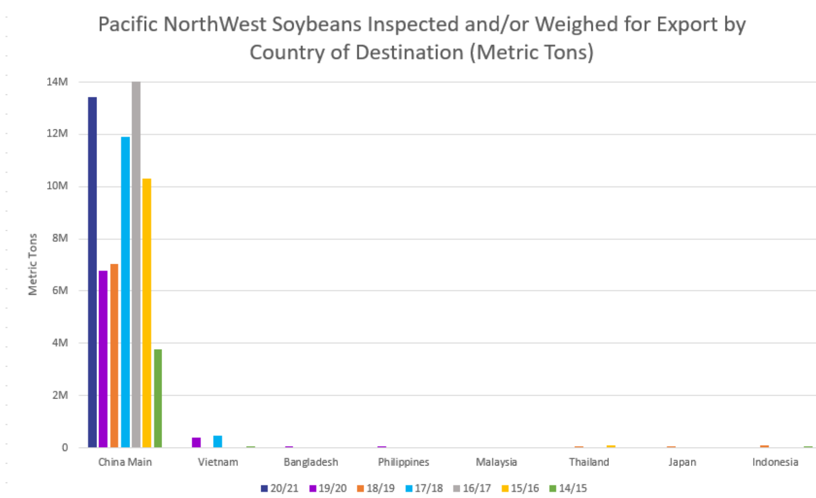

Figure 2.1: PNW cumulative soybean inspected and/or weight for export by country of destination in metric tons (USDA).

The United States in total is less reliant than the PNW is on China. 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.

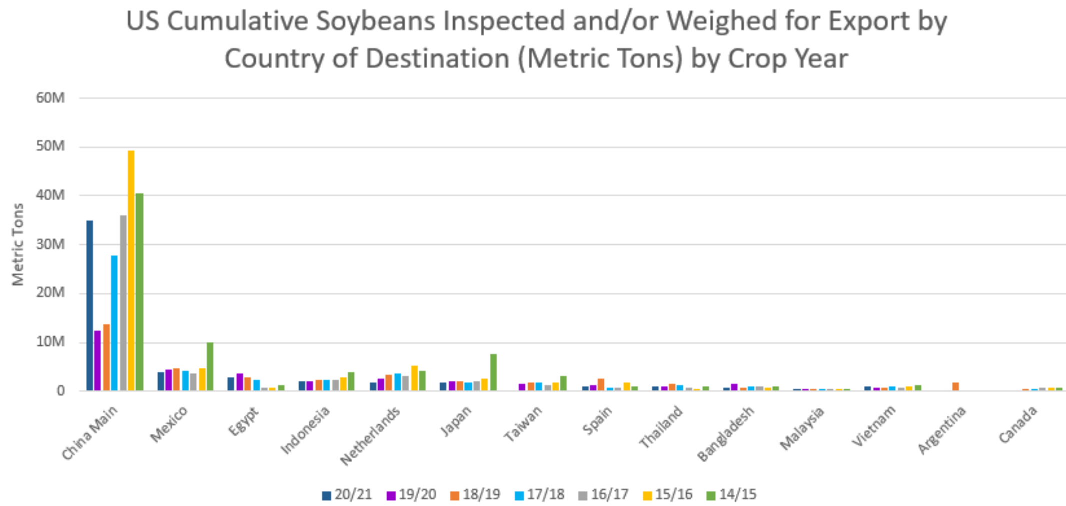

Figure 2.2: U.S. cumulative soybeans inspected and/or weighed for export by country of destination in metric tons (USDA).

Brazil Soybean Production

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). Between 2012 and 2016, Brazil's market share of Chinese purchases 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).

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.

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). Brazil has also proved to be competitive due to higher oil and protein content, and the country’s arable land and production abilities that are unique to its geography.

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 “19^{th} century logistics with 21^{st} 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 Miritituba, 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 several days to just 35 hours and relieved the uncertainty previously presented by the rainy season that in the past has caused travel to port to take week (Salin and Somwaru, 2020). Figure 2.3 displays the state of Brazil’s production and transportation in 2018 (Salin, 2019).

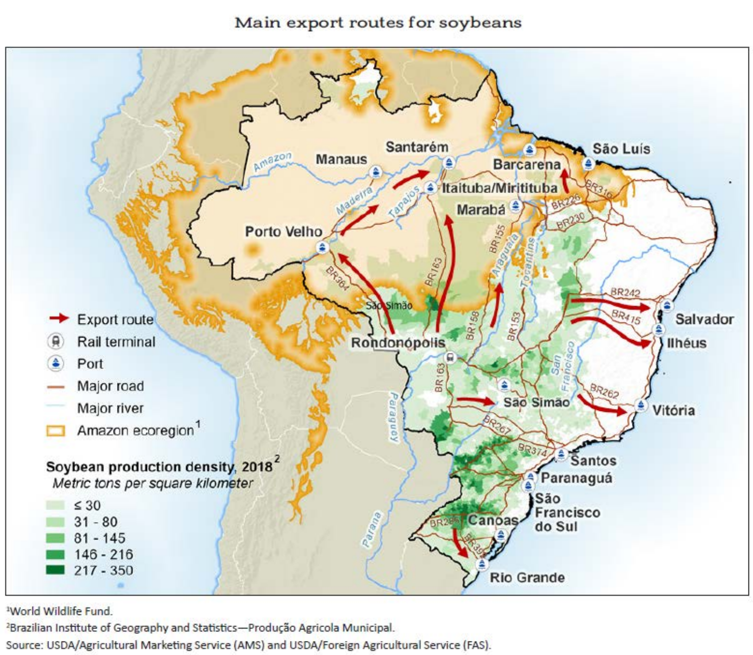

Figure 2.3: Soybean transportation in Brazil (USDA 2019).

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.

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.

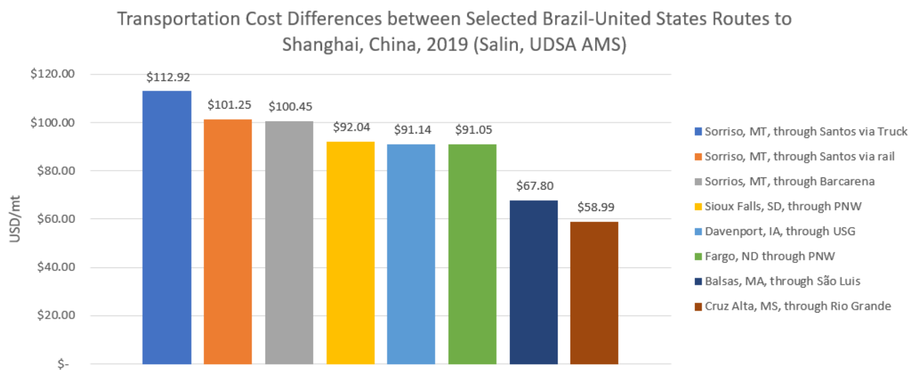

Figure 2.4: Transportation cost differences between selected Brazil-U.S. routes to Shanghai, China, 2019 (Salin, USDA AMS).

Incentives 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 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. China's demand for soybeans is one of the most dominant factors in Brazil's recent expansions in soybean export capacity.

China's Demand for Soy

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 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 as well as produce quality oils. As of 2016 China's own 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 large, with almost 10,000 companies. Most are state-owned, multinational, or private in ownership type, and 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).

Some events have 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. A 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).

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.

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 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 Thompson 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).

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 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 the empirical model.

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, 2019). 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, 2019), 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.

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 include 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).

Previous Studies

The corresponding literature is divided into three areas of focus: basis studies, railing trading within the United States, and spatial arbitrage studies.

Basis

There has been a number of studies that analyze the basis and have important findings relative to this thesis. Many of these studies analyze 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). 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. 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. Additionally, the export basis for a marketing year is more sensitive to interior rail shipping than barge or ocean freights (Bullock and Wilson, 2019).

The defining factors of origin basis has also been analyzed (Baldwin, 1986, Wilson and Dahl, 2011, Hart and Olson, 2017). Wilson and Dahl (2011) found that shipping costs, ocean rate spreads between the USG and PNW, 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. 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). Higher export sales raise origin basis (Wilson and Dahl, 2011, Hart and Olson, 2017). 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). Congestion is a defining factor as well; Steadman et. al (2019) found that 12% to 58% of transportation cost can come from delay costs.

Recently the interaction of terminal and origin basis has been of focus. Hart and Olson (2017) found terminal basis to have a positive statistical significance for origin basis. Lakkakula and Wilson (2020) found that simultaneous discovery of the origin and terminal basis occurs. 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).

Rail Trading Within the United States

The primary rail car market in the United States consists of shippers bidding to secure allocation of cars or trips for a future time period. Price discovery in the primary market occurs through a bid allocation system. The Certificate of Transportation (COT) guidelines contain provisions for forward shipping guarantees and penalties for buyer and/or seller defaults as well as transferability (Lakkakula and Wilson, 2020). 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 consists of the buying and selling of railcars that were purchased in the primary market. 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 are very volatile and can vary between a discount of $1000 USD/car and a premium of $5000 USD/car (TradeWest).

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). A recent report by Wilson, Lakkakula, and Bullock (2021) demonstrates that secondary rail values have significant effects on the total cost of transporting corn from the United States to various destinations and also that decreasing DCV would gain market share for the United States.

Spatial Arbitrage

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. 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.

An additional relevant study is Wilson, Lakkakula, and Bullock (2021) which models logistical competition between corn producing and exporting countries of the United States, Ukraine, Brazil, and Argentina. The focus lies on the two main producing countries, the United States and Ukraine, and they found that the cost advantage for the United States occurs when exporting to China, Japan, and South Korea. Ukraine has the advantage in the EU and Indonesia. Wilson, Lakkakula, and Bullock (2021) guides this study through their use of key variables such as origin basis, barge and rail freight, and ocean rates as well as sensitivity analysis that includes transportation cost changes, structural improvements, supply chain disruptions, and trade interventions.

3. EMPIRICAL SPECIFICATION

The study 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.

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 Grove, 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.

Soybean shipments 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 3.1 displays the origins and ports in each country.

Figure 3.1: Model origin and port locations.

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 3.2 shows the path of soybean from the place of growth to the destination in China.

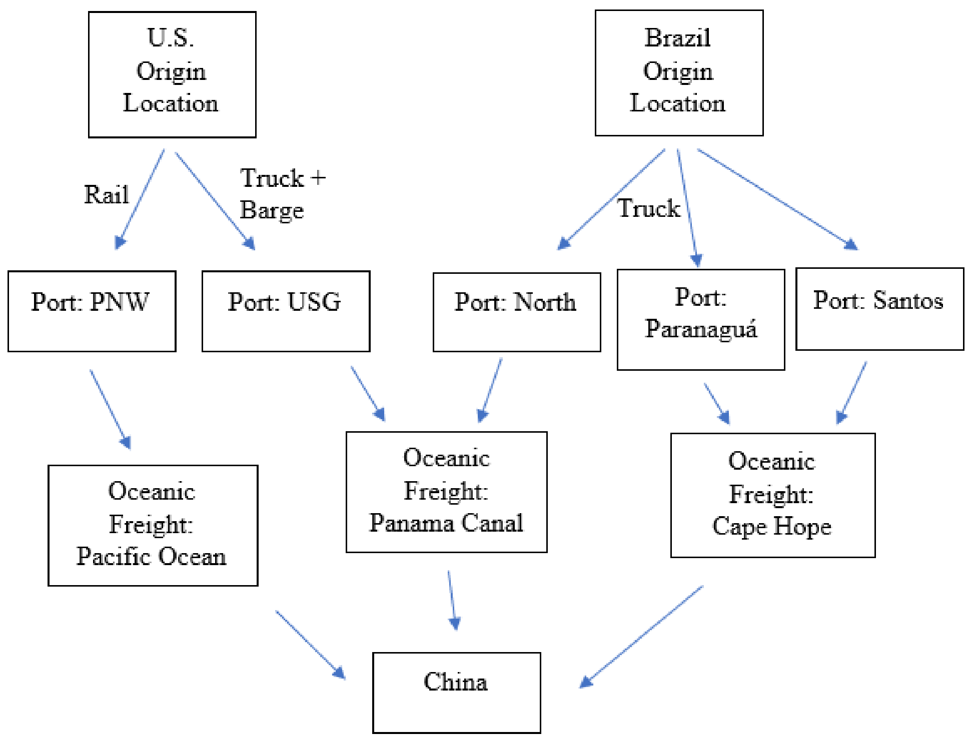

Figure 3.2: Soybean path from origin to destination China.

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.

Mathematical Specification

The model is based on previous work done in a special report by Wilson, Bullock, and Lakkakula concerning spatial competition for wheat exports to Mexico (Wilson et. al 2020) and a concurrent study (Wilson et. al, 2021) that analyze spatial competition in international corn markets using a similar model. 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 a stochastic optimized Monte Carlo simulation (Wilson et. al 2020, Wilson et. al, 2021). 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 is a cost-minimizing spatial model where the optimal soybean procurement location is found for each month. The mathematical expression for Equation 3.1 is as follows:

$$\min_{x_{i,t}} C = \sum_{i=1}^{n} \sum_{t=1}^{12} \tilde{c}_{i,t} \cdot x_{i,t}, \tag{3.1}$$

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.

Detailed Data Specification

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. Basis is equal to the cash price less the futures price.

The interior basis for Brazil origins is shown in Figure 3.3, and the interior basis for U.S. origins is shown in Figure 3.4. Both are displayed from 2013 to 2019, showing the data used in the study.

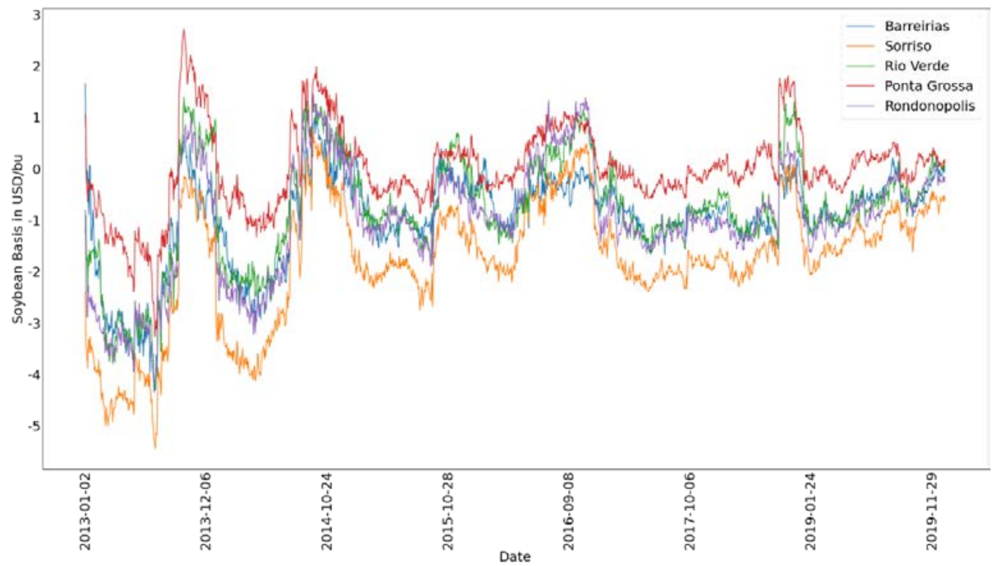

Figure 3.3: Brazil origin basis January 2013 to December 2019.

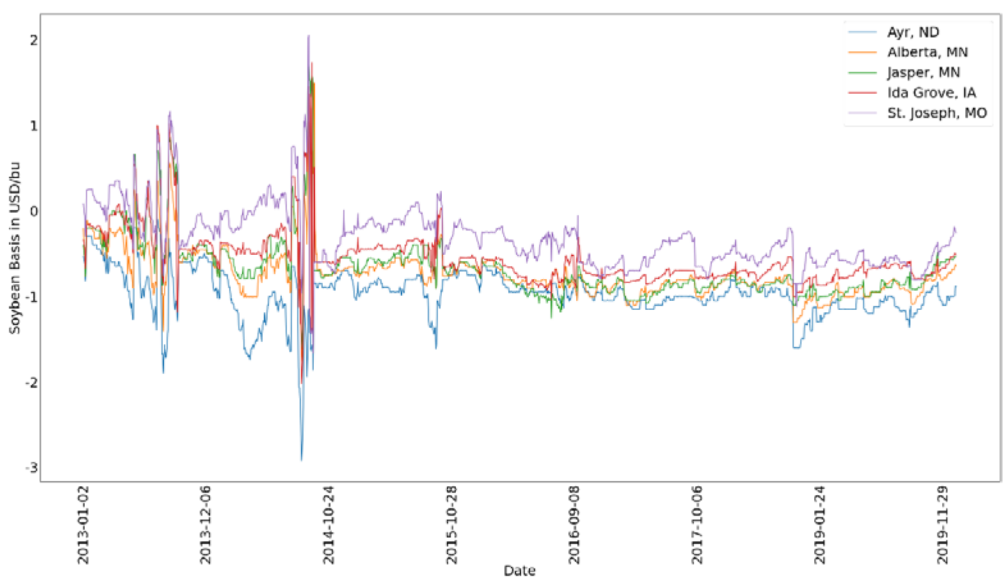

Figure 3.4: US origin basis January 2013 to December 2019.

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.

Interior Transportation Cost

Transportation to ports involves trucking in both countries. In Brazil, only a limited rail system exists, so a great majority of soybeans are trucked to the origins by farmers and then to the ports by trucks as well. Interior shipping costs for Brazil are sourced from 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 3.2 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.

$$JANTransCost_{AyrtoUSG} = MIN\big(Truck_{AyrtoTWC} + JANBarge_{TWC}, Truck_{AyrtoMM} + JANBarge_{MM}, Truck_{AyrtoILL} + JANBarge_{ILL}, Truck_{AyrtoSTL} + JANBarge_{STL}, Truck_{AyrtoCINC} + JANBarge_{CINC}, Truck_{AyrtoLOH} + JANBarge_{LOH}, Truck_{AyrtoCAR} + JANBarge_{CAR-MEM}\big) \qquad (3.2)$$

U.S. soybeans are also transported west via the rail system. This cost is comprised of 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 shown in Figure 3.5.

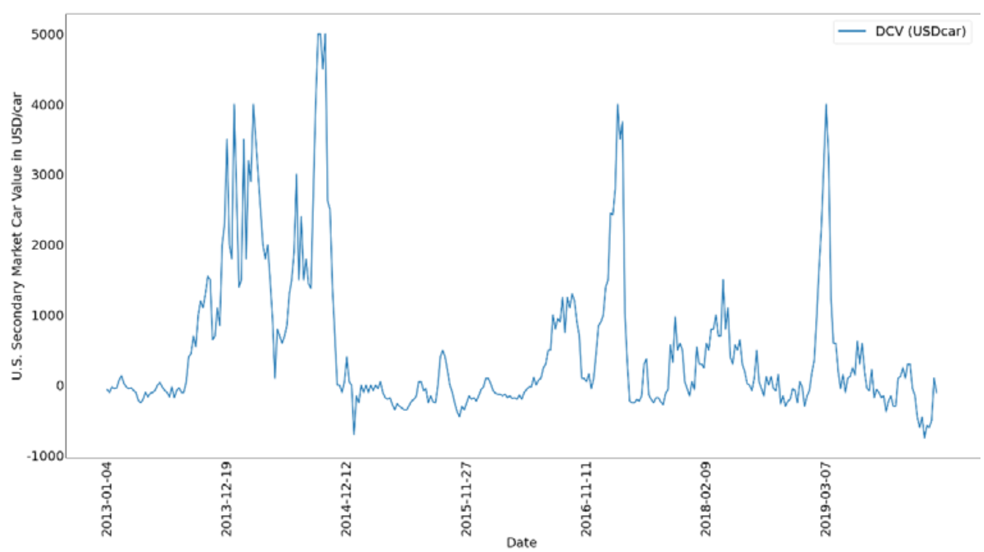

Figure 3.5: Daily Car Value (DCV) from 2013 to 2019 in the United States.

The sum of the constant rail tariff from each origin and the DCV is the total rail cost to the PNW. Equation 3.3 shows the transportation cost example for soybeans traveling west. $JANTransCost_{AyrtoPNW}$ is the shipping costs for January from Ayr to the PNW.

$$JANTransCost_{AyrtoPNW} = JANDCV + RailTariff_{AyrtoPNW} \tag{3.3}$$

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 3.6 displays the monthly average wait times measured in days from 2013 to 2019 for three ports in Brazil, Santarem, Paranaguá, and Santos.

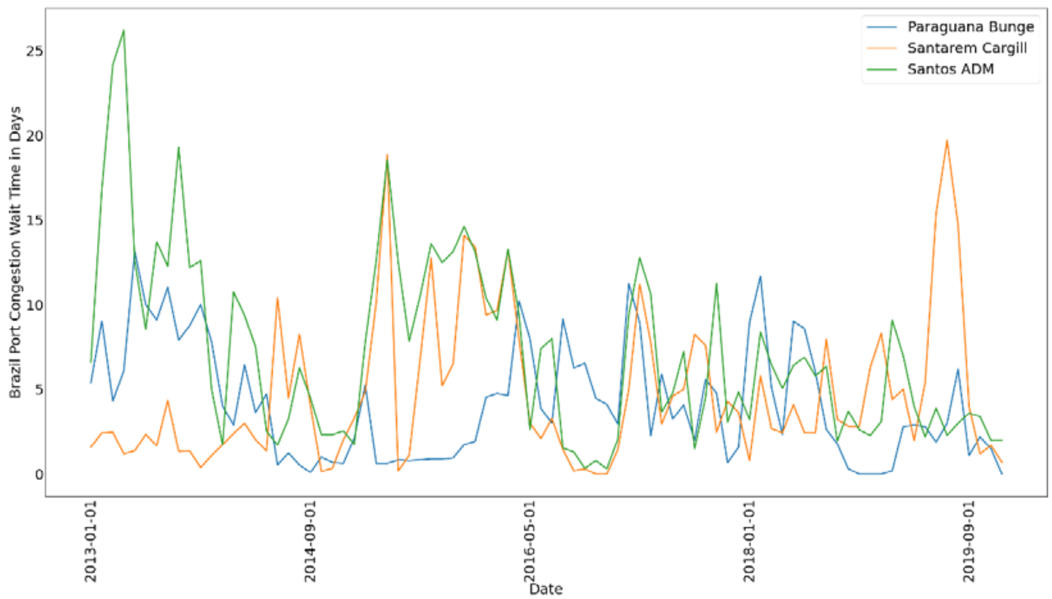

Figure 3.6: Wait times in Brazil from 2013 to 2019 for Paranaguá, Santarem, and Santos.

A distribution of wait times for the ports is derived in the simulation to derive demurrage costs. 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 3.4 shows demurrage cost as an IF function with IF(logical test, value_if_true, value_if_false).

$$DemurrageCost = IF(WaitTime > ExpectedWaitTime, WaitDays * DemurrageRate, 0) \tag{3.4}$$

Ocean Shipping Cost

Ocean shipping 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 3.7 below.

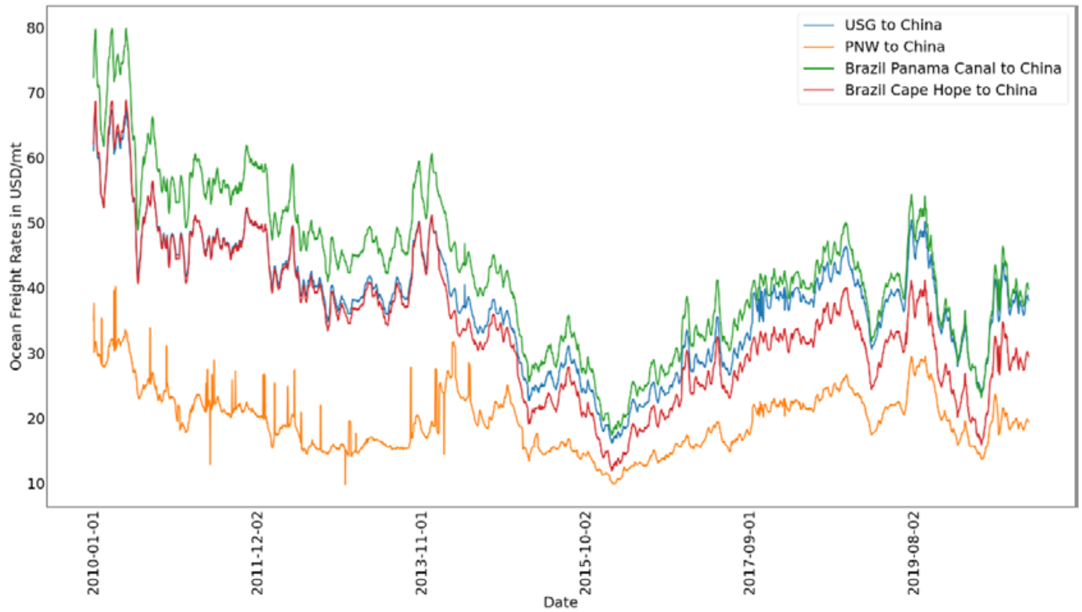

Figure 3.7: Ocean freight rates for USG through Panama Canal, PNW, Brazil through Panama Canal, and Brazil around Cape Hope from 2010 to 2019.

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.

Random Inputs and Best Fit Distributions

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 to monthly averages from which the time series distributions were built to forecast the random values. Random inputs for the model are summarized in Appendix A.

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. The distributions are illustrated in Appendix A. The process and correlations are noted below.

The best-fitting time series distribution for each value is chosen based on Akaike information criterion (AIC). Graphical analysis indicates that series are stationary and homoscedastic; therefore, no differencing was performed, and wide-tailed distributions 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 distribution predicts a forecast length or interval that the user specifies (Palisade Technology).

The first BestFit batch consisted of the Brazil origins, ports, wait days, and Real/USD exchange rate. Table 3.1 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. Of note, the basis values are negatively correlated with the waiting time in days.

Table 3.1: 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. Their correlation matrix is shown in Table 2. 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 3.2: 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

The 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.

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 3.3, and those for the Brazil side are in Table 3.4.

Table 3.3: 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 3.4: 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 other 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 3.5 summarizes the user inputs that are present in the base case.

Table 3.5: 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

Base Case Definition

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. The U.S. transportation costs for soybeans procured through the PNW are aggregated using Equation 3.3, minimized transportation cost to the USG for any origin is described in Equation 3.2 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 3.5 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.

$$AyrthroughPNW_{Jan} = AyrBasis_{Jan} + AyrTransCost_{PNW} + AyrOcean_{fromPNW} \quad (3.5)$$

Equation 3.1 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.

The intuition behind this model is that of a trader planning to sell 1 million metric ton per month to China. These quantities 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.

Sensitivities Definition

Sensitivity analyses were performed to show how the quantity of soybeans shipped from each country changes relative to the established base case. The sensitivities include changing the model to analyze the effects of trade policy, shipping variables, distribution changes, and structural variables.

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

Shipping variables are another set of sensitives. Those examined in the United States include DCV. For Brazil, sensitivities were used to evaluate impacts of demurrage and interior cost reductions. Finally, impacts of quality discounts for US soybeans are analyzed.

Many structural variables influence the market shares as they are distributed between the two countries. One of these is the rail "unload incentive." The incentive represents a payment from the rail company to an exporter for filling or completing a shipment early (RJO'Brien, 2021).

Interior shipping costs in Brazil are static values due to inadequate data to form time series distributions. Interior shipping costs are changing in Brazil as investments in infrastructure are made and demand for Brazilian soybeans grows. The effect of these prospective changes are analyzed in a sensitivity. In addition, reducing vessel wait times would increase Brazilian competitiveness. A reduction in wait time and therefore demurrage costs incurred represents another sensitivity measure.

4. RESULTS AND SENSITIVITIES

The base case model assumes quality discounts of 10 cent per bushel (c/bu) applied to the USG under Brazil, and the PNW port is discounted 15c/bu under the USG (R.J. O'Brien, 2017, Hertsgaard et. al, 2018). The base case assumes 0% import tariffs. 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.

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. These values 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 4.1 below shows the graphic illustration of each countries' market share throughout the U.S. crop year September to August.

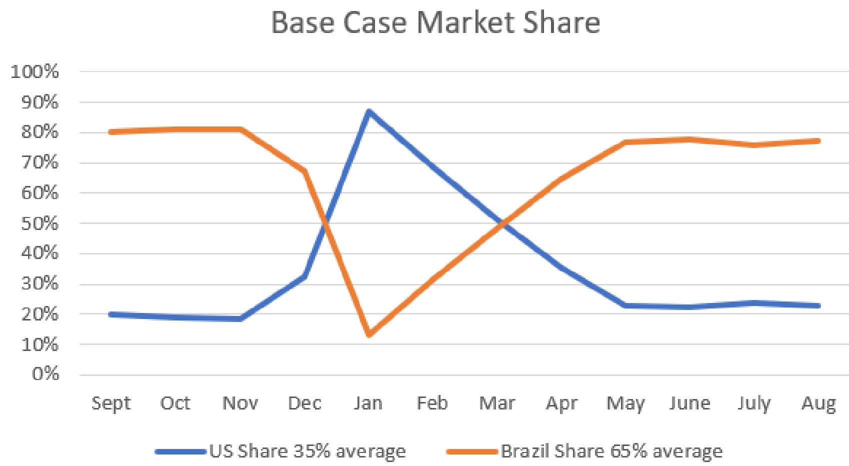

Figure 4.1: Base case market share illustration.

March and in-between December and January 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.

Table 4.1 Base case results: average market share and cost delivered for each month

Month	**Crop Year Share**		**Cost Delivered to China**		
	U.S.	**Brazil**	**From Brazil**	**From USG**	**From PNW**
September	20%	80%	$0.76	$1.63	$1.30
October	19%	81%	$0.73	$1.63	$1.29
November	19%	81%	$0.67	$1.63	$1.29
December	33%	67%	$0.67	$0.82	$1.29
January	87%	13%	$1.57	$1.56	$1.07
February	69%	31%	$1.68	$1.58	$1.19
March	51%	49%	$1.48	$1.60	$1.25
April	35%	65%	$1.20	$1.61	$1.28
May	23%	77%	$0.84	$1.61	$1.29
June	22%	78%	$0.80	$1.62	$1.30
July	24%	76%	$1.01	$1.62	$1.30
August	23%	77%	$0.86	$1.63	$1.30
Average	35%	35%	$1.02	$1.55	$1.26

The delivered price reported is the average aggregated price from the iterations of the optimized Monte Carlo simulation. Figure 4.2 shows the 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. It is clear these results are inversely related to the market shares in Figure 4.1.

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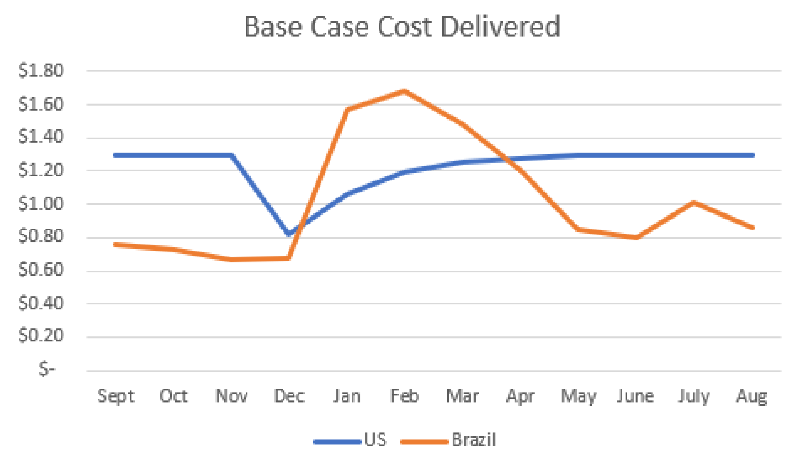

Figure 4.2: Base case cost delivered displayed graphically over the crop year.

The distributions of delivered cost show prospective ranges of costs. The values shown above are averages across all origins and months for each specified market: USG, PNW, and Brazil. Figure 4.3 displays the distribution comparisons for delivered cost from Brazil, USG, and PNW. The width of the cost distribution is a graphical representation of standard deviation Brazil has the lowest average cost, but the widest distribution by far indicating costs from that origin are riskier compared to those from US origins.

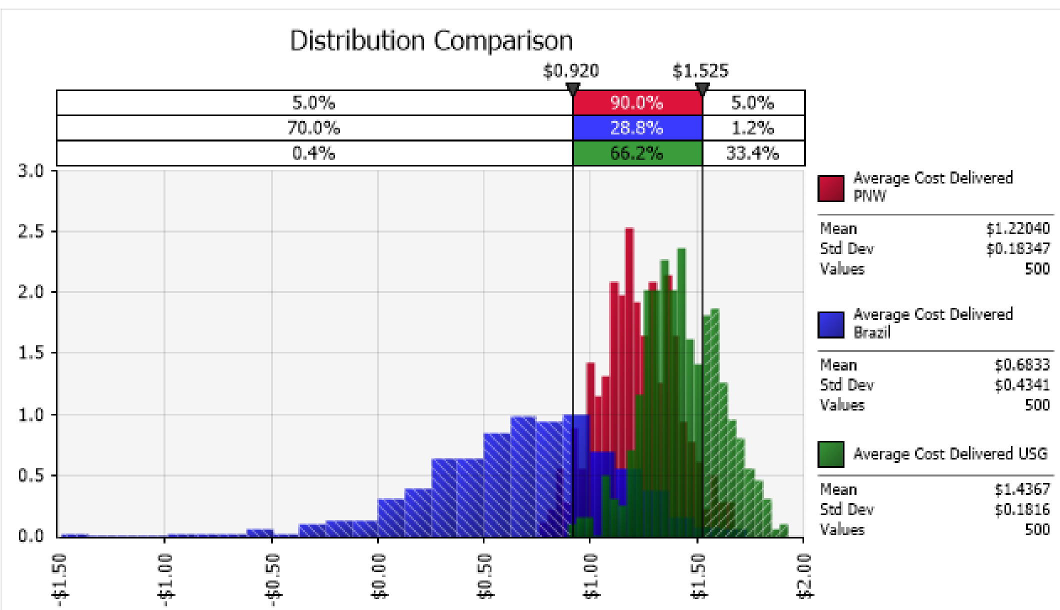

Figure 4.3: Distribution overlay of cost delivered to China from Brazil, USG, and PNW.

Figure 4.4 below shows the composition of these costs across the elements included in 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 comprises the bulk of the cost.

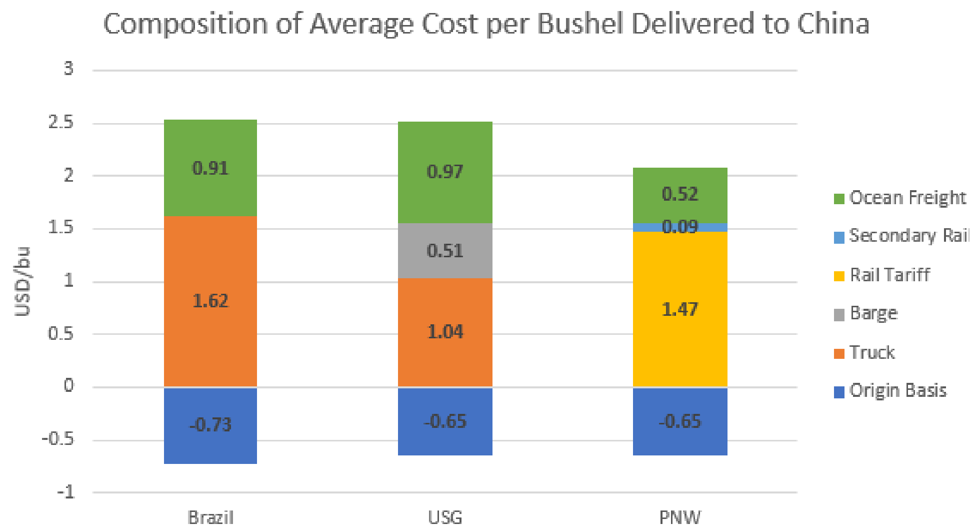

Figure 4.4: Composition of average cost per bushel delivered to China.

An intuitive way to analyze output distributions is through tornado graphs generated across the simulation. A tornado graph ranks random inputs according to how much they affect the specified output cell. Tornado graphs for cost elements delivered through three export locations, USG, PNW, and Brazil, in the very competitive month of March (51% U.S. market share, 49% Brazil) illustrate which variables are ranked important for the simulation outcome. Figure 4.5 shows the tornado graph for cost delivered in China from Brazil in March. 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.

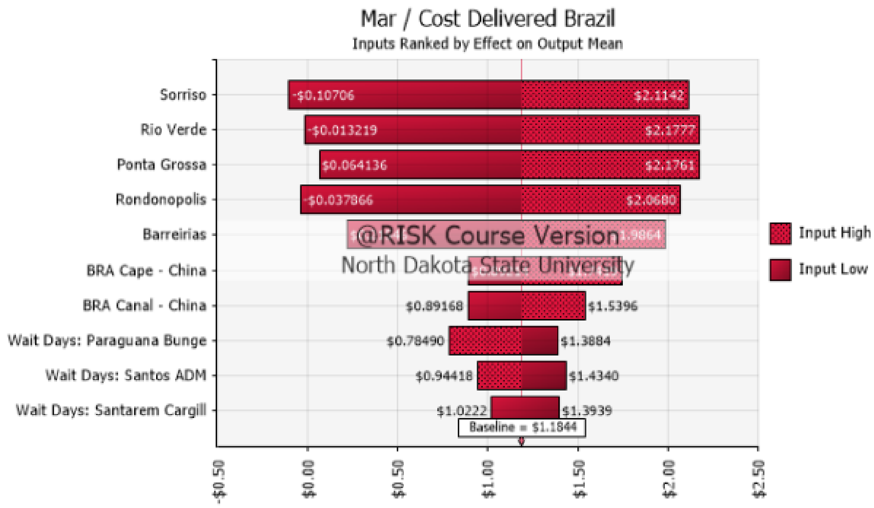

Figure 4.5: Tornado graph: March cost delivered to China from Brazil.

The USG experiences similar input significances. Figure 4.6 illustrates the USG tornado graphs for March. 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, which include the Twin Cities (TWC), Mid-Mississippi (MM), Cincinnati (CINC), Illinois (ILL), Memphis (CAR-MEM), and St. Louis barge loading locations, all of which are ranked as important to the cost delivered through USG in March.

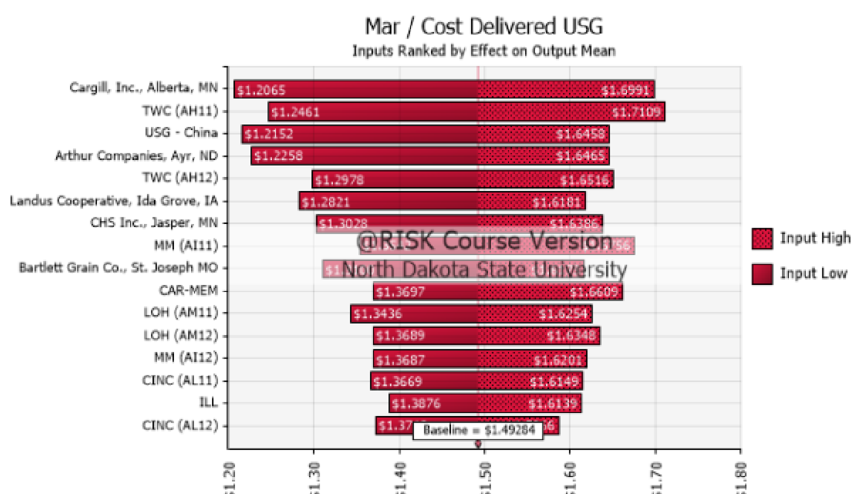

Figure 4.6: Tornado graph: March cost delivered to China from USG.

The PNW tornado graphs are shown in Figure 4.7. 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.

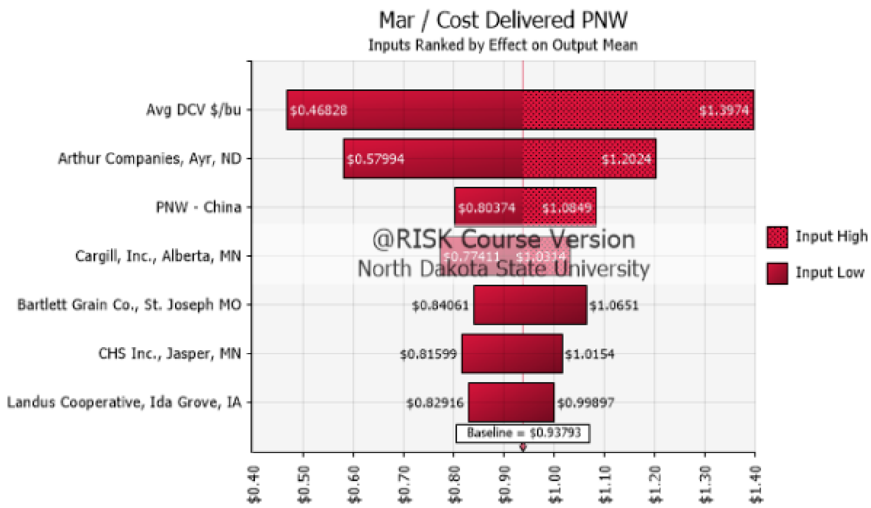

Figure 4.7: Tornado graph: March cost delivered to China from PNW.

Total cost over an average of the simulation has a right-skewed distribution as shown in Figure 4.8. 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.

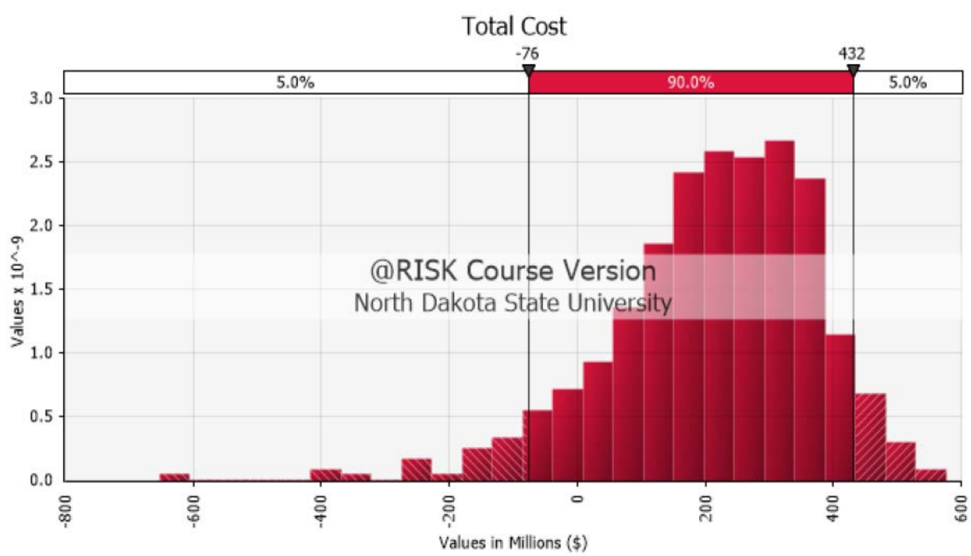

Figure 4.8: Distribution of average total cost delivered to China.

Figure 4.9 shows the distribution of the average crop year market shares for the two originating countries. The center of the distribution, shown by the tallest vertical bar, for U.S. market share is positioned at about 0.35, and that of Brazil is located at 0.65. The distribution shows that the 90% confidence interval has the Brazil market shares falling between 0.33 and

0.91 probability. There is a 0.05 or less probability of Brazilian market share falling below 33%, whereas in the case of the U.S. there is a 0.57 probability of this occurrence. (DB comment : Show just one histogram (U.S. or Brazil) and note that the other country's share is just 1 – the share from other country. Or, you can show the histograms separately (or side-by-side). Because of the linear relationship, the common area of the overlapping histograms does not have any statistical interpretation)

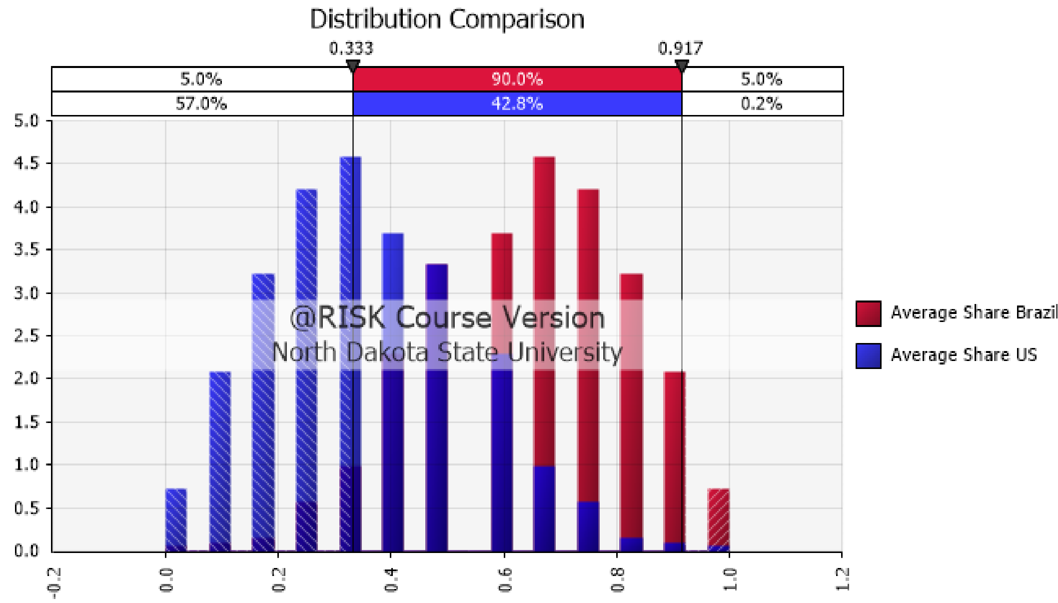

Figure 4.9: Distribution overlay of U.S. and Brazil average market share.

Sensitivity Analysis

This section conducts four sets of sensitivity analysis: trade competition, shipping variables, structural variables, and supply chain interruptions. Table 4.2 summarizes the results from all sensitivity analyses for comparison purposes across the study. Results for each are described below.

Table 4.2: 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
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
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
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
$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
No US Discount	44%	56%	$1.02	$1.45	$1.01
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	51%	49%	$2.62	$3.38	$2.30

Trade Policy/Competition Sensitivities

The base case assumes nil import tariffs on U.S. soybeans. 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 4.3 and Figure 4.10 summarize the trade policy sensitivity.

Table 4.3: 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

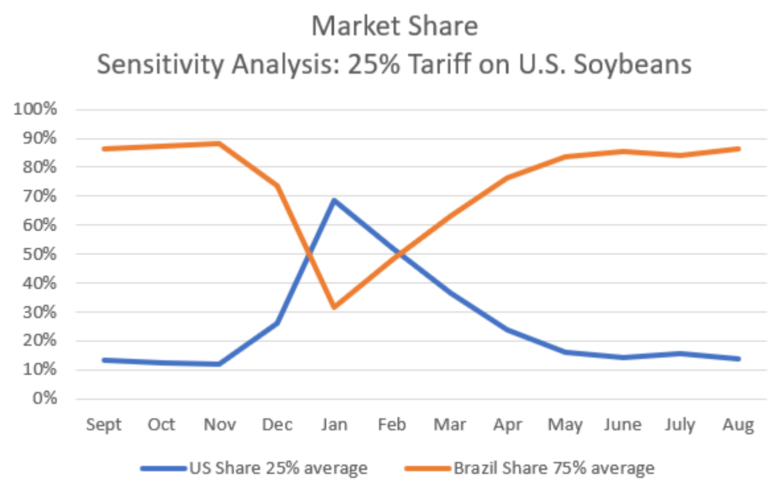

Figure 4.10: Monthly market share results from 25% tariff on U.S. soybeans sensitivity.

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 was simulated to explore the prospective impacts of diversification of purchases, rather than purchase based on minimum costs. The results are summarized in terms of cost and standard deviation of costs (as a measure of risk).

The results are illustrated in Table 4.4 and are very clear. The lowest cost, and risk solution is that of the base case which is the minimum cost solution. The effect of a 25% import tariff on US origin soybean is to raise cost and raise risk substantially. 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 United States. 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 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 reduced, 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 4.4: 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%

Shipping Variables

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 deterministic values from ($1000) to $5000 per car, or -26 c/bu to 133 c/bu, each in its own simulation. The results are in Table 4.5 and Figure 4.11. It is clear that changes in DCV have a very important impact on US market shares. Specifically, as the DCV increases, the US market share declines.

Table 4.5: 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

In these results, the 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, moves 2% of the market share.

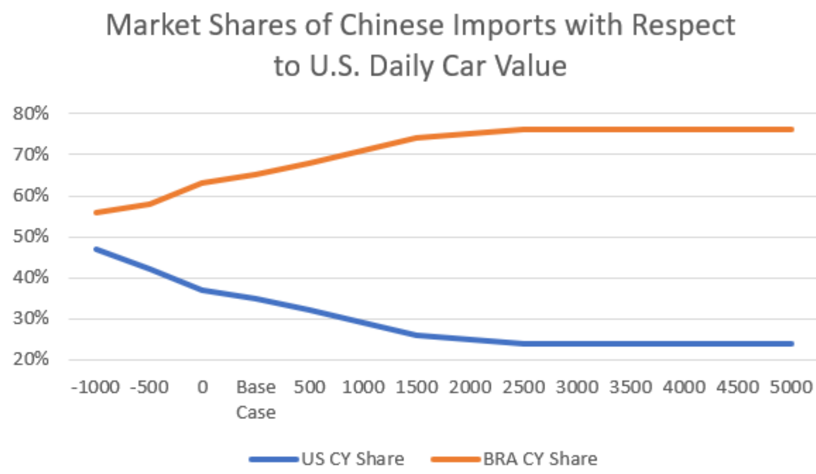

Figure 4.11: Graphic representation of U.S. and Brazil market share as DCV changes.

Ocean shipping costs have important impacts on spatial competition. In this sensitivity, ocean freight is increased from the base case in intervals of 25%, up to 100% increase. Table 4.6 shows results of each simulation communicated as averages across all optimal solutions. Ocean freight rate increases favor for the United States. 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 4.6: 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

Structural Variables

There exist several structural variables that impact spatial competition. One of these is referred as the rail ‘unload incentive.’ In the United States, it has become not uncommon for the rail companies to periodically offer unload incentives to shippers for targeted export quantities. These incentives are designed to make the U.S. supply chain more competitive. In practice, this is a direct payment to the exporter for a targeted quantity/route. These were analyzed in this sensitivity. The results are tabulated in Table 4.7 and Figure 4.12 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 4.7: 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 4.12 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%.

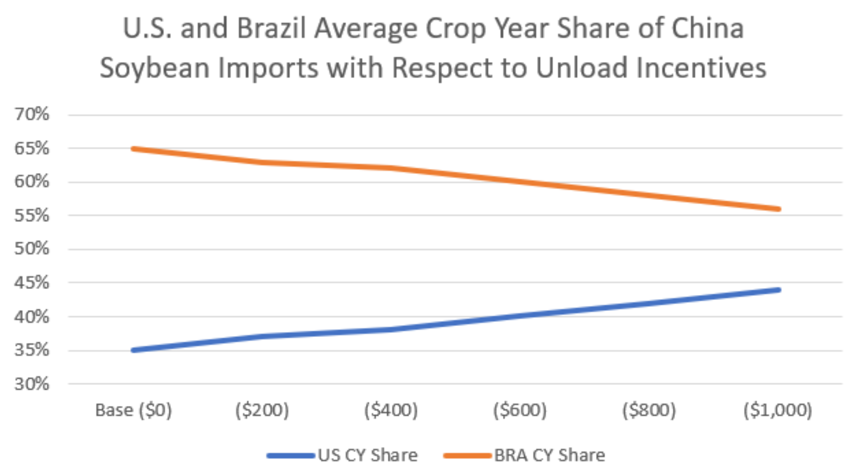

Figure 4.12: Graphic representation of unload incentive sensitivity.

The model was used to approximate the ‘optimal unload incentive.’ In practice, these incentives are targeted, but this analysis shows what the change in market share is when implemented over all. Table 4.8 shows the calculations. The result is that in the base case, an unload incentive of $800 would increase average U.S. market share enough to raise revenue the most. Of course, this value would be highly sensitive to the underlying specification of the base case parameters.

Table 4.8: 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

As U.S. market share grows, it compensates for more than the loss the railroad might expect from offering an unload incentive (Figure 4.13). This simply demonstrates that decreasing the cost of moving soybeans via rail causes more soybeans to move through the PNW, increasing rail revenue. Offering an unload incentive is an expense to the rail company, whereas decreasing cost through controlling for some of the volatility in the secondary car market would impact traders and shippers' cost portfolios. Therefore, it would be more beneficial to the rail company to control for DCV volatility in order to increase the market share moving through the PNW, rather than offer unload incentives to meet export targets.

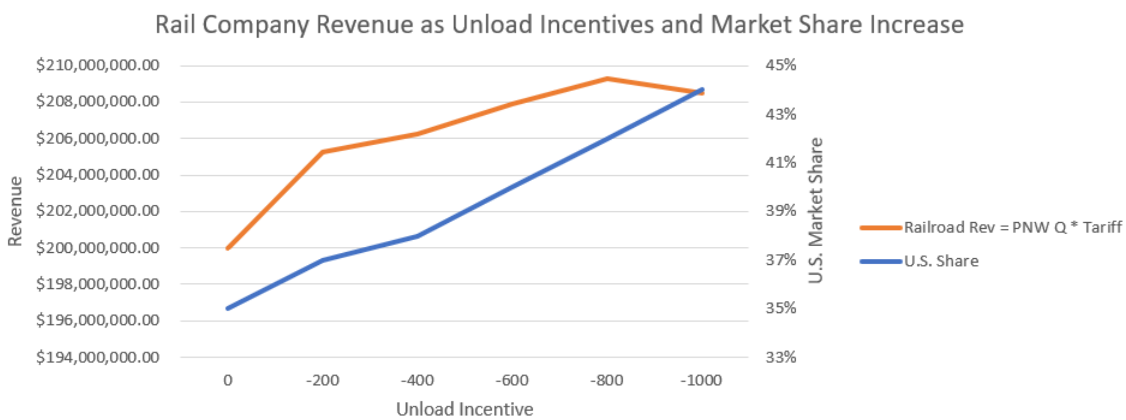

Figure 4.13: Rail company revenue as unload incentives and U.S. market share increase together.

As discussed in the background section, 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. This sensitivity 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 slightly but does not let the Brazilian market share fall below 64% (Table 4.9).

To explore the impacts of changing shipping costs for interior Brazil, 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 4.9: 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 (R.J. O'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 4.10 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 4.10: 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 4.14 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.

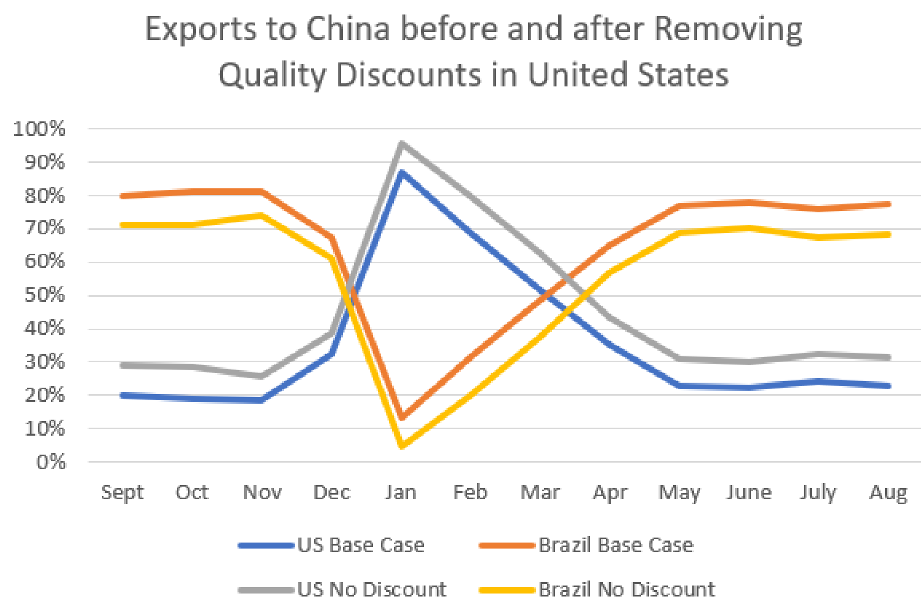

Figure 4.14: Graphic representation of the presence and absence of quality discounts.

Supply Chain Shock

In the period following our base case specification, there has been unprecedented distribution in the supply chain for all commodities. These have also impacted soybean and other agricultural bulk commodities. During this study the world experienced the COVID-19 pandemic which caused shocks in many supply chains right away and also at different lags. 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. The 2015-2019 model is shown alongside the base case results (Table 4.11). 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 4.11: 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	51%	49%	$2.62	$3.38	$2.30

Figure 4.15 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%.

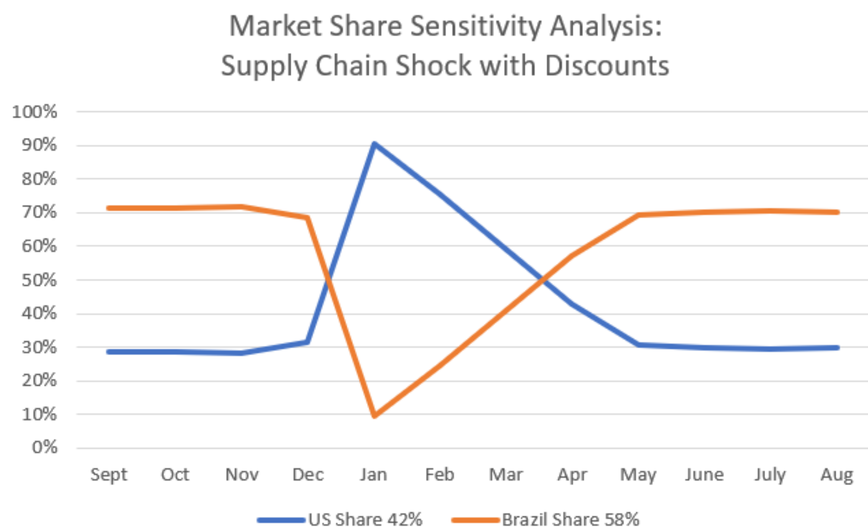

Figure 4.15: Supply chain shock sensitivity results with discounts.

If during this crisis/shock time Chinese buyers do not treat U.S. soybeans as discounted, then the competition is all but gone. Figure 4.16 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%.

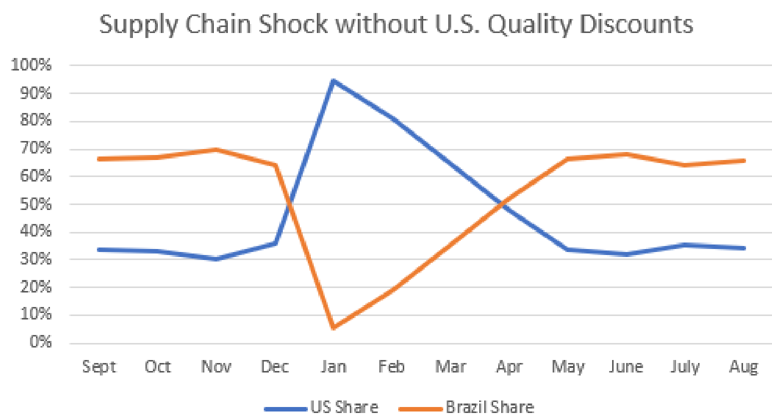

Figure 4.16: Supply chain shock without discounts.

5. SUMMARY AND IMPLICATIONS

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.

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.

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.

Base Case Results

The model was simulated using monthly data between 2013 and 2015. The distribution of average market shares and average cost delivered are reflected in the results.

The base case results indicate:

1) The country with the lower average cost delivered each month captures more market share in that month. Brazil's average crop year market share is 65%; therefore U.S. market share on average is 35% for the crop year. 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%.
2) The average market shares can be and are interpreted as the probability that a location is the least-cost location. Over the crop year, there is a probability of 0.65 that Brazil is the least-cost origin.
3) The most competitive months are March and December, when the difference between the delivered price from each origin to China is so slim that the probability of either location being the least cost origin is 50%.
4) The average cost delivered is comprised of ocean freight, transportation, and origin basis. Transportation costs represent the bulk of the cost composition, and therefore improving logistics presents an opportunity to capture more market share for either origin.
5) The distribution of outcomes for average delivered costs demonstrate how on average overall the PNW and USG have higher delivered costs to China, but their distributions have much smaller standard deviation that Brazil. This means that although Brazil may have a lower mean cost, the origin itself still poses more price risk than the United States.
6) The distribution of average market shares illustrates that Brazil's market share is unlikely to fall below 33% at the 0.90 confidence level. There exists overlap in the two distributions where the true competition occurs.

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 5.1.

Table 5.1: 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
Supply Chain Shock without discounts	51%	49%	$2.62	$3.38	$2.30
Brazil Interior Trans down 20%	25%	75%	$0.72	$1.55	$1.26

The notable sensitivity results indicate:

1) 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.
2) Diversification is demonstrated through measuring the risk associated with three scenarios: a 25% import tariff on U.S. soybeans, 100% of soybean purchases originating from the United States, and 100% soybean purchases originating from Brazil. In regard to the import tariff, the U.S. still garners some market share due to diversification of risk. Brazil is shown to be the lower cost option, but the standard deviation of cost is much larger than that of the 25% tariff or 100% U.S. purchases, demonstrating that pursuing a least-cost scenario without regards to riskiness is not favorable for Chinese buyers.
3) 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.
4) 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.
5) 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.
6) 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.

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 model demonstrated the need for diversification either as a trader, the government of China or as a Chinese buyer. The results show that China would be subject to more risk and cost 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 relates to soybean quality. It is common knowledge that U.S soybeans are discounted for quality relative to Brazil. 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 the background, 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 costs are more stable than Brazil's, but transportation costs in the United States are frequently higher. This paper demonstrates how any rise in transportation costs in the United States causes market share to be transferred 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.

Limitations and Further Research

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 consider 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 the background section, 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.

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

Further Details about the Empirical Model

Table A1: 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 A2: 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

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.

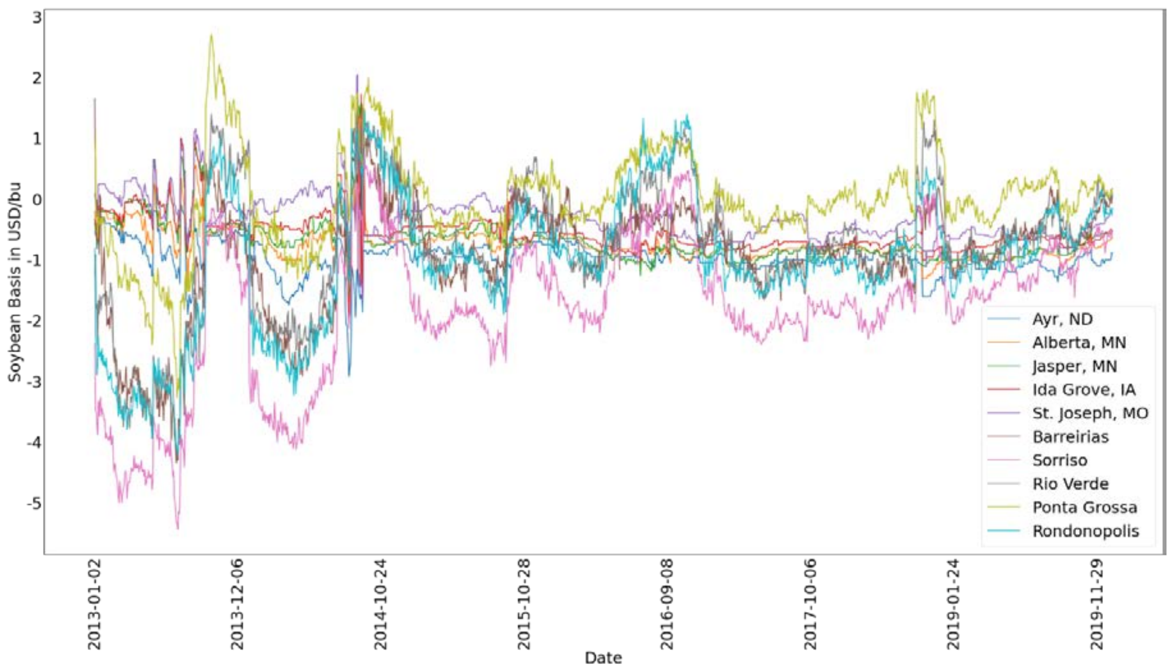

Figure A1. Origin basis (Thomson Reuters Eikon, DTN *ProphetX)*

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.

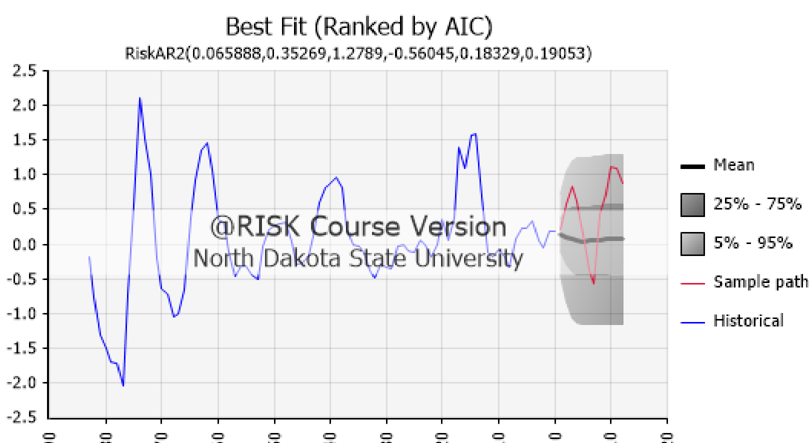

Figure A2: Time series forecast of Ponta Grossa, basis (@Risk).

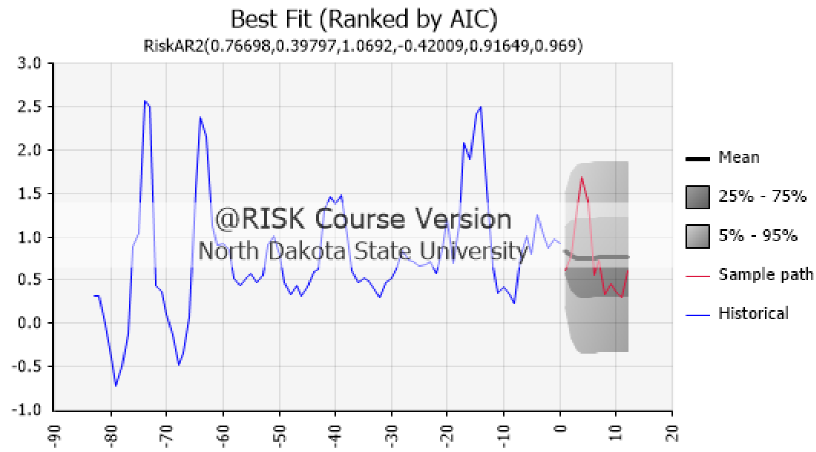

Figure A3: Time series forecast of FOB Paranaguá basis (@Risk).

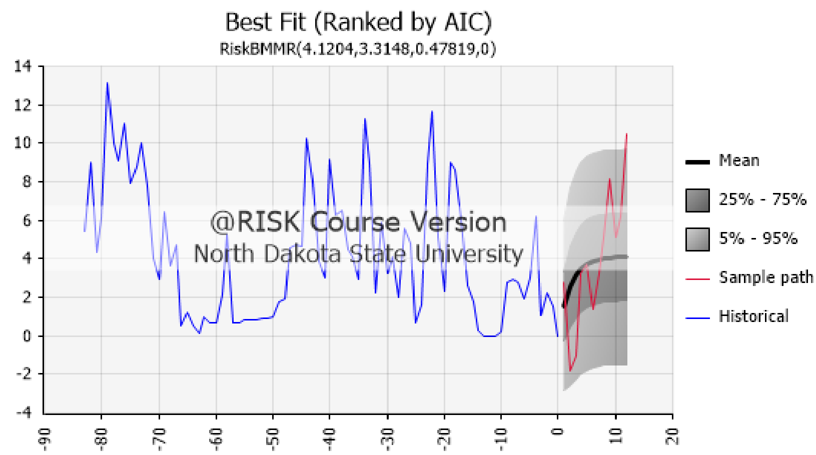

Figure A4: Time series forecast of Paranaguá Wait Days (@Risk).

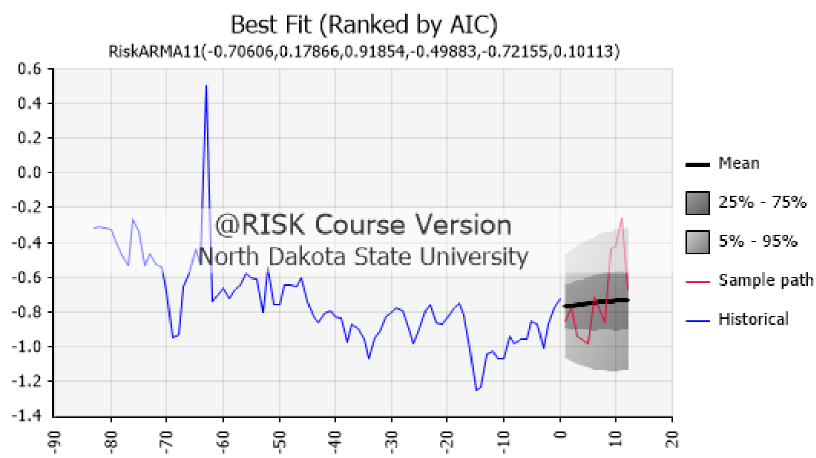

Figure A5: Time series forecast of Alberta, MN basis (@Risk).

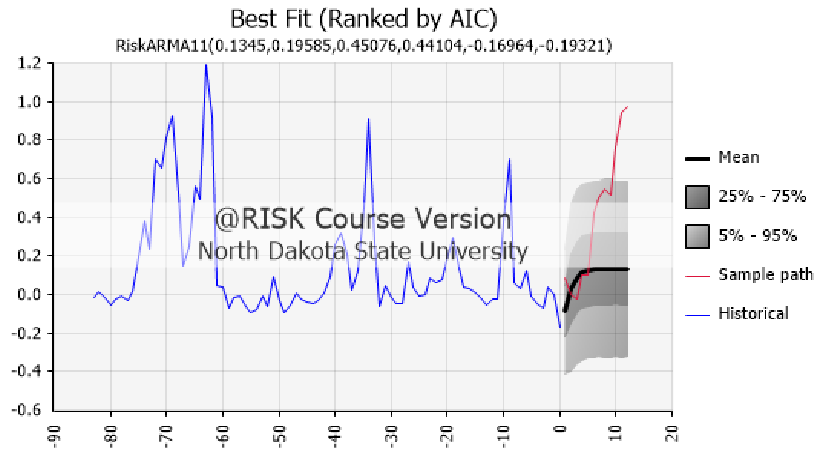

Figure A6: Time series forecast of DCV (@Risk).

Table A3: 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

Table A4: 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 A5: 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

Risk-Optimization Procedures

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 A6: 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.

APPENDIX B

Further Results

Alternative Time Span

The origin basis prices are displayed from 2013-2019 as shown below in Figure 5.17, and 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.

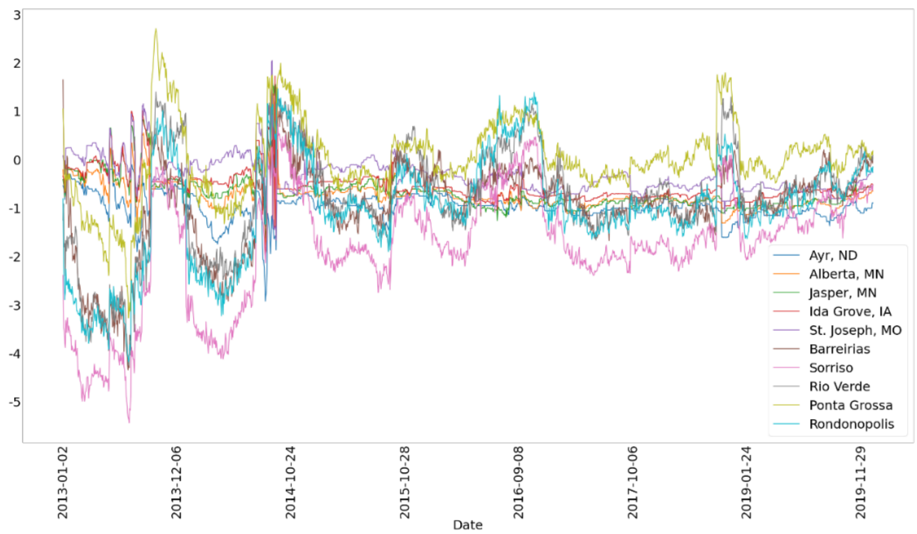

Figure B1: Origin basis prices over time.

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 B1: 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 _ 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.

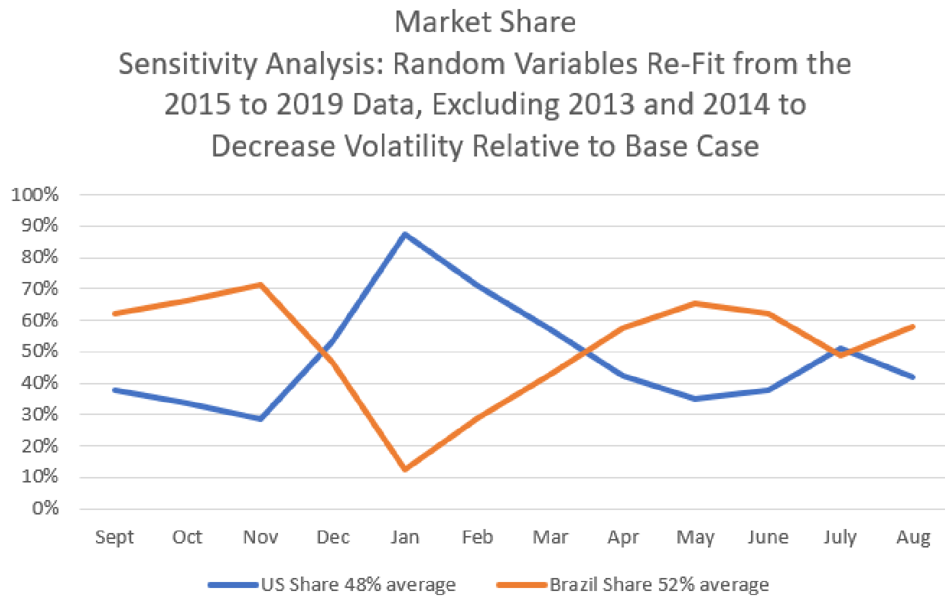

Figure B2: Sensitivity results random variables re-fit excluding 2013 and 2014.

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.

$$Residual_i = \sum_i reported\_port\_basis - \sum_j cost\_to\_port \qquad (5.1)$$

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 B2: 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.

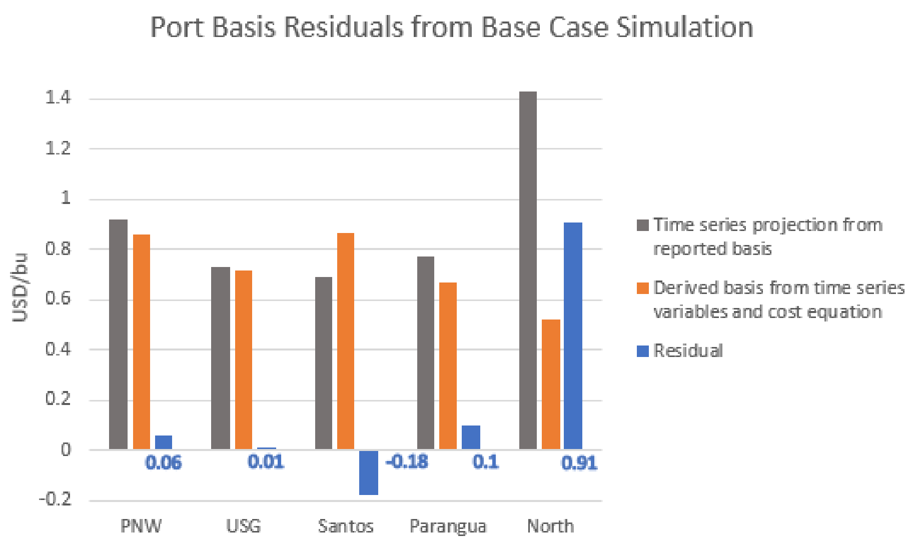

Figure B3: Port basis residuals from base case simulation.