VALUING ORIGIN SWITCHING OPTIONS USING MONTE CARLO SIMULATION

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Valuing Origin Switching Options Using Monte Carlo Simulation

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ABSTRACT

Commodity trading firms work to remain competitive in the evolving agricultural industry. They work to become more efficient by increasing economies of size and scale, vertically and horizontally integrating, and diversifying geographically, or any combination of these avenues. Geographically diverse firms have access to multiple origins between which, spatial arbitrage opportunities can occur. When spatial arbitrage opportunities occur, firms take advantage of them to generate profit. Origin switching options are one way to take advantage of these opportunities. Origin switching option allow the seller of grain to fill a contract with any listed origin at the cost of the premium negotiated. This thesis helps to determine the value of these origin type switching options by developing a Monte Carlo simulation model with real option analysis. Soybean and corn markets are analyzed in the U.S. Gulf, Pacific Northwest, Brazil, Argentine, and origins with China and Japan as the respective destinations.

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CHAPTER 1: INTRODUCTION

Overview

Commodity trading is becoming more competitive every day. Small commodity trading firms struggle to compete with the larger firms which continue to grow. Larger firms can take advantage of opportunities unavailable to smaller firms. Larger firms can continue to invest in strategic assets that help to give them the competitive advantage over said smaller firms. These strategic investments must be analyzed which is often done through the process of real option analysis (ROA).

There is also risk and uncertainty in commodity trading. Price risk is a concern for commodity trading firm and something firms need to do their best to mitigate. Hedging is useful in helping to mitigate price risk. This is often efficient, but with the current landscape of the commodity industry, likely not enough. Firms must continue to remain competitive and be creative in generating more profit through avenues that are uncommon or even unheard of.

A couple of things that commodity trading firms can do and have been doing is going through processes of mergers and acquisitions. Larger firms are generally more competitive. These firms are not just merger with or acquiring any firms though, these firms are analyzed carefully to ensure that merging or acquiring another company is beneficial to both parties. The ROA is often a useful tool to analyze the deals that are presented to the firms. Benefits that the commodity trading firms are looking for include, but are not limited to vertical and horizontal integration, economies of size and scale, or geographical diversification, to name a few.

Mergers and acquisitions for the purpose of geographical diversification is becoming more prevalent as the global commodity industry continues to become more interconnected. The current commodity trading landscape is a great example of the global commodity industry working as one. The U.S. – China trade war and COVID-19 pandemic have put a lot of strain on the global commodity trading industry. In either case, there is a simple rule of supply and demand that applies. When there is a shortage of a commodity in one area, there is a shift in markets to fill that void.

The value that is generated off the shortage in one area is known as a spatial arbitrage opportunity. This is the value difference between two geographically diverse origins. Spatial arbitrage can be captured by commodity trading firms that are geographically diverse but is lost in cases where the firm is not geographically diverse or only has access to one origin. This thesis develops models that use real option analysis to value geographically diverse commodity trading firms by analyzing the value of an option that gives the owner the ability to switch between two or more origins to originate grain from.

Problem Statement

Switching options in the general sense, have many different applications. They are useful in modeling and analyzing flexible facilities with the ability to switch commodity inputs and outputs, switching processes, or switching between origins (Pinto et. al, 2007; Dockendorf and Paxon, 2013; Johansen and Wilson, 2018).

Commodity trading firms are working to become more geographically diverse to mitigate risk and position themselves to take advantage of spatial arbitrage opportunities that arise. Strategic acquisitions and mergers can help to improve spatial arbitrage opportunities that the commodity trading firm is able to participate in.

Access to multiple origins can be viewed as a switching type real option that allows the seller of the grain the ability to ship grain from any origin, they have access to. The ability to ship from any origin would be granted by the buyer of the grain for an agreed upon price. This application of the switching option would be compared to a long call option, where the "strike price" would be the minimum cost origin. Firms with access to more origins can ship out of more locations which leads to greater amounts of spatial arbitrage opportunities. The value of this switching option can be evaluated using real option analysis.

Purpose for Research

The purpose of this thesis is to develop a model that determines the real option value of a switching option from the perspective of a commodity trading firm. The goals of this thesis are broken into three main sections:

1. Develop a base case model as a standard for comparison based on specifications that are adjusted in further sensitivities. The option value calculated in the base case is used as the standard to determine how each sensitivity affects the option value.
2. Develop sensitivities that analyze a change in inputs and analyze how the option value shifts after making said change. The option value of the sensitivity is compared with the base case to determine what affects the change in inputs have on the option value.
3. Analyze the option value by adjusting the "sharing parameter" to determine the profitability of the option at varying percentages of option value paid in the form of premium. The parameter is adjusted to determine how profitable the option could be at each level of premium paid.

Procedures

This thesis develops models using real option methodology and analyzes both soybeans and corn. Both are similar with key differences specific to the commodity. Different time periods were used for each respective commodity, and corn has an additional origin in a couple of sensitivities. This will be explained in greater detail further on in this thesis.

Both commodities followed the same general process for generating models to calculate option values. Each data set is tested and analyzed before fitting the data with proper transformations. Bestfit™ in Palisade's @Risk™ fits the data after proper transformations have been made. @Risk™ then projects data a set number of data points following the most recent data point. These projections are done for basis and freight. The basis and freight are then added together to determine the net price projections. The net price projection of the minimum cost origin is compared to the net price projection of the U.S. Gulf origin to determine the average option value. Monte Carlo simulation then runs multiple iterations to allow the values to all converge and determine more accurate mean values. Sensitivities are conducted to see how changes in inputs affect the mean option value.

Organization

The remainder of this thesis is divided into five more chapters:

- Chapter 2 provides background and previous studies related to spatial arbitrage and switching options.
- Chapter 3 develops an analytical framework related to real option analysis related to switching options.
- Chapter 4 applies the previously developed analytical framework in an empirical application of a switching option in the international grain market.
- Chapter 5 calculates and explains the results of models previously developed.
- Chapter 6 summarizes and discusses the findings in practical applications.

Chapter 2 provides background in spatial arbitrage, real option, analysis, and switching options. The review of spatial arbitrage discusses commodity trading firms attempting to become geographically diverse to take advantage of spatial arbitrage opportunities. The review of switching options discusses other's attempts to value switching type options using real option analysis.

Chapter 3 presents the analytical framework of real option analysis and its relation to switching type options. Chapter 3 develops framework on financial options as well do help develop their application in the real option analysis. Chapter 3 also presents details of Monte Carlo simulation and its implementation in this thesis.

Chapter 4 applies real option analysis in origin switching options in soybean and corn markets. The application analyzes the two markets and determines the best origins and destinations to use. The data is analyzed further. The application then develops a base case scenario along with sensitivities to determine how changing the inputs effect the option value.

Chapter 5 presents the option values through the models developed previously. The option values of the sensitivities are compared with the option values in the base case of each respective commodity. The option values for the base case are then used to determine the profitability of the option when paying varying premiums ranging from 25-100% of the mean option value.

Chapter 6 summarizes and discusses the results from chapter five further. Chapter 6 also includes the implications that this study has and recommendations of future research on the topic.

CHAPTER 2: BACKGROUND AND PREVIOUS STUDIES

Introduction

The goal of commodity trading is to gain a competitive advantage to create a more successful firm. A commodity trading firm can gain a competitive advantage by unloading grain quicker, having better infrastructure, having access to more markets, or decreasing the cost per unit of a good, to name a few. Commodity trading firms that capitalize on their competitive advantages become more successful, more prominent competitors. They also have more longevity and can sustain tough times.

Economies of Size and Scale

One avenue to become more competitive is economies of size and scale. Economies of size and scale is increasing the number of units handled to decrease the fixed and variable costs per unit produced or handled (Kenton, 2020). Commodity trading firms can increase the size or scale of their company in a few different ways. The first way would be to build a new facility. This could include building a new elevator or a new processing facility. It is very expensive to do so because of the land purchase costs along with new buildings, storage, or processors. In addition to that, if the facility is to have rail or barge access, it may be difficult due to limited area along the rail and river systems. Many commodity trading firms would go another route to increase their size and scale: mergers and acquisitions.

Mergers and Acquisitions

Mergers and acquisitions in the commodity trading industry are not uncommon. Mergers and acquisitions are one way for commodity trading firms to increase the size and scale of their company and decrease the per unit cost to handle grain or other products. An example of this would be the merger approved on February 1, 2018 between Wheat Growers and North Central

Farmers Elevator to form Agtegra Cooperative in Aberdeen, SD. By merging, the cooperative was able to better serve their patrons and decrease inefficiencies. Although the locations of the two Legacy cooperatives were near each other and had overlapping draw areas, there were inefficiencies in the logistics. The way that most elevator chains work is that they would have a few larger shuttle loading facilities and more truck loading facilities. The truck facilities feed into the shuttle facilities to get the price advantage of shipping grain via shuttles. A shuttle is a train with 100-115 cars, that can hold up to and around 400,000 bushels, depending on the type of car, number of cars, and the commodity being shipped. While shipping via rail, commodity trading firms can receive load incentive to load their shuttle within a certain period. The incentives make it cheaper to ship grain and increase in the profitability of commodity trading firms. This is just one way that a merger or acquisition can make a commodity trading firm more competitive.

Geographical Diversification

There are getting to be fewer commodity trading firms, but these commodity trading firms are continuing to increase in size. Meersman et al. (2012) attribute this to the firms working to increase their geographical diversification. Geographical diversification through mergers and acquisitions is another way to make a commodity trading firm more competitive. More geographically diverse commodity trading firms can participate in more markets that have greater price differentials. This is also a way for commodity trading firms to reduce risk by participating in multiple markets. Certain areas can become less profitable due to seasonal or long-term trends in the commodity market. When those areas become less profitable, the geographically diverse commodity trading firms can participate in other, more profitable markets.

Meersman et al. (2012) and Johansen and Wilson (2018) both illustrate that there is a trend towards larger commodity trading firms through mergers and acquisitions in order to become more geographically diverse. The trend shows that commodity trading firms are working towards greater geographical diversification to help reduce risk and increase profit opportunities. Meersman et al. (2012) states, “Baar-based commodity trader Glencore International recently bought the Calgary-based global food ingredients company Viterra Inc. for $6 billion.” Glencore is working to increase their geographical footprint by expanding into Canada. This expansion would give Glencore International the ability to take advantage of the profit opportunities that arise from that market. Meersman et al. (2012) did not stop there though, they finish their statement saying, “… just months after announcing a nearly $80 billion merger with Zug-based mining giant Xstrata.” The quote from Meersman et al. shows that both mergers and acquisitions are occurring in commodity trading firms throughout the world. Glencore International expanded and increased geographic diversity by purchasing Viterra Inc. and merging with Xstrata. Glencore International is an example of a commodity trading firm that is going through both avenues to become more geographically diverse.

Johansen and Wilson (2018) refers to multiple mergers and acquisitions and specifically states that these mergers were for the purpose of increasing the commodity trading firm’s geographical footprint and available optionality. Johansen and Wilson indicated Archer Daniels Midland’s (ADM’s) work trying to acquire GrainCorp in 2013. In ADM’s statement, they stated that GrainCorp would be an advantageous acquisition to ADM due to the geographical footprint that GrainCorp would bring as well as the grain they handled. ADM also mentioned that it would be complementary to the assets that ADM had already. This acquisition would have allowed ADM to become more competitive in the international grain market by increasing ADM’s geographical diversification. ADM's motives were also very strategic because the new locations that they would acquire would complement their current locations and not be in direct competition of their current locations.

Vertical Integration

Another acquisition that Johansen and Wilson (2018) reference is Japanese commodity trading firm, Marubeni's acquisition of Gavilon in their pursuit to become more vertically integrated and eliminate the middleman. Gavilon is a commodity trading firm that has locations predominately in the Midwest. The acquisition of Gavilon allowed Marubeni to source grain from the Midwest (an area that Marubeni had previously been unable to source grain from). According to Emoto and Kim (2012), "A combination of Marubeni and Gavilon is seen by analysts as a good commercial fit, marrying Gavilon's presence in the Central Plains and Midwest with Marubeni's operations in the Pacific Northwest..." Marubeni made the strategic decision to acquire Gavilon. Marubeni increase their geographical diversification and opened a significant market to source grain from. When considering Marubeni's other assets, it was very strategic as a good portion of the grain in the Midwest flows to the Pacific Northwest in most years. This is a way for Marubeni to become more vertically integrated and eliminate the middleman. In doing so Marubeni also increased their geographical diversity. They would not only be able to participate in more local markets but could use those locations to feed their export terminals in the Pacific Northwest as well.

Spatial Arbitrage

One way to capture the advantages of geographically diverse commodity trading firms is through spatial arbitrage opportunities. According to Skadberg, et al. (2015), "Arbitrage refers to buying and selling commodities to take advantage of price differentials." The individual must have access to these different markets in order to participate in these arbitrage opportunities. The goal of arbitrage is to gain a greater return that one would otherwise receive. This is where additional value can be derived from having access to more markets.

In the grain market, commodity trading firms that have access to multiple markets can take advantage of spatial arbitrage opportunities. Skadberg et al. (2015) states that, "One of the most common forms of arbitrage in grain is spatial arbitrage, which involves buying grain at an origin, simultaneously selling at a destination, and accruing the cost of shipping." Firms that have access to multiple markets can take advantage of the spatial arbitrage opportunities. Spatial arbitrage opportunities are due to price differential between different geographical locations. Commodity trading firms that are geographically diverse can take advantage of the spatial arbitrage opportunities that arise which enables them to become more profitable and sustainable in the long run.

Spatial Arbitrage in the Midwest

An example of spatial arbitrage that Skadberg et al. (2015) refers to in their paper is spatial arbitrage opportunities that arise and become available to shuttle elevators in the Midwest. Skadberg et al. determine that spatial arbitrage opportunities occur but then number of occurrences depend on the location of the shuttle elevator in proximity to the export elevators or grain terminals. Skadberg et al.'s research determines that there is a line that divides which locations are better off shipping to the Pacific Northwest (PNW) and the United States Gulf (US Gulf). This line is constantly shifting depending on which port has a greater demand and must increase their draw area by offering better prices. Therefore, Skadberg et al.'s research helps to illustrate the spatial arbitrage opportunities that arise for commodity trading firms on the local level, which can translate into the more geographically diverse commodity trading firms that have a much larger footprint on the international level as well.

Causes of Spatial Arbitrage and Price Differentials

Spatial arbitrage opportunities on the international level are often due to black and gray swan events. “A black swan is an unpredictable event that is beyond what is normally expected of a situation and has potentially severe consequences.” (Chappelow, 2020) Black swan events can cause major disruption in the flow of goods and can lead to major commodity price discrepancies. The shifts can occur due to lack of supply in one area, or likewise, an increase in demand of another. One more notable black swan event in United States’ history was the financial crash of the U.S. housing market in 2008. The financial crash was unpredictable and caused major disruption to world markets. Gray swan events are like black swan events but are predictable, though unlikely. Gray swan events still cause major disruption to the normal flow of commodities and economic goods. Examples of gray swan events include natural disasters such as earthquakes and tsunamis and would also include events such as the Great Depression. Both black and gray swan events can lead to spatial arbitrage opportunities.

Meersman et al. (2012) references a tsunami that hit Japan in 2011 as an example of a gray swan event that led to spatial arbitrage opportunities. This tsunami caused their nuclear power plant to shut down. Japan had to switch to an alternate source of energy, so resorted to natural gas. Switching to natural gas for electricity caused a steep increase in the demand and price of natural gas in Japan. Local commodity trading firms were able to take advantage of this price hike because they were a competitor in the market but were restricted to the supply and resources that the commodity trading firm had. International commodity trading firms that had locations in Japan were also able to take advantage of the spatial arbitrage in the market by sourcing their natural gas from elsewhere and shipping it to Japan. Commodity trading firms without locations in Japan were unable to take advantage of this event because of their inability to participate in the market. For commodity trading firms to partake in these spatial arbitrage opportunities, they must be geographically diversified. Geographical diversification gives commodity trading firms the advantage of being able to participate in spatial arbitrage opportunities. (Meersman et al., 2012)

Value of Spatial Arbitrage in Geographically Diverse Assets

Geographical diversification helps to give commodity trading firms the ability to participate in spatial arbitrage opportunities and therefore, elevators in a chain have more value than a stand-alone elevator of the same caliber. Johansen (2013), illustrated that an elevator that is part of a chain has a greater value than that of a stand-alone elevator. The increased value of the physical asset is due to increasing the number of accessible markets of the commodity trading firm. With more locations and markets, the commodity trading firm can participate in more spatial arbitrage opportunities. With more locations, a commodity trading firm can be more strategic about the markets that they participate in and focus on participating in the more profitable markets, while participating less in the less lucrative or less profitable markets. The commodity trading firm can originate grain more cheaply from certain markets and ship it into other markets to derive the greatest profits. Therefore, there is added value to having more geographically diverse assets within a commodity trading firm.

Switching Options

It is important to understand scenarios in which a switching option is used. Some examples of switching options are giving the owner the choice to switch between two or more processes or commodities. For example, Pinto et al. (2007) evaluate the value of switching between processes. The plant they analyze allows the processor to switch between processing sugarcane for sugar or for ethanol. The input remains the same, but in the case mentioned in Pinto et al.'s study, the owner of the option can switch the process used to yield different outputs depending on the value of the outputs. Pinto et al.'s goal is to determine the value of having the option to switch processes to become more profitable. A crucial result of Pinto et al.'s study is that the plant process sugar, with small amounts of ethanol as a by-product, a portion of the time and strictly ethanol a portion of the time, depending on which output commodity has a higher relative price.

Dockendorf and Paxon (2013) analyze the value of switching between inputs and outputs in a flexible processing facility to determine when the option to switch is valuable. Dockendorf and Paxon determined that there are certain times when a flexible facility is more advantageous and times where it is less advantageous. Dockendorf and Paxon (2013) state, "We find that the switching boundaries generally narrow as prices decline." It may not be worth going through the process of switching the facility over to process a different commodity if it only slightly increases the margins or profitability. The time and costs associated with switching the facility over could be too high and take away from the additional profit gained from processing the different commodity. The value of the option to switch is more valuable in times of greater commodity price differences.

Determinants of Switching Value

Dockendorf and Paxon also determine that the value of the flexible asset is higher in cases where commodity markets are more volatile. Dockendorf and Paxon also determined that the option to switch is still valuable in the case of two output commodity prices that are highly correlated. Dockendorf and Paxon's (2013) research in correlated commodity prices focuses a flexible fertilizer plant's model that can produce ammonia and urea. "… the value of flexibility is significant despite the high correlation between the two alternative commodities and also exceeds the required investment cost for the specified parameters." Volatility is seen as opportunity in the grain industry and Dockendorf and Paxon help to illustrate this in their findings. What may be surprising is that there is value in flexible facilities, even when the prices of the two commodities that the facility can switch between are highly correlated. Dockendorf and Paxon prove that there is value in markets with highly correlated prices, which adds to the value of the flexible facility. Volatility in the international grain market is not only beneficial to flexible facilities. It is also helpful in creating spatial arbitrage opportunities for geographically diverse commodity trading firms.

Johansen and Wilson also determine that the value of the option is dependent on the correlations among margin distributions. Johansen and Wilson (2018) state, "In markets with greater correlations, the value of optionality persists, but declines." This statement is consistent with Dockendorf and Paxon's findings. Johansen and Wilson's findings conclude that geographical diversification into markets that are less correlated to a commodity trading firm's current market would be more advantageous and valuable in an origin style switching option.

Origin Switching Option

Commodity trading firms can take advantage of spatial arbitrage opportunities through multiple avenues, most notably, origin switching option. Origin switching options are options in which the seller of the grain has the option to ship the grain sold out of multiple origins. The price differentials and spatial arbitrage are what help to give this option value. According to Johansen (2013), the value of a switching option is driven by imperfections in the market.

Weather can cause imperfections in the market and can help to create spatial arbitrage opportunities. Weather can cause large shifts in supply and demand in local markets. Shifts in supply and demand cause imperfections in the market and creates the spatial arbitrage opportunities. Weather is what drives crop production in the given area. A recent example that illustrates this is the spring/ summer of 2019. In South Dakota and most of the corn belt, it was very wet and caused a lot of prevent plant acres. Because fewer acres were planted, the production decrease significantly. There is an abundance of ethanol plants located throughout South Dakota that keep the local corn demand high in South Dakota. Because of less planted acres in South Dakota and the high demand, basis levels in South Dakota increased drastically. This imperfection led to some of the South Dakota ethanol plants increasing their draw area and reaching further into North Dakota. This gave farmers the opportunity to take advantage of better prices in other geographical areas that may not be more profitable in a normal year.

Weather can also cause imperfections by affecting logistical networks. Bottlenecks in the logistical networks can slow down the transportation of grain. For example, in the summer of 2019, rain caused the Mississippi River to reach extremely high levels. Because of this, barges were unable to travel on the Mississippi River, which led to increased demand for truck and rail. This increases the prices for these modes of transportation and leads to imperfections in the market. One of the more common cases where logistics problems precipitated switching is related to Brazilian soybean. It is not uncommon for logistical problems in Brazil during and after harvest results in excessive wait times. This causes problems for exporters committed to meet delivery dates for sales to China. As a result, quite often, sales are deferred and/or shifted to U.S. PNW which has lower transit times to China.

As mentioned previously in this thesis, commodity trading firms are working to obtain a competitive advantage that give them the edge over their competition. Meersman et al. (2012) states that the commodity trading firms that are leading the industry are those with the most well established global logistical networks and those who are masters of optionality. The commodity trading firms that do not have the global footprint or are unable to engage in options, are falling behind. The commodity trading firms that do not have access to a global network and optionality need to work towards it. The global network is not the only factor that can limit optionality in the international grain market though, another important characteristic is the usability of the switching option.

Industry Practices of Switching Options

In an interview with Jeff McPike of McDonald Pelz (2019), he explained that switching options are more likely to be useful in more homogeneous commodities and useful while using processing technologies that rely less on the quality of the input to generate the same output. He also stated that the option is not only useful in generating a profit, but in scenarios where the commodity trading firm must fill an order from a different origin due to a shortage in the initial origin.

Homogeneous Commodities

McPike of McDonald Pelz (2019) explained that the value of a switching option varies significantly from commodity to commodity. A commodity that is more homogeneous with less quality and characteristic differences would have more value in switching. This is due to less variabilities in the commodity and less requirements on the processing side of things. A couple examples of commodities that are more homogeneous would be soybeans and corn. Processors may pay a premium for the slightly higher quality soybeans and corn, but the processors can process a wider variety of quality soybeans and corn and produce the same product. The processor may produce a higher percentage of oil per bushel of soybean or higher protein meal, but the oil quality and meal quality remain the same.

A switching option would likely not be as valuable in a commodity such as durum or wheat in general. This is not to say that they would not be useful or have any value. The lower value in the switching style option for durum is due to durum being highly quality sensitive. A processor that mills durum needs high quality that meets certain specifications. If a mill is expecting durum of a certain quality from a certain area, it is crucial that they receive the grain they expect. A mill would not likely be willing to engage in a switching option if quality and characteristics were important to creating the semolina and pasta (in durum) (McPike, 2019)

Processing Technologies

McPike also mentioned that different mills have different technologies and produce varying qualities of breads. Mills that are not concerned about the quality of the bread would be more likely to engage in a switching option due to quality and different milling characteristics being of less importance. A mill that produces flour for more specialty breads such as baguettes or pastas would require more precise qualities and characteristics in the grain that they mill. Mills with higher technology would be less likely to engage in a switching style option due to the quality requirements (McPike, 2019).

Inability to Ship from Intended Origin

McPike also mentioned another important scenario in which a switching style option would be useful that is not necessarily for generating the most profit. The example he used was when there was a shortage of wheat in Russia due to a drought. A Russian company had sold wheat but was unable to fulfill the contract due to the shortage of wheat in Russia. In this case, the seller could fill the contract from a different location. This makes it evident that a switching option is not only useful in scenarios where spatial arbitrage opportunities are available, but also for strategy in the international grain market. If a firm is unable to fulfill their contract or is needing to move grain from one location, they could exercise the switch in order to put the company in a better situation. This could be true for an elevator that is full, so they need to move grain, or perhaps there is different attributes of the grain quality in a different area. (McPike, 2019)

Another example of a switching option implication used when ports shut down. This can happen for many different reasons, but a more recent reason for port closures is due to the COVID-19 outbreak. Thompson Reuter wrote an article about the General Authority for Supply Commodities (GASC) which is Egypt's state grain buyer. The article mentions that the upcoming wheat tender contracts are going to be shifted to optional origin. GASC is allowing for any origin wheat to allow the seller to fill the contract (Dahan and Awadalla, 2020).

Other Examples

Over the past year, there have been many examples of switching options in the international grain trade. Though anecdotal, they are mentioned for illustration below:

- The Pacific Northwest has been struggling to compete with Black Sea prices in the nearby corn markets. Argentina becomes more competitive in further out months due to an increase in supply from harvest. Because of the more competitive prices, buyers have been switching to the cheaper origins being the Black Sea and Argentina for their respective time periods. This locks out the PNW origin until the price becomes more competitive. This is another example of the practical application of switching options in the international grain market ("Corn Commentary: Futures Slide," 2020).

- The grain agency in Algeria, OAIC is believed to have purchase 400,000 tonnes of durum wheat at a CIF price of about $333 to $335 a tonne for April 2020. It was optional origin and was expected to include Mexico, Canada, and possibly the United States ("Algeria Said to Buy," 2020).
- U.S. Department of Agriculture released a report of a China soybean purchase in April 2020. The sale was reportedly for 198,000 tonne of soybeans for the 2019/2020 marketing year. The purchases were for shipment from U.S. Gulf or PNW export terminals beginning in July. (Bagh, 2020)

Real Switching Option Valuation Methods

The empirical model used in this thesis is that of real options which are developed in Chapter 3. Below is a brief description of the evolution of these studies/ methods.

Commodity prices are generally thought to have mean reverting characteristics. The mean reverting characteristics in commodity prices are due to more of the commodity being produced when the price increases. The increase in production of the commodity creates a greater supply, which in turn shifts the price of the commodity back down and towards the long term mean price of the commodity. Because of this characteristic of commodities, it is important to make sure that when modeling the commodity prices, to use a model that reflects the mean reverting phenomenon in commodity prices.

Recombining Binomial Lattice

One of the techniques for real option analysis to determine the value of a switching option is that used by Hahn and Dyer. Hahn and Dyer (2008) use a recombining binomial lattice approach to develop a binomial model for mean-reverting stochastic processes that are often used to model commodity prices. Hahn and Dyer build upon the initial recombining binomial lattice approach (done in previous studies) to allow for two correlated one-factor mean-reverting models. Their additions help to allow for correlations between the prices of different commodities. In Hahn and Dyer's study, they develop an option valuation method that can determine the value of a real option that allows for an oil and gas producing plant to switch between the two commodities. Their implementation of the binomial lattice approach can be applied in other situations than the two commodities mentioned.

Hahn co-wrote another paper with Pinto and Brandao (Pino et al. 2007) that uses a similar technique as Hahn and Dyer (2008). Pinto et al. (2007) use the same binomial lattice techniques used in Hahn and Dyer and use a discrete time approach to model uncertainties in sugar and ethanol prices as two mean reverting stochastic process combined into a bivariate lattice. Pinto et al. compare their results to that of a model using Geometric Brownian Model (GBM) and acknowledge that the GBM model yields a significantly higher value which helps to validate why one needs to ensure that the prices model follow the mean-reverting process. When the process does not follow a mean reverting trend, the value can be significantly overvalued or undervalued.

Quasi-Analytical Solution with Numerical Lattice

Dockendorf and Paxon (2013) and Adkins and Paxon (2011) both use similar approaches to determine the real option value of a flexible facility. Both studies use a quasi-analytical solution for determining the value of continuous switching. Both studies determine a quasi-analytical solution for a one-way switch with the option of abandonment. The study by Adkins and Paxon does not progress any further with the modeling but the Dockendorf and Paxon study takes it one step further. In the third step Dockendorf and Paxon follow the first two models with a numerical lattice. This is used to value the two output products and determine which is the best. The approaches used by Dockendorf and Paxon and Adkins and Paxon take a different approach to real option valuation of flexible facilities than the previously mentioned studies. However, this is not the only way to value a switching option.

Binomial Lattice with Monte Carlo Simulation

Johansen (2013) uses a Monte Carlo simulation model to value switching options. He uses real options to value the physical assets that allow for commodity trading firms to take advantage of origin switching options. Johansen's study combines the Monte Carlo simulation model with a binomial lattice to help illustrate the value of the option with price uncertainty at the origin locations. His model first determines the value of a stand-alone elevator and then determines the value of an elevator as part of a chain. Johansen can determine the additional value of being a part of a chain of elevators. Johansen's model also allows for the option to cease operations (suspension). The final part of Johansen's model is determining the optimal amount to contract, given price behavior and correlation of prices at the origins.

Johansen and Wilson (2018) is an extension of Johansen (2013) and follows similar approach by using a binomial tree with Monte Carlo simulation. Johansen and Wilson first determine an arbitrage margin for each origin location and then apply this value, with price distribution, to a binomial tree. Each future up and down movement is given a probability as well to help in the calculation of the value of the option. Johansen and Wilson (2018) apply this to both an elevator without the ability to switch and an elevator with the ability to switch to determine the addition value gained with access to switching. Other have used a numeric solution to solve switching option values.

Stochastic Numerical Solution

Fackler (2018) used Matlab to determine a numeric solution to optimal switching problems. Fackler's solution focuses on the ability of a firm to run when profitable and shut down when not profitable. The framework of the model is a stochastic process that is characterized by its drift and diffusion functions, by a stream of rewards described by function f, by a discount rate p and by a switching cost matrix. Fackler states that there are numerous advantages including it being generic and simple to apply in many different cases, it can solve models with general multidimensional diffusion processes, and it eliminates the need for the user to guess the qualitative nature of the optimal solution. Fackler's approach to switching option valuation is different than most as it does not use a binomial lattice or tree to solve the value of the option.

Option Models Generalized

Bullock et al. (2019) generalizes the above and breaks the models down into four different categories: closed form option formulas, Monte Carlo simulation, lattices, and decision trees. They go on to mention that the first two categories are more often used in European style exercise option. The last two categories are more often used in American and Bermudan style exercise options. The models can also be use more than one type of models as well, which adds to the complexity of the model. Within these two more complex models, there are specific uses for each. Lattices work best for modeling market- based processes and decision trees work best for modeling non-market base processes such as research and development projects.

The model in Bullock et al. (2019) works to determine the real option value of a potential research and development project in which they compare gene edited and genetically modified crops. Their paper uses a combination of a decision tree and a binomial lattice. The analysis done in this paper is valuing the research and development project over time and not just at the end. Therefore, the models they used were chosen over both the closed form option and Monte Carlo simulation.

CHAPTER 3: ANALYTICAL FRAMEWORK

Introduction

Commodity trading firms have high levels of risk as commodity markets are very volatile. Because of this, commodity trading firms work to mitigate their risk by hedging their grain or by using financial options. Hedging in commodity markets eliminates the futures price risk, but there is still risk in a volatile basis market. In options, the futures prices risk is decreased based on the correlation of the premium and futures price or delta. There is also risk in the option premium. An option becomes worthless if the futures price for the specified option futures contract month is above the price of the option in the case of a put option or below in the case of a call option at the last date or expiration date of the option. If there is no value in the option when the expiration date arrives, the owner of the option lets the option expire and only loses the premium that they paid to purchase the option.

Another way for commodity trading firms to decrease risk that was alluded to earlier in this thesis is through greater geographical diversification. This is due to the commodity trading firms' ability to participate in multiple origins and their ability to focus more on more profitable origins. The commodity trading firms are spreading out their risk into multiple origins rather than relying on one origin to participate in for example, a commodity trading firm with only locations in the US Gulf. In the summer of 2019, water levels were very high which slowed down and eliminated all barge traffic at times. This really hurt the US Gulf origin because most of the grain that is shipped to that location is shipped via barges along the river system. If the same commodity trading firm had locations in the PNW, they would still be able to receive grain efficiently to their PNW origin because PNW origin relies predominately on the rail system.

The purpose of this chapter is to lay the analytical framework for the remainder of this thesis. This chapter discusses financial and real options, geographical diversification and spatial arbitrage opportunities, and modeling of switching type options.

Financial vs Real Option

Real and financial options have similarities, but also have some key differences. Similar characteristics include the option exercise or option type. The main differences are that real options are not tradable and evaluate physical or real assets. Financial options are tradable and rely on shifts in market to generate more profit. Real options often build on financial options such as puts and calls, but also values investment opportunities such as access to multiple origins like in the case of this thesis.

Real Option

In this thesis the real option evaluation method is used. This thesis determines the fair market price that a seller of grain should pay (or discount the grain) to have the option to deliver from multiple origins in which they do not specify the origin until the date of delivery. It uses financial option call options to help place a value on switching style options. The value of the call option is derived from a commodity trading firm with access and the ability to originate grain from multiple origins.

Financial Option Insight: Puts and Calls

Puts and calls are more commonly thought of as financial options because they are often traded in commodity futures exchanges. There are also cases where the underlying option is not tradable such as with insurance policies. Put and call options are used to establish a price floor (put) or price ceiling (call) and can be used strategically for a commodity trading firm to eliminate risk in the grain price volatility in the grain that they own. A put gives the owner (purchaser), the right but not obligation to sell at an established price by paying a premium to the writer (seller). In the case of the switching option, the premium may be negotiated into the contract. Alternatively, it could simply be implied in an offer price. A call gives the owner, the right but not obligation to buy at an established price by paying a premium to the writer. Establishing price ceilings and price floors for commodity trading firms help to reduce the risk in a volatile commodity market.

Most commonly, puts and call that are exchanged and traded in the U.S. are American type options, whereas this thesis takes a European type option approach. The differences are explained in detail below.

Both put and call options in exchange traded commodity futures have certain agreed upon specifications: strike price, premium, and option style. The price established in exchange traded puts and calls are known as the strike price and are based on a specified futures contract month. The strike price is based on a futures contract month and a set price. The contract month establishes the period when the option can be exercised, and the strike price is the price level established for the option. The strike price can by at three different points relative to the futures price, in-the-money, at-the-money, or out-of-the-money. An in-the-money strike price for a call option is in the money if the call strike price is below the current underlying futures price, with the opposite true for a put. An at-the-money strike price for both puts and calls is when the strike price is at the same price as the current underlying futures price. An out-of-the-money strike price for a call option would be when the strike price is above the underlying futures price, with the opposite true for a put option. The strike price is one of the three predetermined specifications of an option contract that establishes the price at which the commodity can be bought (call) or sold (put) if the option is exercised.

Option Value

The value of the put or call option is known as the premium, which is the value paid by the buyer of the put or call option (or negotiated into the contract), in order to have the ability to exercise the option. The value is negotiated using open outcry through electronic (more common) or pit trading. This is the only aspect of the exchange traded options that can be negotiated. The different levels of coverage (ex. Strike prices) are considered to be different options with varying premium levels.

The value of the premium is made up of two different components: the intrinsic value and the extrinsic value. The intrinsic value of the option is the difference between the underlying futures price and the strike price when the option is in-the-money. For example, if you bought a corn call at $4.00, and the current futures price for corn was at $4.10, the option would have an intrinsic value of $0.10. The owner of the option can buy corn at the $4.00 by exercising the call option, which is $0.10 below the current market price. The intrinsic value is what makes up a portion of the value of the premium value in options.

The extrinsic value is comprised of four different components: time to maturity, volatility, interest, relation of market price to strike. The greater the time to maturity, the more value the option has because there is more time for the option to increase or decrease in value and add to the intrinsic value of the option. Volatility in the market is the uncertainty or risk in the market. A volatile market is one that could change drastically, very quickly due to uncertainty in the market. The interest rate is the value of money and is a value that is forgone by engaging in options. The relation of the market price to strike price is like the intrinsic value of the option, at a specific point in time. The relationship is constantly changing as the futures price is constantly moving up and down. The extrinsic helps to capture a portion of the value of the option premium.

Option Characteristics

Real Option Types

Real options are often used in conjunction with discounted cash flows (DCF) to value different investment opportunities. Discounted cash flows value of the project based on how much revenue the project generates over a certain period. Real options allow for the right but not obligation to exercise a given option. These different types of real options that are explained in Mun (2010). Table 3.1. below highlights the options in Mun (2010) and gives a brief explanation for them all.

Table 3.1. Types of Real Option

Real Option Type	Description
Abandonment Option	Gives the holder the right but not obligation to abandon (or sell) the project or asset.
Expansion Option	Gives the holder the right but not obligation to expand operations by increasing production, expanding into other markets, or switching strategies.
Contracting Option	Gives the holder the right but no obligation to contract operations by reducing production or scale back existing workforce for the purpose of reducing costs. The excess capacity is filled by the vendor that the agreement was made with.
Chooser Option	Gives the holder the right to choose among the three prior strategic options: abandon, expand, or contract.
Option to Wait	Gives the holder the right but not obligation to wait until more information is available to make the decision on how to move forward.
Barrier Option	Gives the holder the right but not obligation to exercise the option when an artificial barrier is breached. There is only value when the artificial barrier is breached.
Sequential Compounding Option	An option where the underlying project has multiple phases where the latter phases' value depends on the success of the previous steps.
Switching Option	Gives the holder the right but not obligation to switch resources, assets, technology, or markets.

Mun (2010)

This thesis determines the value of having the imbedded switching option. In the general sense of a switching option there are various interpretations of a switching style option. As stated in Mun (2010), "A switching option provides the right and ability but not the obligation to switch among different sets of business operating conditions, including different technologies, markets, or products." In the case of this thesis, the switching option would refer to the right to switch origins.

This interpretation of the switching type gives the seller the option to ship the grain out of the location that would be the cheapest to originate grain and ship it to destination. This allows for more flexibility for the sellers but allows the buyer to receive payment (or pay less for the grain) due to the uncertainty of the grain origin. The flexibility allows the seller to take advantage of the cheapest delivered basis (basis at origin + ocean freight to destination) and generate the greatest profit from this decision. The origin would be established at the time of shipment.

Alternative Option Specifications

The option style helps to establish the terms of exercising an option and includes European Option, American Option, Bermudan Option, and Asian Option. The different styles reflect the differences in exercise timing. A European Option can only be exercised on the expiration date, whereas an American Option can be exercised on any trading day on or before expiration. A Bermudan Option may only be exercised on specified dates on or before expiration. An Asian Option has a payoff that is determined by the average of underlying price over some preset time period (Johansen, 2013).

The Appropriate Option

The goal of this thesis is to determine the imbedded value of an optional origin contract. The option allows for the seller of the grain to establish the different origins that they would have access to originate the grain from and determine the origin they intend to ship grain out of on the date of shipment. While there are several types of options as described above, the switching option is appropriate in modeling the problem in this thesis.

Given the nature of the option, the problem would best be modeled using a European style call option with the strike price of the call option being the lowest delivered basis amongst the established seller locations. It would be a European style due to the decision being made at the time of shipment. A call option would best describe the problem because the seller is able to buy the grain at any origin. They would then ship the grain with the lowest delivered cost in order to generate the most profit. The seller of the grain would choose to not exercise if their initial origin was the lowest price for grain delivered to the destination.

Geographical Diversity

Commodity trading firms that are more geographically diverse are less risky because they can participate in multiple origins. This is because a non-geographically diverse commodity trading firm is stuck participating in one origin. If their only origin is not profitable, the non-geographically diverse commodity trading firm is only going to be able to continue to operate at a loss. This is different from a geographically diverse commodity trading firm that can be more selective in the origins they participate in. They can participate more heavily in more profitable origins and less heavily in the less profitable origins.

Spatial Arbitrage Value in Geographically Diverse Origins

As mentioned previously, spatial arbitrage is derived from the difference in prices between two different locations. Buying in the underpriced origin and selling in the overpriced origin. The spatial arbitrage value is dependent on local supply and demands which are highly dependent on the weather. Spatial arbitrage opportunities generally arise from black and gray swan events. Geographically diverse commodity trading firms can capitalize on spatial arbitrage opportunities. The value derived from the geographical diversification is due to capitalizing on spatial arbitrage opportunities. More geographically diverse firms are more valuable because they have access to more origins and hence more spatial arbitrage opportunities (Johansen, 2013).

Contracting’s Effects on Flexibility

Flexibility is important in commodity trading firms. It can allow the commodity trading firm the ability to increase profitability. In the case of a switching style option, a commodity trading firm that can ship out of multiple facilities should limit contracting if it inhibits the commodity trading firm's ability to switch origins (Johansen, 2013). Contracting with origin specific commodities prohibits the ability to switch, so the option to switch origins should be negotiated into the contract the seller makes with the purchaser of grain. Negotiating the option to switch origins is crucial in commodity trading firms that have access to multiple origin markets in order take advantage of spatial arbitrage opportunities as they arise.

Valuation Method

Value Derivation

The value of the switching style option is based off the delivered basis difference between the initial origin and the least of all origins the firm has access to. The delivered basis is a calculated value that is derived from adding the basis at the origin (FOB basis) and the ocean freight rate (to the established destination). Whichever delivered basis, of the available origins, is the lowest would be where the seller should ship the grain from if the seller's goal is simply to make the most profit. Both the basis and ocean freight rate are determined from separate time series projections that project t periods forward. The delivered basis is calculated for all origins within the given scenario.

For example, if a commodity trading firm's initial origin was the US Gulf and they had the option to ship from Argentina too and were delivering the grain to China. If they were able to originate grain and ship it to China from the US Gulf for $2.00/bu basis or from Argentina for $1.00/bu the seller should ship from Argentina because they are able to make an additional $1.00/bu more using the Argentina origin instead of the US Gulf origin.

Origin Correlation Effect on Value

Less correlation amongst origins provides a greater opportunity for spatial arbitrage (Johansen, 2013). An example of less correlated origins would be the US Gulf when compared to either Brazil or Argentina. There is still valuing in having the ability to switch when origins are highly correlated (Dockendorf and Paxon, 2013). An example of more correlated origins would be the US Gulf and PNW or even Brazil and Argentina. Although Dockendorf and Paxon focus on a facility with the ability to switch inputs and outputs, their study still provides insight to other applications, such as the origin style switching option that is illustrated in this thesis. For a commodity trading firm with a facility in the US Gulf, it would be more beneficial for them to expand or contract for the ability to switch origin to a facility in Brazil or Argentina rather than the PNW. This is due to the weak correlation between the US Gulf and South American origins and stronger correlation between the two US origins.

Monte Carlo Simulations

Monte Carlo Simulation is a simulation process that generates multiple iterations that illustrate possible paths of the projected outcome. In this thesis, it is used to run multiple price path simulations while calculating the option values at each iteration ran. The iterations are recorded, and the mean and standard deviation statistics are calculated off the iterations. This helps to simulate many scenarios based upon the formulas used.

Conclusion

The base case model in this thesis represents a commodity trading firm with access to US Gulf, PNW, Brazil, and Argentina origins that is shipping to China (soybeans) and Japan (corn) respectively. In the base case, the commodity trading firm can switch between any origin at the end of the contracting period and so it would be deemed a European style contract. The option type is a call option with the strike price being the lowest value of the given origin prices and transportation costs. The values of the call option are generated off the correlation amongst the origin and destination origins, volatility within the origin and destination origins, and the price spread between the origins and destination. (Pinto et al., 2007) (Adkins and Paxon, 2011).

CHAPTER 4: METHODOLOGY

Introduction/Overview

Chapter 4 develops the methodology on how this research was conducted to answer the question: What is the real option value of an origin switching option? The thesis develops models that help to answer that question. Switching options were valued for both the soybean and corn markets. Each model was created using the same structural data set for the respective commodity. Different time periods within this data were used for sensitivity analyses. The base case models both represent a commodity trading firm with the ability to switch between any of the listed origins. The commodity trading firm would ship the grain out of the lowest cost origin to generate the greatest profit. The value of the options is derived from the difference in the lowest cost origin and the base case origin, US Gulf. Chapter Four will be organized in the follow order: Methodology, Scope of Analysis, Data Sources, and Data Behavior.

Methodology

Options to be Examined and Why?

This thesis considers a few different options types when evaluating the option value. The base case scenario and sensitivities 1-5 are European type options. Each sensitivity focuses on a different scenario to value the option. The European option type is used because the decision of which origin the grain will be shipped from is made at the end of the of the contract or at expiration.

Other option types used are the Asian and lookback options. These options help to lay out the boundaries for an American type option that could be exercised at any period up to expiration. The American type option does not work well because the model and stochastic processes used in this thesis do not correspond well with a binomial tree model which would be appropriate for an American type exercise option. The minimum lookback option is the maximum option value because the commodity trading firm can originate and ship the grain at the lowest point across the entire period. The maximum lookback option is the minimum bound option value because it allows the commodity trading firm the ability to originate and ship grain at the highest price across the period. The Asian option is an averaging option and sets a likely average price somewhere between the minimum and maximum lookback options.

Model Specifications

The model used in this thesis is used to determine the real option value of an origin switching option. The option value is derived from the spatial arbitrage opportunities across grain origins. The base case scenario is a European type because the decision of the commodity trading firm that is selling the grain is able to make the decision on where to ship the grain out of at expiration. There are also sensitivities that consider the option types to shift and be an Asian option, minimum lookback option, or a maximum lookback option. The decision would still be made at expiration, but the option value is determined differently and is explained the paragraphs to follow.

The European type option approach values the option at the option expiration date. The value of the option is the difference in the current delivered basis for the initial origin (US Gulf) and the minimum price origin. This would be a call option with the strike price being the least cost origin. The call would give the user the option to ship out grain from any origin that they are able to originate from. It would be considered a call option because the owner has the right but not obligation to originate grain at that price and use the grain from that origin towards the agreed upon contract.

In some of the sensitivities, other option types used are the Asian option and lookback options. These are used to set up the upper and lower bounds as well as average of an American type option. Asian options use the average net price across all periods (12 periods). It then compares this with the current net price of the initial origin. This would be the average expected value of the American type option.

The lookback options look at the minimum or maximum net price (respectively) across the periods that the option is active over. The minimum lookback option compares the current net price with the net price of the absolute minimum price throughout all periods leading up to expiration (12 periods in this case). The absolute minimum price looks at each of the 12 period minimums and takes the minimum value of all 12 period values. The minimum lookback option would be the highest priced option because it allows the owner of the option, the ability to purchase the grain at the lowest possible net price across the contract period. The maximum lookback option is like the minimum lookback option, but after determining the 12 minimum period values, takes the maximum value of the 12 values. The maximum lookback would be the lowest price option because one would be just as well off contracting at any point across the contracting period. In this case, the seller can take advantage of switching, but would only contract at the maximum period price of all periods.

Monte Carlo and Alternative Methods

As mentioned previously, real options are normally calculated using one of four general methods. Two of which work best with fixed exercise dates, like in this thesis and two of which have flexible exercise dates. Closed form option pricing and Monte Carlo simulation work well for fixed exercise dates and lattices and decision trees work well for flexible exercise date options. In the case of this thesis, the exercise date is fixed, so closed form and Monte Carlo would to be the better choices. Closed for option pricing, such as Black Scholes, are commonly used in European option price calculation when the exercise price is known. In the case of this thesis, the exercise price is unknown because it will be what the spot delivered basis is on the day of expiration.

Though lattices and decision trees were not used, they are recognized to work well for option valuation. In the case of this thesis, they were not chosen for a couple reasons. The first reason, as Bullock and Wilson mentions, they generally work better for options with flexible exercise dates, which is not true for the case of this thesis. Additionally, if lattices were used, there would need to be multiple origin price lattices. The option price would then be derived by calculating the value at each node and discounting back to the initial date at time t0. These calculations would assume that the prices were 100% correlated because the calculations would be made at the same node of each tree. There would be no real way to incorporate the origin price correlation which is a big part of the option prices that can be derived from origin switching options.

Sensitivity Analysis

Soybeans Base Case

The base case serves as a standard for comparison. The base case scenario represents the full period, which in soybeans is from 1/7/2005 – 1/10/2020. The base case includes all four origins (USG, PNW, Brazil, and Argentina) and includes the ocean freight. The standard number of periods out is 12 weeks (about 3 months) and the risk-free discount rate is 0%.

Soybeans - Sensitivity 1 – Time Period

In the first sensitivity, this thesis analyzes the effect of using different time periods for the data source. The first time period sensitivity is from 1/1/2016 – 1/10/2020 which includes a time period with more normal markets for the first half and more volatile markets for the second half. The second time period sensitivity represents a more volatile market time period representing uncertainties in the market. This period is from 1/5/2018 – 1/10/2020. The same four origins were used in sensitivity 1. Ocean freight was included as well. The number of time periods out remained at 12 and the discount rate remained at 0%.

Soybeans - Sensitivity 2 – Origins

In the second sensitivity, this thesis analyzes the effect of the different origins on the value of the option. The time period for both sensitivities is the same as the base case: from 1/7/2005 – 1/10/2020. The first origin sensitivity includes only the US Gulf and PNW, which are both US origins. PNW is the most highly correlated with US Gulf of all of the origins (shown in Data section), which is expected because they are within the same origin market and have the same production and harvest period as well as handle grain from similar, if not the same areas. Their harvest and marketing periods are also within the same time frame. This sensitivity represents a commodity trading firm with an export terminal in both the US Gulf and PNW.

The second origin sensitivity includes US Gulf and Brazil, which are less correlated. This represents a commodity trading firm with a location in the US Gulf and Brazil. Brazil has a different harvest period due to being located within the Southern Hemisphere. The seasonality in each market likely brings rise to spatial arbitrage opportunities in the markets. Brazil is also a very volatile market with less developed infrastructure that the US, which can affect FOB Brazil prices. Ocean freight was included in each model. The standard 12 periods out were used for each scenario along with the 0% discount rate.

Soybeans - Sensitivity 3 – No Ocean Freight

The third sensitivity eliminates the ocean freight price and focuses on only uncertainties in the FOB/cash market and uses the full time period. The PNW is expected to reflect the greatest effect on this value due to having the cheapest freight rate to China of the four origins. A larger percentage of the delivered basis is due to the origin basis, whereas in the other markets, freight plays an equally large part in the determination of the delivered basis. Again, the standard 12 periods out were used for each scenario along with the 0% discount rate.

Soybeans - Sensitivity 4 – Number of Periods Out

In the 4th sensitivity, the time period remained the same as the base case (1/7/2005 – 1/10/2020) and all four origins were used. Ocean freight was also included. The number of periods out was changes and analyzed from 1 to 20 periods (weeks) out. This was done using the Advanced Sensitivity Analyses tool in @Risk™. This tool simulates the option value at each period out running 10,000 iterations at each period out and averages them. This illustrates the effects on the time periods out on the option value. It is expected that the further out the option is, the more expensive it would be because there is a greater chance for the prices to vary by a greater amount. There is more market volatility, further out. The initial discount rate of 0% was used for this sensitivity as well.

Soybeans - Sensitivity 5 – Risk Free Discount Rate

The 5th and final sensitivity follows the same format as the base case, with a time period from 1/7/2005 – 1/10/2020, all four origins, includes ocean freight, and uses 12 periods (weeks) out. The variable that changes in this sensitivity is the discount rate used. The same Advanced Sensitivity Analyses tool is used in @Risk™ to simulate how a changing discount rate will affect the option price. Because the time periods only go out to 20 weeks (about 5 months), one would not expect much of an effect on this variable changing. The discount would have to be very extreme for the option price to realize this change. Formula (8) shows how the option value was calculated while accounting for the discount rate.

$$DeliveredBasisWithDiscountRate = DeliveredBasis * (1 - (r^t)) \quad (1)$$

Soybeans - Other Options

The other options types that were evaluated, Asian and lookback options, used the same data set as the base case. The full time period (1/7/2005 – 1/10/2020) was used. All four origins were included. Ocean freight was included. The number of time periods out was the standard 12 and the risk-free discount rate was 0%. The Asian option uses the average of the 12-period lows for the net price from the US Gulf to evaluate the Asian option net price. The minimum lookback uses the lowest net price across all 12-period low values. The maximum lookback uses the highest net price across all 12-period low values. One would expect there to be the most value in a minimum lookback option due to the value being the absolute low over the 12-period time period. The maximum lookback option is expected to have the least amount of value because it is the greatest value amongst the 12-period minimums. The Asian option would be expected to be right in between the two other option values because it is the average across the 12-period minimums. These help to set the bounds for an American type option.

Corn - Base Case

The base case for corn used a data set that spanned the entire time period from 6/13/2008–1/24/2020. The base case includes US Gulf, PNW, Brazil, and Argentina origins, but excludes Ukraine due to unavailability of data over the entire period. The results would be inaccurate due to basis being projected only over the last four years when compared to the past twelve years for the other origins. Ukraine was excluded to avoid inconsistency of projecting basis. All ocean freight rates were delivered to Tokyo, Japan as the destination. The standard number of periods used was 12 periods (12 weeks or about 3 months). The discount rate was 0% for the base case.

Corn - Sensitivity 1 – Time Period

The first time period used was from 9/23/2016-1/24/2020. This was chosen to represent a similar time period as the first soybean time period sensitivity. It also encompassed the entire Ukraine data set. This gave the option to add Ukraine as another origin to ship out of. There were two sensitivities ran with this time interval: one with US Gulf, PNW, Brazil, and Argentina, and one with all four initial origins, and Ukraine. This is to highlight the effect of having the option to switch out of another origin and encompass a greater percentage of total world corn exports. Ocean freight was included and the standard 12 time periods out and 0% discount rate were used in these sensitivities.

The second time period used was from 1/5/2018-1/24/2020. This is the same as the second soybean sensitivity and is also used to determine the value of the switching option in a more volatile market. Like the previous time period sensitivity, two sensitivities were ran. The first sensitivity includes the initial four origins, and the second one includes the initial four origins and Ukraine. Similarly, this sensitivity included ocean freight and used the standard 12 periods out and 0% discount rate.

Corn - Sensitivity 2 – Origins

Though there were some sensitivities ran within sensitivity 1 that included shifting origins, others were ran to determine how option values would change when including only US origins and one with only the US Gulf and Brazil. The first of the two sensitivities used the full time period from 6/13/2008-1/24/2020 and included only the US Gulf and PNW origins. Ocean freight was included and the standard 12 periods out and 0% discount rate were used. This sensitivity represents a commodity trading firm that only has locations in the United States. Similarly, the second sensitivity used the full time period. The difference here was that only the US Gulf and Brazil origins were used. The ocean freight was included along with the standard 12 periods out and 0% discount rate. This show a commodity trading firm with the ability to originate grain from both the US Gulf and Brazil.

Corn - Sensitivity 3 – No Ocean Freight

The third sensitivity uses the full time period and the initial four origins. It does not include the ocean freight rate. The standard 12 periods out and 0% discount rate was used for this sensitivity as well. This sensitivity is to see how the option value differs when only including the basis. One would expect PNW to have a higher basis and be less valuable because a smaller percent of the total delivered basis is due to ocean freight than the other origins. The other origins' delivered bases are less influenced by basis because there is a greater portion of the delivered basis from freight.

Corn - Sensitivity 4 – Number of Periods Out

In the 4th sensitivity, the time period remained the same as the base case (6/13/2008 – 1/24/2020) and all origins besides Ukraine were used. Ocean freight was included in this sensitivity. This sensitivity analysis looks at periods 1-20 periods (1-20 weeks) out. This was done using the Advanced Sensitivity Analyses tool in @Risk™. 10,000 iterations were used for each simulation of the 20 time periods out. The average is recorded and graphed at each time period. This sensitivity illustrates the effect of time on the option value. It is expected that further out options have a greater value due to prices having more volatility in the markets further out. The discount rate of 0% was used in this sensitivity.

Corn - Sensitivity 5 – Risk Free Discount Rate

The final sensitivity uses the same time period as the base case. It also includes the four main origins and ocean freight rates. This sensitivity was done holding the time periods out at 12 throughout the sensitivity. Discount rate was what was observed in this sensitivity. The advanced sensitivity analyses tool within @Risk™ used previously is used in this analysis as well. The risk-free discount rate fluctuated between 1%-12% annually. As mentioned with soybeans, one does not expect much effect of discount rate on the option value. Because the discount rate must be adjusted to weekly discounts, it would take a significant discount rate to affect the option price.

Corn - Other Options

The other options types that were evaluated, Asian and lookback options, used the same data set as the base case. The time period was the full time period (6/13/2008 – 1/24/2020). US Gulf, PNW, Brazil, and Argentina were included, Ukraine was excluded due to data availability over the entire time period. Ocean freight was included delivered to Japan. The number of time periods out was the standard 12 and the risk-free discount rate was 0%. To determine the Asian option value, the average of the 12-period lows for the net price from the US Gulf was used. The Asian option helps to give an idea of where the average American type option value would be.

The minimum lookback uses the lowest net price across all 12-period low values. There would be great value in this because the seller of the grain would be able to originate grain at the cheapest possible price over the course of the option. Therefore, a minimum lookback option would be the most expensive. The maximum lookback uses the highest net price across all 12-period low values. The maximum lookback option would be expected to have the least amount of value because it is the greatest value amongst the 12-period minimums. The maximum lookback option is less risky for the seller of the contract because the basis that is set is the lowest of the 12 periods.

Time Series Projections

Because the option value is derived from the difference in net price between US Gulf and the option net price, the delivered basis must be calculated. The delivered basis is made up of the projected basis and ocean freight. To project the basis level, Palisade's @Risk™ decision tool was used. The time series batch fit function was used with Bestfit™ with the data used that is explained further in the data section for each commodity below. Bestfit™ determines which model best fits each of the variables in the data set using Maximum Likelihood Estimation (MLE) and by following Akaike's Information Criteria (AIC). AIC is the default setting in Bestfit™ and allows for more complex functions to be chosen more often. Bestfit™ observes autoregressive (AR), moving averages (MA), autoregressive moving average (ARMA), Brownian motion models (GBM, BMMR, GBMJD, BMMRJD), autoregressive conditional heteroscedasticity (ARCH), and generalized auto regressive conditional heteroscedasticity (GARCH). This process was used for each set of data (each time period for each commodity) to determine which model was the best fit for each origin within each set of data. Due to commodities mean reverting characteristics (Pinto et. al 2007), models without mean-reverting characteristics were excluded. This includes many of the Brownian motion models, though two Brownian models were included in the Bestfit™ due to their mean reverting characteristics, BMMR and BMMRJD. The models that were used in the basis batch fitting process were AR1, AR2, MA1, MA2, ARMA, BMMR, BMMRJD, ARCH, and GARCH. The freight batch fit included all of the models that were used in the basis batch with, with the addition of GBM and

GBMJD. Table 4.1. below shows the description of each of the available functions to fit and whether they were used in each Batch Fit.

Palisade's @Risk™ was used for the freight projections too. The same process was used for the ocean freight. MLE using AIC was used for Bestfit™ in the freight data. AIC is the standard criterion used in Bestfit™ and allows for more complex models. The Bestfit™ for freight data included all functions and is shown in Table 4.1. below.

Table 4.1. Time Series Functions to Fit

Time Series Function	Specifies	Basis Batch Fit	Freight Batch Fit
RiskAR1(mu,Sigma,A,R0, StartValue,WhatToReturn)	Calculates an auto-regressive AR(1) time series with these parameters	X	X
RiskAR2(mu,Sigma,A1,A2,R0, RNeg1,StartValue,WhatToReturn)	Calculates an auto-regressive AR(2) time series with these parameters	X	X
RiskMA1(mu,Sigma, B1, StartValue,WhatToReturn)	Calculates a moving average MA(1) time series with these parameters	X	X
RiskMA2(mu,Sigma, B1, B2, StartValue,WhatToReturn)	Calculates a moving average MA(2) time series with these parameters	X	X
RiskARMA(mu,Sigma,A1,B1, R0, StartValue,WhatToReturn)	Calculates an auto-regressive moving average time series with these parameters	X	X
RiskGBM(mu,Sigma,Times, StartValue,WhatToReturn)	Calculates a geometric brownian motion time series with these parameters		X
RiskBMMR(mu,Sigma,Alpha, R0,Times, StartValue,WhatToReturn)	Calculates a geometric brownian motion with mean reversion time series with these parameters	X	X
RiskGBMJD(mu,Sigma,Lambda,JumpMu,JumpSigma,Times, StartValue,WhatToReturn)	Calculates a geometric brownian motion with jump diffusion time series with these parameters		X
RiskBMMRJD(mu,Sigma,Alpha,R0, Lambda,JumpMu,JumpSigma, Times, StartValue,WhatToReturn)	Calculates a geometric brownian motion with mean reversion and jump diffusion time series with these parameters	X	X
RiskARCH(mu,Omega,A,R0, StartValue,WhatToReturn)	Calculates an auto-regressive conditional heteroskedastic time series with these parameters	X	X
RiskGARCH(mu, Omega, A,B,R0, Sigma0, StartValue,WhatToReturn)	Calculates a generalized auto-regressive conditional heteroskedastic time series with these parameters	X	X

Examples of US Gulf soybean basis time series projections are show below in Figures 4.1. – 4.9. The two GBM functions are shown in Figures 4.10. and 4.11. and use US Gulf soybean freight. In blue, the graphs show the historic US Gulf soybean basis/freight from

1/5/2018 – 1/10/2020 as negative values along the x-axis indicate historical values. Positive values along the x-axis indicate the projected basis values. The red line shows one sample iteration that the basis could follow given the function identified. The black line is the average of all iterations. The darker shaded area shows the middle 50% of where all iterations should occur, or 25% above or below the mean. The lighter shaded area shows an additional 40% and account for 90% of the iterations when including both shaded areas. There is a 5% chance that the iteration (basis/freight) would be above or below the light gray shaded area.

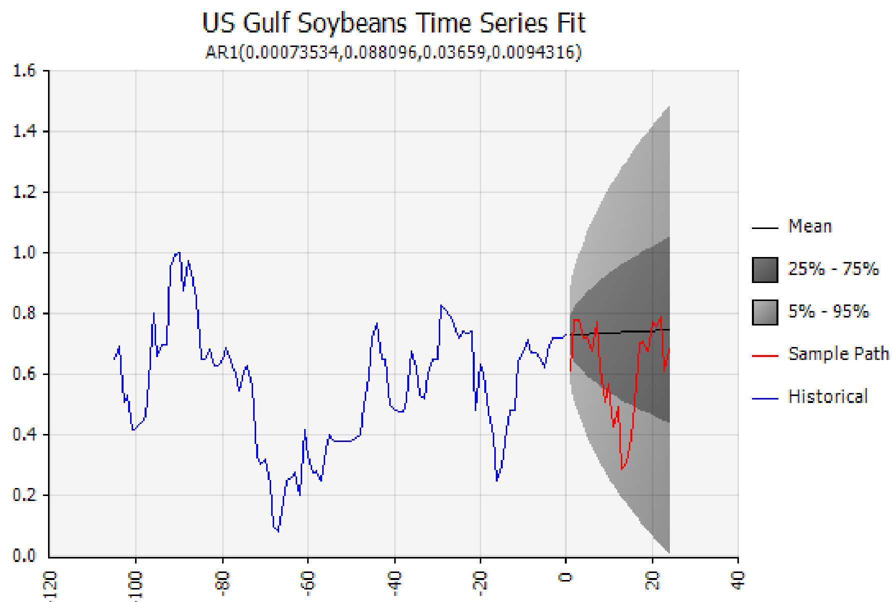


Figure 4.1. US Soybean Basis Time Series Fit – AR1

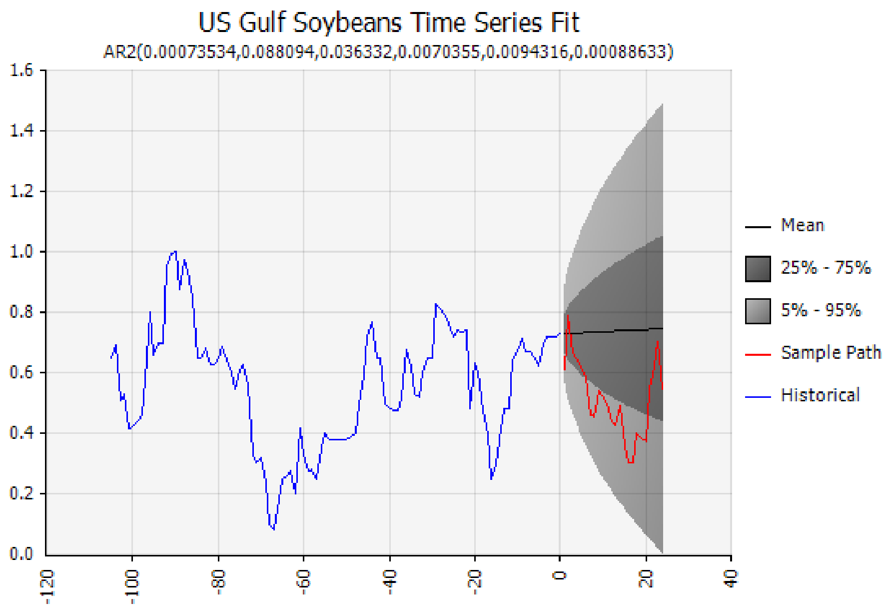


Figure 4.2. US Soybean Basis Time Series Fit – AR2

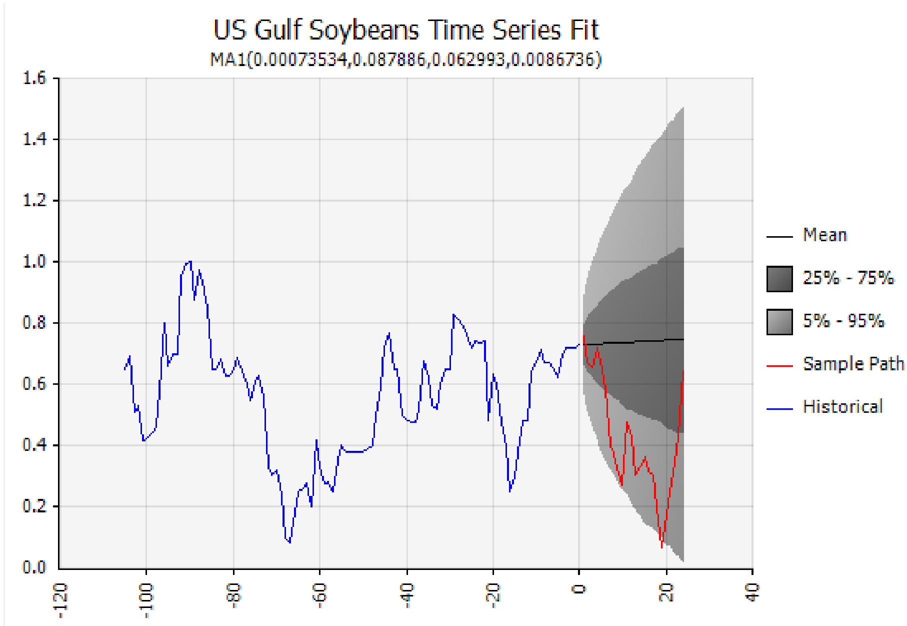


Figure 4.3. US Soybean Basis Time Series Fit – MA1

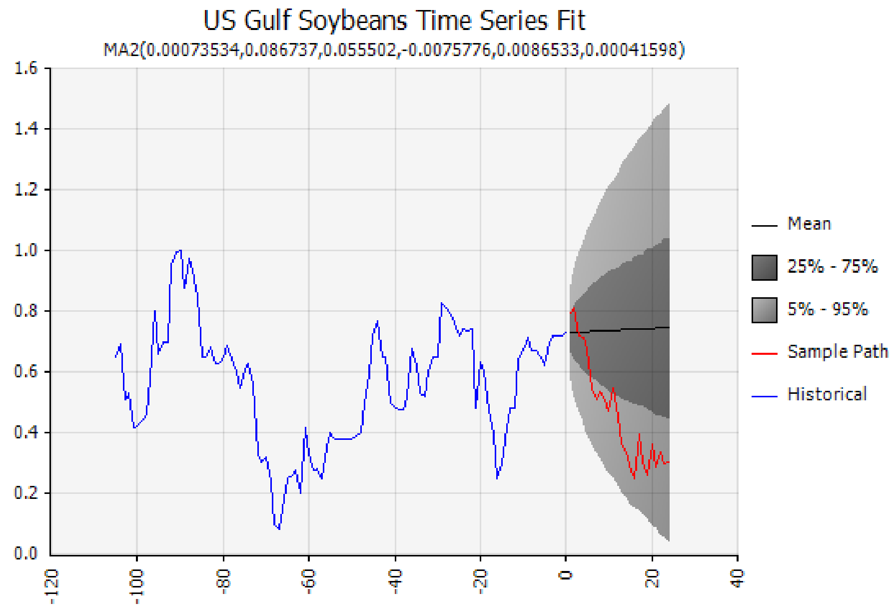


Figure 4.4. US Soybean Basis Time Series Fit – MA2

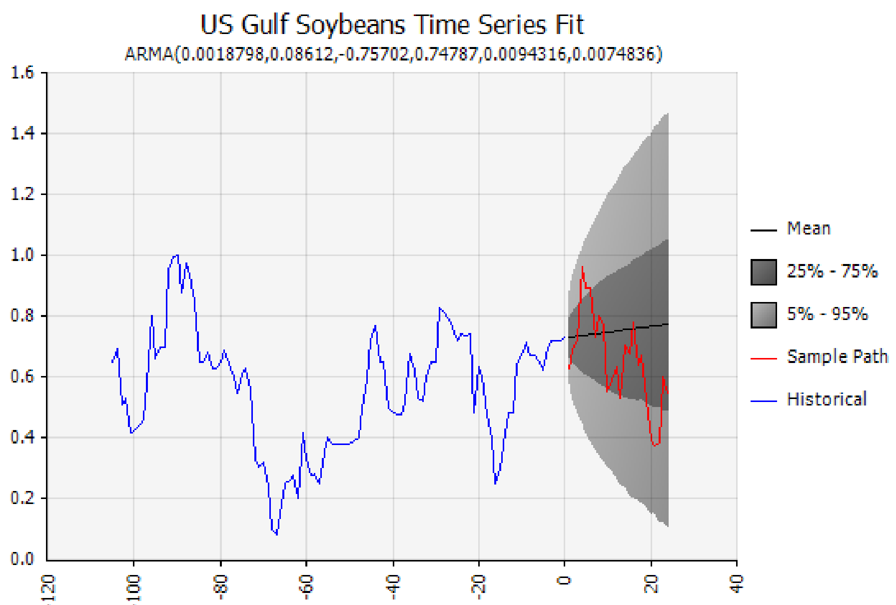


Figure 4.5. US Soybean Basis Time Series Fit – ARMA

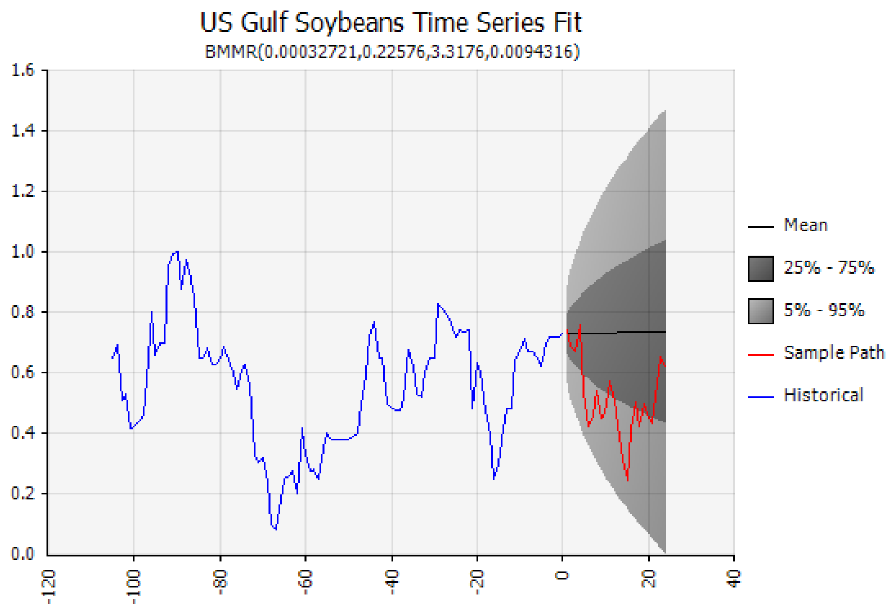


Figure 4.6. US Soybean Basis Time Series Fit – BMMR

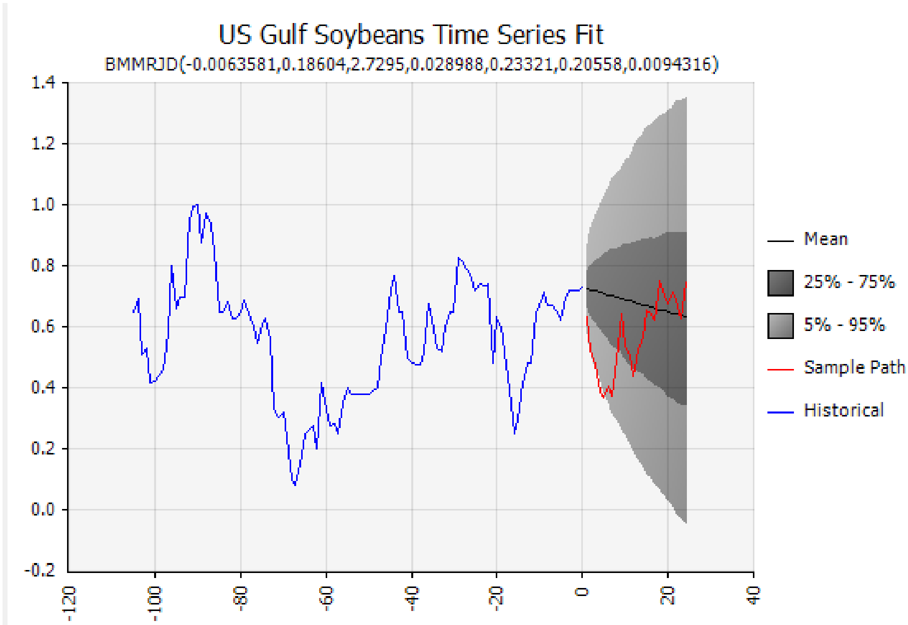


Figure 4.7. US Soybean Basis Time Series Fit – BMMRJD

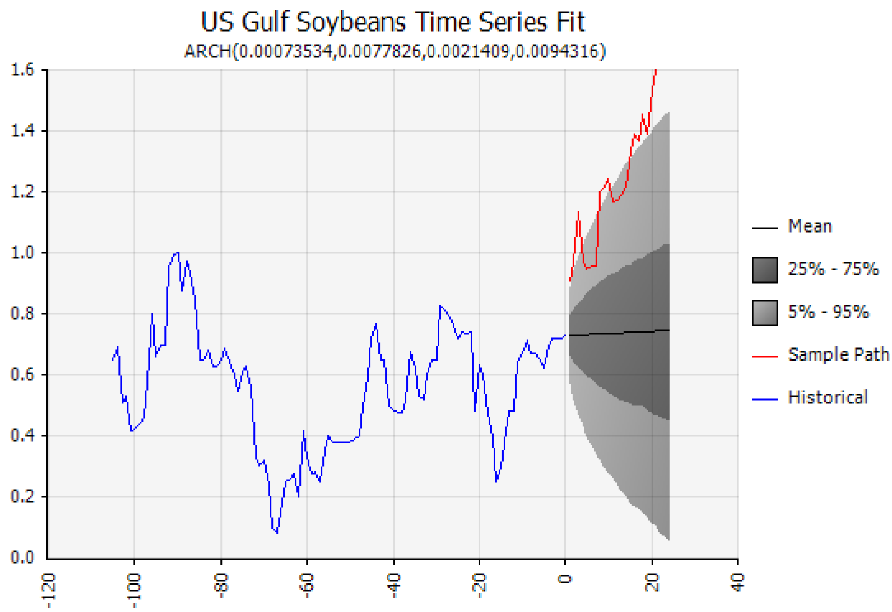


Figure 4.8. US Soybean Basis Time Series Fit – ARCH

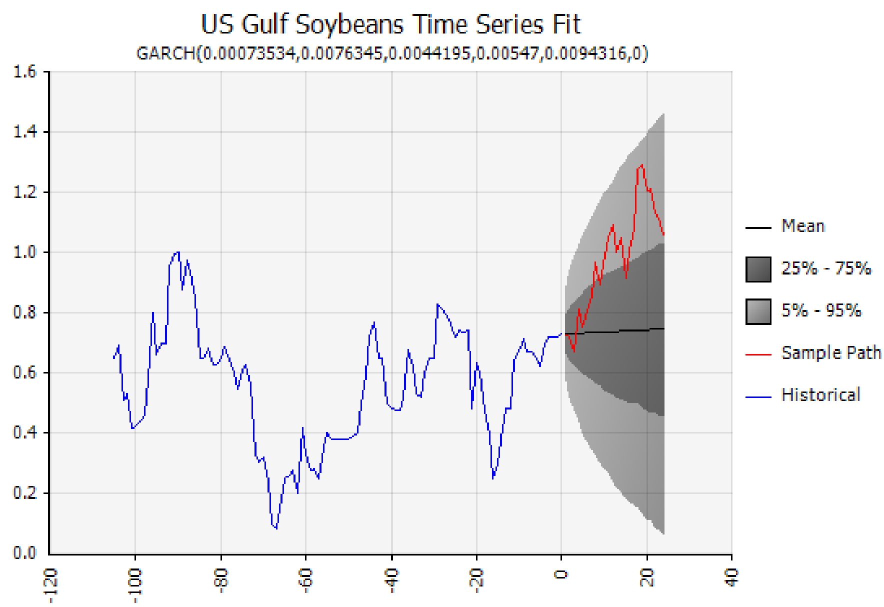


Figure 4.9. US Soybean Basis Time Series Fit – GARCH

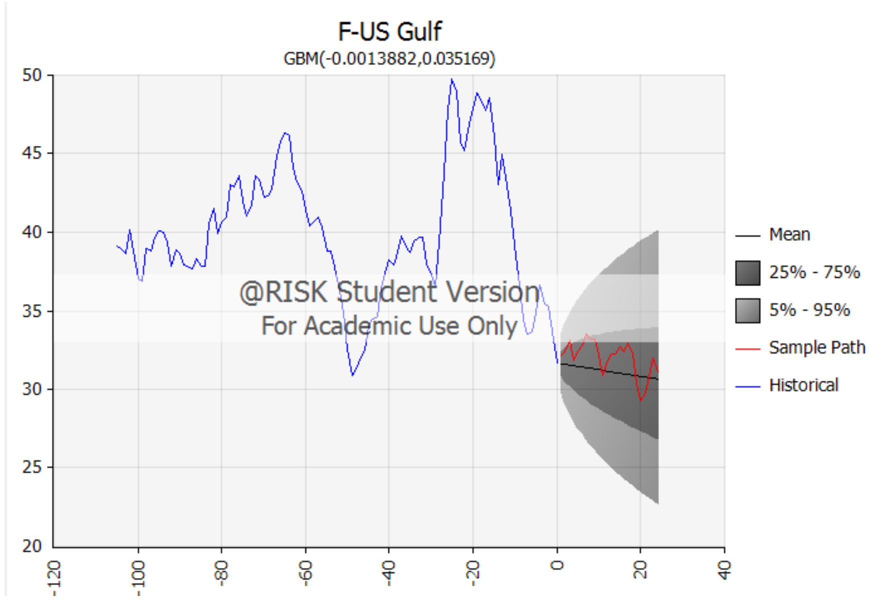


Figure 4.10. US Soybean Freight Time Series Fit – GBM

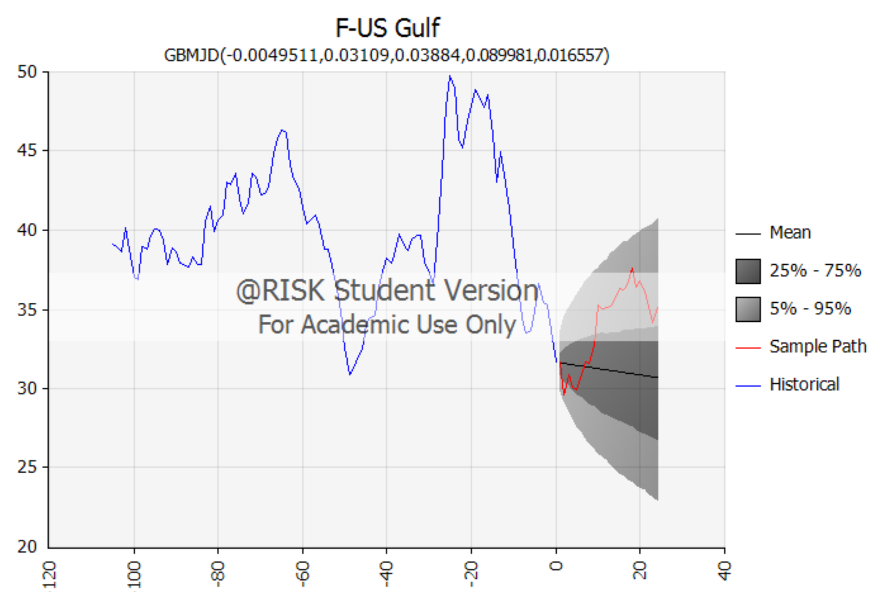


Figure 4.11. US Soybean Freight Time Series Fit – GBMJD

When working with time series data, it is important to ensure the data is stationary. This can be tested using the Augmented Dickey-Fuller test. Each different set of data was tested for stationarity at the 0.01, 0.05, and 0.1 level of significance. The results of the basis Augmented

Dickey-Fuller tests are in Table 4.2. below. This thesis uses the 0.05 level of significance when testing for stationarity. If data is not stationary, the first difference will be taken to adjust and ensure stationarity. Because @Risk™ can only make transformations across all origins, if any origin is not stationary, the whole data set will be adjusted using the first difference. As the results indicate, the only two data sets that are completely stationary are the soybean base case and corn base case.

Table 4.2. Basis Augmented Dick-Fuller Test Results (p-value)

Data	US Gulf	PNW	Brazil	Argentina	Ukraine
Soybean Basis Base Case	0.000***	0.015**	0.000***	0.000***	N/A
Soybean Basis 1.0	0.002***	0.009***	0.001***	0.105	N/A
Soybean Basis 1.1	0.192	0.130	0.156	0.396	N/A
Corn Basis Base Case	0.000***	0.011**	0.009***	0.000***	N/A
Corn Basis 1.0	0.095*	0.000***	0.109	0.201	0.011**
Corn Basis 1.1	0.161	0.000***	0.495	0.373	0.091*

Indicates Stationarity at *** 0.01, ** 0.05, and *0.10 Level of Significance

The freight data was also tested for stationarity. The results are found in Table 4.3. below. There were no full data sets that were completely stationary, so the first difference was taken throughout all the data sets. Additionally, because freight data must remain positive, the data was transformed using a logarithmic transformation too. All freight data was transformed using both the first difference and a logarithmic transformation.

Table 4.3. Ocean Freight Augmented Dick-Fuller Test Results (p-value)

Data	US Gulf	PNW	Brazil	Argentina	Ukraine
Soybean Ocean Freight Base Case	0.028**	0.212	0.032**	0.041**	N/A
Soybean Ocean Freight 1.0	0.208	0.233	0.219	0.217	N/A
Soybean Ocean Freight 1.1	0.028**	0.212	0.032**	0.041**	N/A
Corn Ocean Freight Base Case	0.175	0.041**	0.204	0.211	0.348
Corn Ocean Freight 1.0	0.181	0.042**	0.112	0.109	0.127
Corn Ocean Freight 1.1	0.192	0.260	0.203	0.203	0.014**

Indicates Stationarity at *** 0.01, ** 0.05, and *0.10 Level of Significance

In both basis and freight, values were projected forward using the functions that were determine by Bestfit™. Values were projected 20 periods forward using @Risk™. The projections start with the most recent data point (t=0) and project forward 20 periods (t=20). The starting points were 1/10/2020 for soybeans and 1/24/2020 for corn.

$$Basis(t) = TSProjBasis\ (t) \tag{2}$$

$$Freight(t) = TSProjFreight\ (t) \tag{3}$$

At each iteration, the delivered basis (Net Price) was calculated for each origin. Additionally, the option value was calculated at each of the 10,000 iterations as well. The value of the European option was calculated by taking the difference between the US Gulf delivered basis and the delivered basis of the minimum amongst all origins (dependent on commodity). The average value of the 10,000 iterations is what is considered the fair option price given the origins available and destination market.

Delivered Basis Formula:

$$DeliveredBasis(t) = ProjectedBasis(t) + OceanFreight(t) \tag{4}$$

Option Value Formula:

$$
\begin{aligned}
&EuropeanOptionValue \\
&= USG\ DeliveredBasis(t) \\
&- (MIN(DeliveredBasis(USG(t), PNW(t), Brazil(t), Argentina(t))))
\end{aligned}
\tag{5}
$$

The Asian type option is calculated using the same data and same simulation process but is calculated slightly different. The primary market price is determined using the same process as the European type option above. The secondary market value or Asian option value is determined based on the average of the minimum net price at each period, a set number of periods forward. This price is compared with the primary market price to determine the option value. The Asian option is an average price option that helps to illustrate a value like that of an average American type option.

$$AsianOptionValue = Average(PeriodMin(1\ to\ t) \tag{6}$$

The lookback options also use the same data. The lookback options take the minimum net price across all origins for each time period from 1 to t time periods. The minimum lookback option observes the minimum net price of each period minimum. This offers a greater value because it locks in the price at the absolute minimum. The maximum lookback option still observes at all the period minimums but assumes the greatest net price throughout these minimums. The maximum lookback option illustrates a case in which a commodity trading firm locked in the net price at the worst point throughout the set period. The commodity trading firm still chooses the origin with the lowest net price at that point in time. It uses the same calculation as the minimum lookback but uses the maximum of all period net price instead of minimum of all period basis. This is less valuable as it would be the worst-case scenario for the seller of the grain. The minimum and maximum lookback options help set the upper and lower bound of the value of an American type option. They are the minimum and maximum value that an American type exercise option could be through the given period.

Minimum Lookback Option:

$$MINLookbackOptionValue = MIN(PeriodMin(1\ to\ t)) \tag{7}$$

Maximum Lookback Option:

$$MAXLookbackOptionValue = MAX(PeriodMin(1\ to\ t)) \tag{8}$$

Scope of Analysis

Soybeans

For the soybean models, the origins are United States Gulf, Pacific Northwest, Brazil, and Argentina. These origins were chosen because the US, Brazil and Argentina are the top three exporters of soybeans, representing nearly 95% of the 2019 soybean exports. The destination chosen was China, which represented nearly 75% of 2019 soybean imports which has been the number one importer of soybeans in recent years. Figure 4.10. illustrates the top soybean exporting countries and Figure 4.11. illustrates the top 10 soybean importing countries.

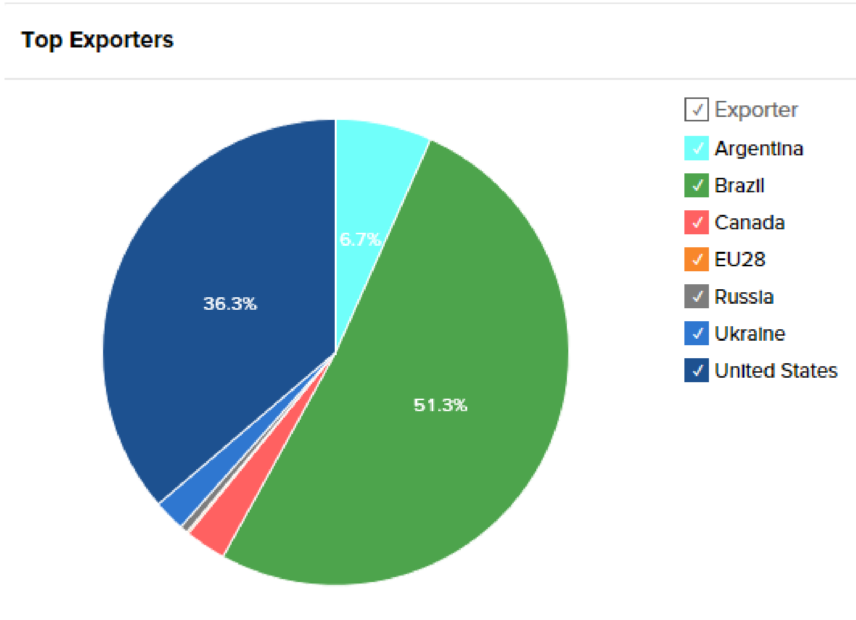


Figure 4.12. Top Soybean Exporting Countries (Agricensus, 2020)

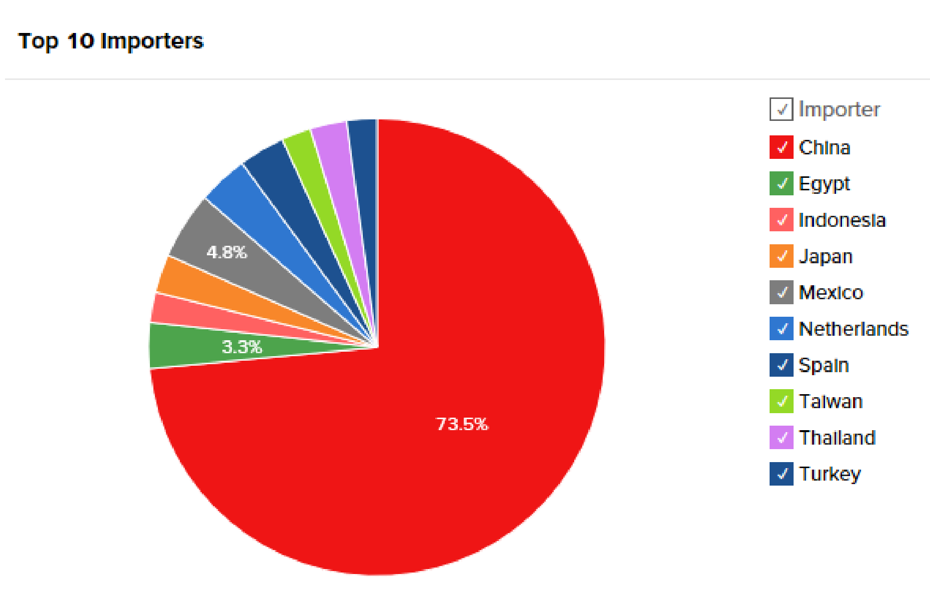


Figure 4.13. Top 10 Soybean Importing Countries (Agricensus, 2020)

Corn

The corn models use United States Gulf, Pacific Northwest, Brazil, Argentina, and Ukraine (only in models using data from 9/23/2016 and 1/5/2018) for origins. These four origins were the top four exporters of corn in 2019 and represented about 95% of the corn exports. The destination chosen is Japan. Japan was the number on importer of corn in 2019 representing 18.3% of all corn imports. Mexico was a close second importer of corn, representing 17.1% of corn imports. In this thesis Japan was used as the destination, not only due to importing the highest percentage of all corn imports, but also because all origins would use the same form of freight to deliver the corn to the destination. If Mexico were used, rail freight would be necessary for United States origins, which could put those origins at an advantage or disadvantage. Japan was chosen to keep the freight consistent amongst the origins as all origins would require ocean vessels for grain shipments to Japan. Figure 4.14. below shows the top corn exporters and Figure 4.15. shows the top 10 corn importers.

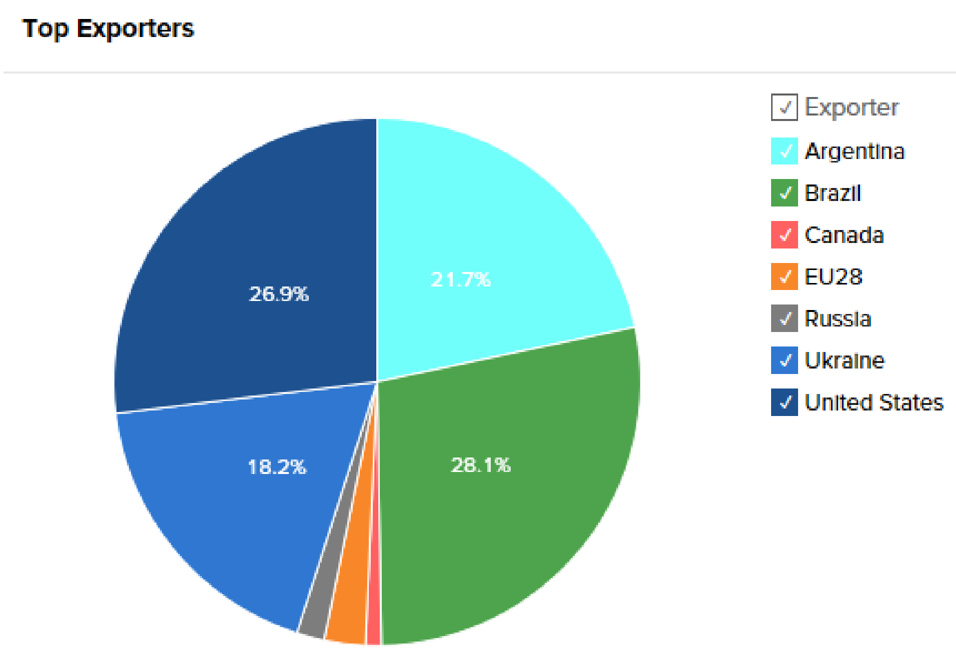


Figure 4.14. Top Corn Exporting Countries (Agricensus, 2020)

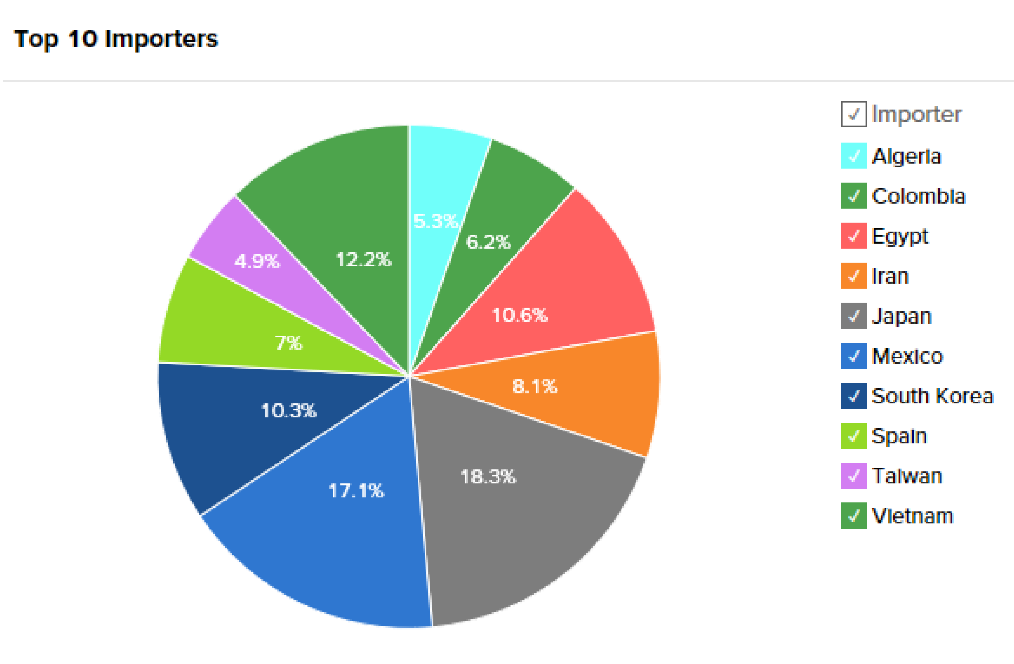


Figure 4.15. Top 10 Corn Importing Countries (Agricensus, 2020)

Data Sources

All soybean and corn price and freight data were obtained from Thompson Reuters and is weekly. All but one price that was collected were Free-on-Board (FOB) values that represented the 1st position or nearby origin price in the corresponding commodity. PNW corn prices were the only prices that were not FOB but were Cost-Insurance-Freight (CIF) due to the unavailability of FOB PNW corn price data. The price data was gathered or converted into both US dollars per metric ton ($/mt) and US dollars per bushel ($/bu.). Soybean data was collected from 1/5/2005 – 1/10/2020 and corn data was collected from 6/13/2008 – 1/24/2020. The data was gathered and organized in Microsoft Excel and any missing data was filled in with the previous value.

Ocean freight was collected in $/mt and was converted to $/bu. It was collected for the same time periods of each respective commodity. In this thesis, soybeans are delivered to China, so the ocean freight for soybeans reflects the cost to deliver the grain from the origin to China.

Corn is delivered to Japan in this thesis, so the ocean freight reflects that as well. Again, data was compiled in Microsoft Excel and any missing data was filled in with the previous value. The data, source, and Thompson Reuters Code are included in Table 4.4. below.

Table 4.4. Data Sources from Thompson Reuters

Data	Source	Code
Soybean US Gulf Spot	Thompson Reuters Contributed Data (TRC)	2YSB-USG-C1
Soybean PNW Spot	Cash Commodity Rates EMEA,	2YSB-PNW
Soybean Brazil Spot	Thompson Reuters Contributed Data (TRC)	S-BRZPAR-C1
Soybean Argentina Spot	Thompson Reuters Contributed Data (TRC)	EXSYB-AR-P1
Soybean Nearby Futures	Chicago Board of Trade (CBOT)	Sc1
US Gulf to China Freight	Thompson Reuters Contributed Data (TRC)	DRYP-DVTDLC-GRA
PNW to China Freight	Thompson Reuters Contributed Data (TRC)	DRYP-PDXDLC-GRA
Brazil to China Freight	Thompson Reuters Contributed Data (TRC)	DRYP-PNGDLC-GRA
Argentina to China Freight	Thompson Reuters Contributed Data (TRC)	DRYP-RVPDLC-GRA
Corn US Gulf Spot	Thompson Reuters Contributed Data (TRC)	C-US2YNOLAF-P1
Corn PNW Spot	Thompson Reuters Contributed Data (TRC)	C-CIFPNW-P1
Corn Brazil Spot	Thompson Reuters Contributed Data (TRC)	C-FOBPNG-C1
Corn Argentina Spot	J.J. Hinrichsen	C-FOBARG-P1
Corn Ukraine	KORTES	KTS-CFUABS-FOB
Corn Nearby Futures	Chicago Board of Trade (CBOT)	Cc1
US Gulf to Japan Freight	Thompson Reuters Contributed Data (TRC)	DRYP-DVTTYO-GRA
PNW to Japan Freight	Thompson Reuters Contributed Data (TRC)	DRYP-PDXTYO-GRA
Brazil to Japan Freight	Thompson Reuters Contributed Data (TRC)	DRYP-PNGTYO-GRA
Argentina to Japan Freight	Thompson Reuters Contributed Data (TRC)	DRYP-RVPTYO-GRA
Ukraine to Japan Freight	Thompson Reuters Contributed Data (TRC)	DRYP-ODSCHI-GRA

Note: Basis values are calculated of off values where price data was available using the futures. Thompson Reuters Contributed Data (TRC)

Data Behavior

Soybeans

Soybean Data Graph

The soybean basis and ocean freight rate delivered to China are shown over the entire time period in Figures 4.16. and 4.17. below. Figure 4.16. shows that there is significantly less variability in the US origins' basis over time. Brazil and Argentina are much more variable as shown by the higher peaks and lower valleys in the graph. South American markets are much more unpredictable because of the lack of infrastructure at those origins. The railroads are underdeveloped and so the grain industry relies heavily on the trucking market to transport grain. This becomes an issue when the truckers go on strike as show by the sharp increase in basis in mid-2018 (Demori and Piero, 2018). Figure 4.16. also helps to illustrate the seasonality within the markets. US markets generally get more depressed around October/ November due to the influx of grain around harvest, whereas the South American markets where this occurs around March/April.

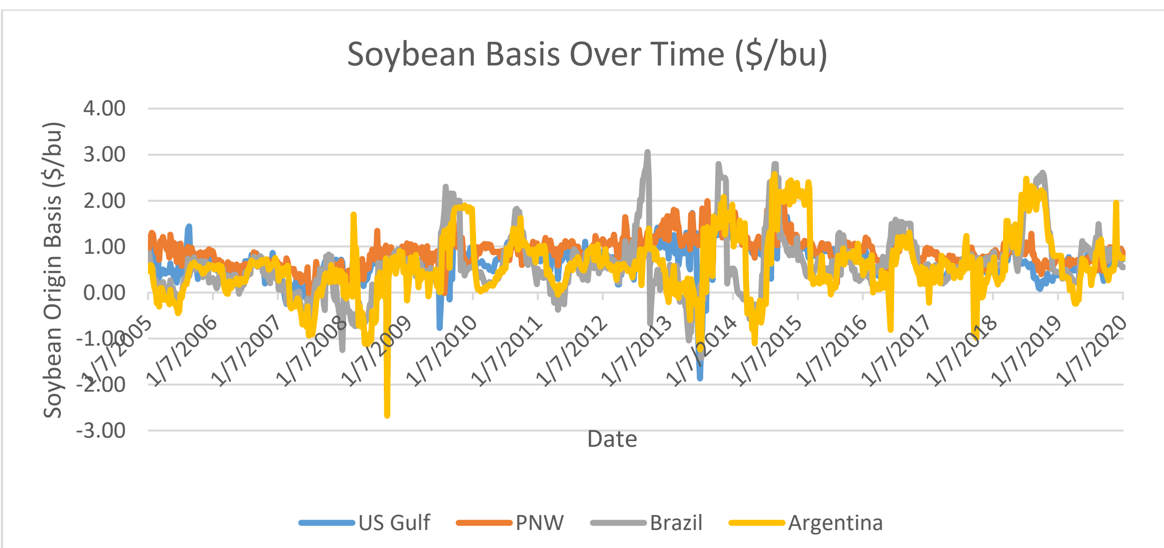


Figure 4.16. Soybean Basis Over Time ($/bu)

Ocean freight values tend to track close with all origins following the same patterns. Due to its closer proximity to China, the PNW is consistently the lowest cost origin. PNW is about half the distance to China as the other three origins. The other origins are closer to the same distance from China, but are in order, from closest to furthest: US Gulf, Brazil, Argentina. The ocean freight rates tend to reflect that in the prices over time. Additionally, there was a steep increase in ocean freight rate around 2007-2008, due to the financial crisis of the time. Apart from that period, the ocean freight values remained consistent, with less volatility.

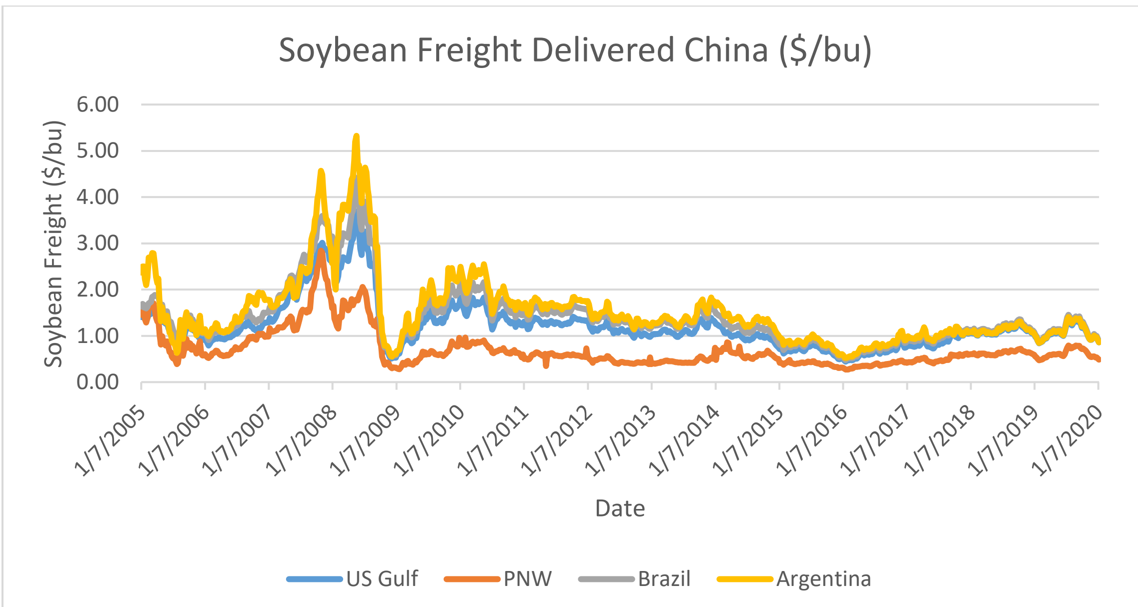


Figure 4.17. Soybean Freight Over Time ($/bu)

Soybean Basis Correlations

The basis correlation for each period was calculated and is shown in Tables 4.5. – 4.7. They indicate that the US origins are more highly correlated, which is expected. The higher correlation is due to the two origins having the same harvest period and being competing locations that both ship out of the US. As expected, both US origins are less correlated with the two South American origins with less than 50% for all time periods. The South American are more highly correlated with each other than the US origins.

Table 4.5. Soybean Basis Raw Data Correlations 1/7/2005

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.00	0.66	0.29	0.48
PNW	0.66	1.00	0.26	0.41
Brazil	0.29	0.26	1.00	0.63
Argentina	0.48	0.41	0.63	1.00

Table 4.6. shows that the period starting in 2016 has a slightly higher correlation between the two US origins and essentially no correlation between the US Gulf and South American origins. The PNW is also less correlated to the two South American origins than the full period correlation. The South American origins are also more highly correlated with each other than the previous correlation.

Table 4.6. Soybean Basis Raw Data Correlations 1/1/2016

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.00	0.69	0.08	0.03
PNW	0.69	1.00	0.10	0.23
Brazil	0.08	0.10	1.00	0.76
Argentina	0.03	0.23	0.76	1.00

Table 4.7. shows the correlations of the data in the final period that starts in 2018. The US origins are less correlated in this data set than both prior ones. Additionally, US Gulf is inversely correlated with both South American origins. This indicates that when the US Gulf basis increase, the South American origins decrease in basis level. Part of this inverse correlation is likely due to the seasonality in the soybean basis as illustrated in the above figure (Figure 4.16.). Brazil and Argentina have their strongest correlation in this period and have the highest correlation of any origin combination.

Table 4.7. Soybean Basis Raw Data Correlations 1/5/2018

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.00	0.60	-0.30	-0.21
PNW	0.60	1.00	0.00	0.20
Brazil	-0.30	0.00	1.00	0.86
Argentina	-0.21	0.20	0.86	1.00

Soybean Correlations (Basis & Ocean Rates)

Table 4.8. below shows the correlation between the soybean basis and ocean freight rates over each period. Each US origin had a slightly negative correlation for each period. Negative correlations indicate that as one value increase, the other value decreases. They have an inverse relationship. The South American origins also had a slightly negative correlation in the first period but has positive correlations in the last two periods. Brazil had the highest correlation in the last period (1/5/2018) and was just over 50% correlated.

Table 4.8. Soybean Basis and Freight Correlation

Period	US Gulf	PNW	Brazil	Argentina
Full (1/7/2005)	-0.225	-0.360	-0.305	-0.240
1.0 (1/1/2016)	-0.313	-0.303	0.353	0.329
1.1 (1/5/2018)	-0.262	-0.213	0.521	0.333

Soybean Volatility

Standard deviations were calculated for each of the time periods used for both soybean basis and ocean freight delivered to China. The US origins have the highest standard deviation in the full period and gradually become less volatile as the period gets shorter and shorter. Brazil had the highest standard deviation in the full period, followed by the last period (1/5/2018), and finally the middle period (1/1/2016). Argentina reacted different again and had the highest volatility in the shortest period, followed by the full period and the middle period. The higher volatility leads to more spatial arbitrage opportunities for origins. Less volatility means that there will be less spatial arbitrage opportunities. The higher volatility in the South American origins helps give value to US options as well as their own option value.

Table 4.9. Soybean Basis Standard Deviation Over Time

Period	US Gulf	PNW	Brazil	Argentina
Full (1/7/2005)	0.380	0.341	0.662	0.678
1.0 (1/1/2016)	0.218	0.172	0.537	0.609
1.1 (1/5/2018)	0.199	0.166	0.629	0.682

The standard deviations for the ocean freight all follow the same trend with the most volatility in the full period and a gradual decrease in each time period following it. The more extreme volatility is easily seen in the graph in Figure 4.17. above. The period from 2007- 2009 was more volatile and had extremely high values. This increases the standard deviation for the full period significantly.

Table 4.10. Soybean Freight Standard Deviation Over Time

Period	US Gulf	PNW	Brazil	Argentina
Full (1/7/2005)	0.531	0.407	0.649	0.780
1.0 (1/1/2016)	0.222	0.126	0.223	0.193
1.1 (1/5/2018)	0.117	0.074	0.134	0.129

Corn

Corn Data Graph

Corn basis and ocean freight values delivered to Japan are show in Figures 4.18. and 4.19, below. Figure 4.18. shows that there is significant variability in all markets. Basis values appear to have been the most volatile around 2012-1013. This what a period with historically high commodity prices and so the transportation costs increased as the demand increased. The increase in transportation costs forced the buyers to shift their basis down to help cover the additional transportation costs. Additionally, the Brazil trucker strike in 2018 played a role in increased basis levels in mid-2018 in corn too.

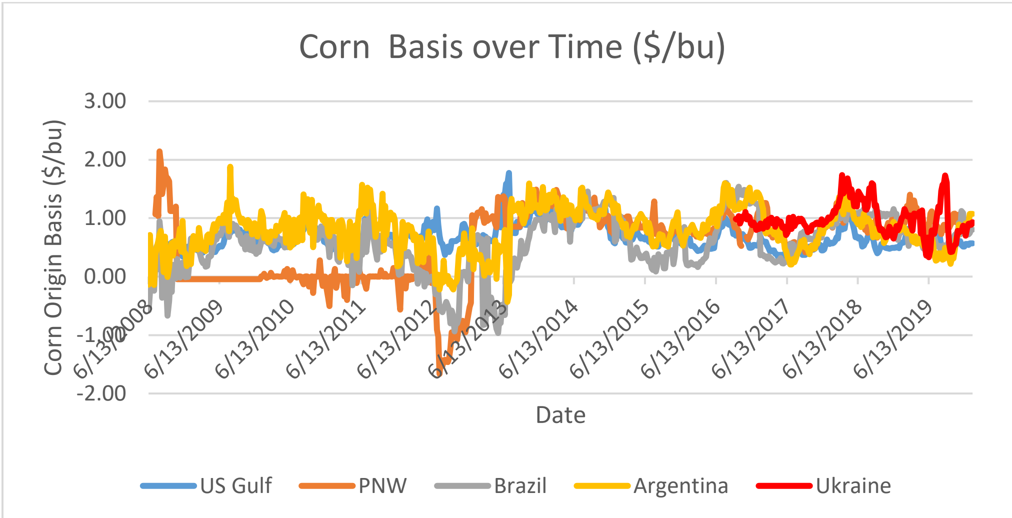


Figure 4.18. Corn Basis Over Time ($/bu)

Corn freight delivered to Japan behaves in a similar way to the soybean freight delivered to China. Figure 4.19. shows the freight rate at the highest levels in 2008. Again, origins proximity to the destination play a key role in the differences in freight prices as shown below. PNW is the closest and is about half the distance of US Gulf, Brazil, Argentina, and Ukraine. Throughout most of the data, PNW is significantly less than the other origins. They do all converge around 2016. This is likely due to freight hitting its low price and PNW not being able to go much lower. The other origins still have more room to decrease.

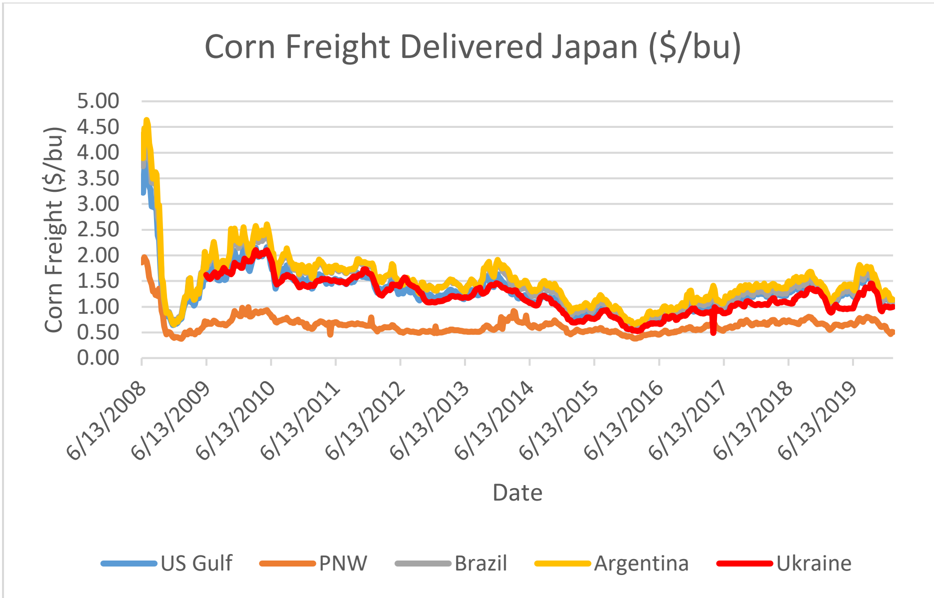


Figure 4.19. Corn Freight Over Time ($/bu)

Corn Correlations

The origin correlations for each period were calculated and are shown below in Tables 4.11. – 4.13 below. Table 4.11. indicates that the US Gulf is most highly correlated with the Ukraine origin but is still not highly correlated with it. The highest correlation is between any two origins is between Brazil and Argentina at 0.69.

Table 4.11. Corn Raw Data Correlations 6/13/2008

Correlation	US Gulf	PNW	Brazil	Argentina	Ukraine
US Gulf	1.00	0.23	0.22	0.38	0.47
PNW	0.23	1.00	0.34	0.31	0.02
Brazil	0.22	0.34	1.00	0.69	0.26
Argentina	0.38	0.31	0.69	1.00	0.31
Ukraine	0.47	0.02	0.26	0.31	1.00

The data from 9/23/2016 forward indicates that there is more correlation within this period. US Gulf was most highly correlated with PNW and the two South American origins were also most highly correlated with each other. The US origins were not as highly correlated with the other origins. US Gulf was the Ukraine's most highly correlated origin.

Table 4.12. Corn Raw Data Correlations 9/23/2016

Correlation	US Gulf	PNW	Brazil	Argentina	Ukraine
US Gulf	1.00	0.63	0.44	0.52	0.47
PNW	0.63	1.00	0.20	0.36	0.24
Brazil	0.44	0.20	1.00	0.67	0.26
Argentina	0.52	0.36	0.67	1.00	0.31
Ukraine	0.47	0.24	0.26	0.31	1.00

Again, the US Gulf was most highly correlated with PNW, but Argentina was not too far behind. Brazil and Argentina were the two most highly correlated origins. Brazil was poorly correlated with every origin besides Argentina. US Gulf was the origin that was most highly correlated with Ukraine in the period as well.

Table 4.13. Corn Raw Data Correlations 1/5/2018

Correlation	US Gulf	PNW	Brazil	Argentina	Ukraine
US Gulf	1.00	0.56	0.23	0.54	0.49
PNW	0.56	1.00	0.05	0.27	0.24
Brazil	0.23	0.05	1.00	0.71	0.33
Argentina	0.54	0.27	0.71	1.00	0.43
Ukraine	0.49	0.24	0.33	0.43	1.00

Corn Correlations (Basis & Ocean Rates)

Table 4.14. below shows that there is little correlation between the corn basis and ocean freight delivered to Japan. The highest correlation for the US Gulf was in the last period and had a negative correlation of -0.312. PNW followed the same pattern as US Gulf. Brazil had little correlation in any period too. Argentina had the highest correlation of any origin with a nearly

50% negative correlation in the last period. There was a strong negative correlation in the last period of Argentina. Ukraine had very little correlation in any period.

Table 4.14. Corn Basis and Freight Correlation

Period	US Gulf	PNW	Brazil	Argentina	Ukraine
Full (6/13/2008)	-0.054	0.121	-0.143	-0.113	0.135
1.0 (9/23/2016)	0.090	0.058	0.003	-0.378	0.135
1.1 (1/5/2018)	-0.312	-0.204	-0.066	-0.487	0.042

Corn Volatility

The corn basis and ocean freight to Japan standard deviations are show below in Tables 4.15. and 4.16. US Gulf is the least volatile origin with the lowest standard deviation at each period. PNW had the highest standard deviation at the first period but decreased from there. Brazil and Argentina were similar as they followed the same pattern as PNW and US Gulf, starting with the highest standard deviation in the full period and decreasing from there. Because the Ukraine data did not start until the second period, no standard deviation was recorded for the full period. From the second period to the final period, there was a slight increase in standard deviation.

Table 4.15. Corn Basis Standard Deviation Over Time

Period	US Gulf	PNW	Brazil	Argentina	Ukraine
Full (6/13/2008)	0.214	0.609	0.477	0.373	
1.0 (9/23/2016)	0.142	0.284	0.321	0.314	0.270
1.1 (1/5/2018)	0.138	0.270	0.231	0.271	0.332

The corn freight delivered to Japan reacted similarly to the soybean freight delivered to China. All origins started out with the highest standard deviations that decreased significantly in the second period. The final time periods showed a slight decrease from the second period. PNW had the overall lowest volatility which is due to the cost of the PNW ocean freight being considerably lower as illustrated in Table 4.16. The South American origins were the most volatile, especially in the first period.

Table 4.16. Corn Freight Standard Deviation Over Time

Period	US Gulf	PNW	Brazil	Argentina	Ukraine
Full (6/13/2008)	0.441	0.192	0.526	0.546	0.340
1.0 (9/23/2016)	0.179	0.073	0.173	0.186	0.159
1.1 (1/5/2018)	0.136	0.069	0.155	0.166	0.145

CHAPTER 5: RESULTS

Overview/ Organization

The goal of this research is to determine the value of being able to originate and ship grain from multiple origins. We refer to this as a switching option. There is value in having more locations to originate grain from. It gives commodity trading firms the ability to take advantage of spatial arbitrage and ship grain out of the least cost origin. Switching options give the commodity trading firm the ability to take advantage of spatial arbitrage opportunities because they can ship grain out of any origin, as compared to origin specific contracts. The value of these options is derived from the differences in delivered basis from each origin to the specific destination.

When the option to switch origins is included in a contract, there is an implied premium for the option. For example, the seller would sell the grain at $12.00/ bu. while specifying an origin (US Gulf). The seller would discount the grain to $11.00/ bu. to have the option to switch from the origin that was initially stated (US Gulf) with other origins that they have access to (PNW, Brazil, Argentina, or Ukraine). The seller has more flexibility in their grain shipments and would be able to take advantage of spatial arbitrage opportunities as they arise. The buyer of the grain (writer of the option) has the uncertainty of which origin the grain comes from.

This thesis develops models that calculate the value of the switching option for soybeans and corn. When determining the option value for soybeans, the base origin was US Gulf and the origins to switch between to, including: PNW, Brazil, and Argentina. In determining the option value for corn, US Gulf was the base case origin and alternative origins include: PNW, Brazil, and Argentina were origins to switch between. Ukraine was added for some sensitivities within the corn models.

Soybean Results

Introduction: Soybean

The European type option is the main type of interest in this thesis and is what the base case as well as sensitivities 1-5 focus on. Other types that are examined include Asian and lookback type options. The soybean section is structured as follows: Description of Data, Base Case Results, Sensitivity Analysis, Summary of Results, Interpretation of Results for Contracting Strategy, and Conclusion: Soybean.

Description of Data

As mentioned in the Scope of Analysis section above, the four origins used for soybeans were the US Gulf (base origin), PNW, Argentina, and Brazil. The destination is China. The results for the best fit basis equations of the full data set (1/7/2005 – 1/10/2020) are shown in Table 5.1. The table shows the distribution chosen, the function for the chosen distribution, and the Akaike information criterion (AIC). No transformations were made because all origin data was stationary according to the Augmented Dickey-Fuller test. Each distribution tested (from Table 4.1.) was compared and the function chosen was the best fit using AIC. The AIC determines how well the distribution fits the data, when compared with the other distributions that were fit.

Table 5.1. Basis Time Series Functions 1/7/2005 – 1/10/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Auto-Regressive Moving Average	Auto-Regressive Moving Average	Auto-Regressive II	Auto-Regressive II
Function:	RiskARMA11(22.109, 9.1651, 0.90005, -0.321, 26.75, 1.0264)	RiskARMA11(32.352, 8.1414, 0.94405, -0.57595,31.232, -1.6158)	RiskAR2(21.95, 10.109, 0.7544, 0.16812, 20.15, 20.103)	RiskAR2(21.267, 12.295, 0.62106, 0.27623, 27.45, 28.103)
AIC Score:	5718.8916	5513.7836	5867	6171.373
Transformation:	None	None	None	None

Table 5.2. shows the correlation of the origin data. As shown in the table, and as shown in Chapter 4, the US Gulf and PNW data sets are more highly correlated than the US Gulf and either Brazil or Argentina. The correlations vary with each batch fit that is ran as some of the batch fits use transformed data to ensure the data is stationary. The correlations are included to ensure that the basis projections move in accordance with the other data sets.

Table 5.2. Soybean Basis Correlation 1/7/2005 – 1/10/2020

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.000			
PNW	0.666	1.000		
Brazil	0.322	0.199	1.000	
Argentina	0.425	0.324	0.622	1.000

The Best Fit™ results for the freight data in the full data set (1/7/2005 – 1/10/2020) are found in Table 5.3. below. The distribution, function, AIC, and transformations are in the table. All freight data was transformed to ensure stationarity by taking the first difference.

Table 5.3. Time Series Freight Functions 1/7/2005 – 1/10/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Moving Average I	Generalized Auto-Regressive Conditional Heteroskedastic	Moving Average I	Moving Average I
Function:	RiskMA1(-0.00062328, 0.045868, 0.29533, -0.047707)	RiskGARCH11(-0.0013952, 0.0060604, 0.00369, 0.0045345, -0.058553,0)	RiskMA1(-0.00077844, 0.046798,0.325 13, -0.048571)	RiskMA1(-0.0012886, 0.066499, 0.22448, - 0.054249)
AIC Score:	-2606.1509	-1771.5388	-2555.9022	-2018.5257
Transformation:	Logarithmic First Difference	Logarithmic First Difference	Logarithmic First Difference	Logarithmic First Difference

Additionally, the data underwent a log transformation to ensure that the freight data remained positive.

The correlations of the transformed freight data are found in Table 5.4. This table shows that the transformed US Gulf freight data is most highly correlated with Brazil. These two origins use the Panama Canal for ocean shipments to China and are about the same distance from China. PNW has a much shorter distance to travel to get to China, so it is less responsive to changes in variable shipping costs.

Table 5.4. Soybean Freight Correlation of Transformed Data 1/7/2005 – 1/10/2020

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.000			
PNW	0.677	1.000		
Brazil	0.994	0.672	1.000	
Argentina	0.857	0.778	0.867	1.000

Table 5.5. below shows the soybean base case and sensitivity specifications. This summarizes the specifications that were covered in Chapter 4.

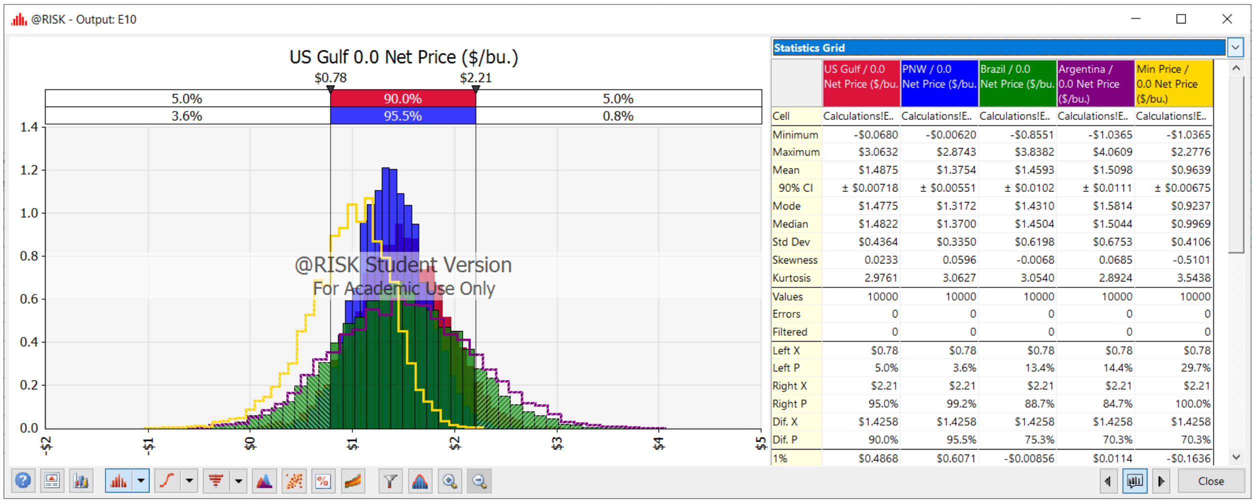
Table 5.5. Soybean Sensitivity Specifications

Sensitivity	Time period	Origins Included	Ocean Freight	Periods Forward	Interest Rate
Base case	1/7/2005 – 1/10/2020	US Gulf, PNW, BRZ, ARG	Yes	12	0
Sensitivity 1.0	1/1/2016 – 1/10/2020	US Gulf, PNW, BRZ, ARG**	Yes**	12**	0**
Sensitivity 1.1	1/5/2018 – 1/10/2020	US Gulf, PNW, BRZ, ARG**	Yes**	12**	0**
Sensitivity 2.0	1/7/2005 – 1/10/2020**	US Gulf & PNW	Yes**	12**	0**
Sensitivity 2.1	1/7/2005 – 1/10/2020**	US Gulf & BRZ	Yes**	12**	0**
Sensitivity 3.0	1/7/2005 – 1/10/2020**	US Gulf, PNW, BRZ, ARG**	No	12**	0**
Sensitivity 4.0	1/7/2005 – 1/10/2020**	US Gulf, PNW, BRZ, ARG**	Yes**	1-20	0**
Sensitivity 5.0	1/7/2005 – 1/10/2020**	US Gulf, PNW, BRZ, ARG**	Yes**	12**	1-12% annually

** indicates same as base case

The base case Net Price results are shown below in Figure 5.1. The graph shows the minimum, maximum, and mean, along with the distribution of prices. Argentina has the highest mean ($1.51), followed by US Gulf ($1.49), Brazil ($1.46), and then PNW ($1.38). Argentina also has the lowest minimum (-$1.04) and the highest maximum ($4.06), so also has the biggest range. Brazil has the next lowest minimum (-$0.86) and next highest maximum ($3.84). US Gulf follows with a minimum of -$0.07 and a maximum of $3.06. Finally, PNW has the highest minimum (-$0.01) and lowest maximum ($2.87). The US origins have less volatility as shown by the tighter distribution and lower standard deviations ($0.34 and $0.44 for PNW and US Gulf respectively). These are much lower than their South American counter parts of $0.62 and $0.68

for Brazil and Argentina, respectively. The simulation results indicate that there should be significant value to a US Gulf origin having the ability to switch to another origin because the mean net price is towards the higher end of all origins.



	US Gulf / 0.0 Net Price ($/bu.	PNW / 0.0 Net Price ($/bu.	Brazil / 0.0 Net Price ($/bu.	Argentina / 0.0 Net Price ($/bu.)	Min Price / 0.0 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	-$0.0680	-$0.00620	-$0.8551	-$1.0365	-$1.0365
Maximum	$3.0632	$2.8743	$3.8382	$4.0609	$2.2776
Mean	$1.4875	$1.3754	$1.4593	$1.5098	$0.9639
90% CI	± $0.00718	± $0.00551	± $0.0102	± $0.0111	± $0.00675
Mode	$1.4775	$1.3172	$1.4310	$1.5814	$0.9237
Median	$1.4822	$1.3700	$1.4504	$1.5044	$0.9969
Std Dev	$0.4364	$0.3350	$0.6198	$0.6753	$0.4106
Skewness	0.0233	0.0596	-0.0068	0.0685	-0.5101
Kurtosis	2.9761	3.0627	3.0540	2.8924	3.5438
Values	10000	10000	10000	10000	10000
Errors	0	0	0	0	0
Filtered	0	0	0	0	0
Left X	$0.78	$0.78	$0.78	$0.78	$0.78
Left P	5.0%	3.6%	13.4%	14.4%	29.7%
Right X	$2.21	$2.21	$2.21	$2.21	$2.21
Right P	95.0%	99.2%	88.7%	84.7%	100.0%
Dif. X	$1.4258	$1.4258	$1.4258	$1.4258	$1.4258
Dif. P	90.0%	95.5%	75.3%	70.3%	70.3%
1%	$0.4868	$0.6071	-$0.00856	$0.0114	-$0.1636

Figure 5.1. Delivered Basis Base Case from Base Case (0.0) Simulation

The increased volatility in the South American origins is likely due to the inefficiencies. South American logistics are underdeveloped and behind the United States, which can lead to bottlenecks in the flow of grain. South American relies more heavily on truck logistics than railways. This significantly increases the volatility in the market. The increase in volatility can lead to greater spatial arbitrage opportunities.

The option value for the US Gulf based origin were the US Gulf net price with the minimum net price among the four origins to determine what value would be derived from the spatial arbitrage opportunities available. The average option value is $0.52 with a standard deviation of $0.47. Due to the volatility in all four markets, there can be times where one price is very low, and another is very high. This leads to an extremely high option price. In the case of the US Gulf option, there is one iteration that resulted in an option value of $2.75. The minimum value is truncated at $0.00 because if there is no value in the option (ex. The US Gulf price is the lowest price), then the option would not be exercised. The seller of grain would ship out of the initial origin of the US Gulf when it is the least cost of the four origins. The results of the simulations are shown in Figure 5.2. below.

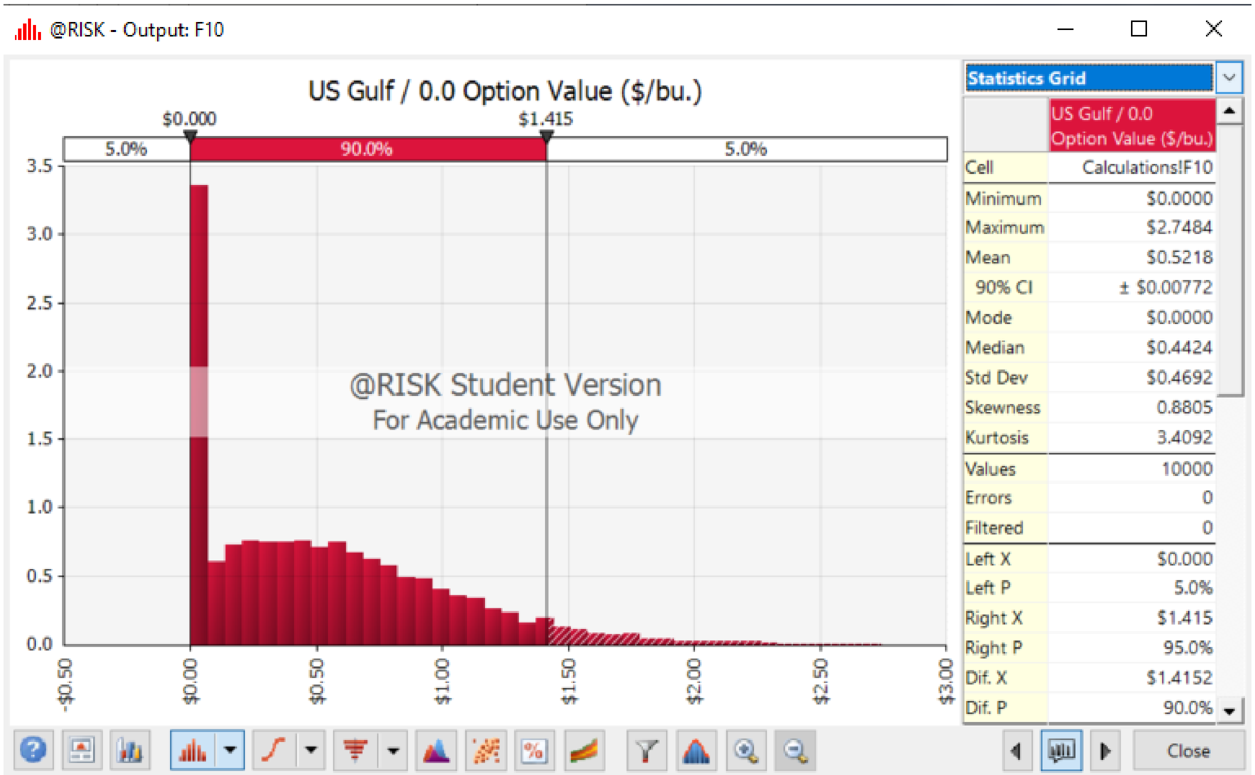


Figure 5.2. US Gulf Option Value from Base Case (0.0) Simulation

The option value interpretation from a contracting strategy perspective are developed in the final section of this chapter.

Sensitivity Analysis

Sensitivity 1 – Time Period

The time period sensitivity is used to illustrate the difference in option value when projecting basis forward from different time periods with different volatilities and correlations. More volatile time periods are expected to produce a higher valued option because the increase in volatility leads to an increase in price differences. This would allow for a more valuable option. This is important, as when projecting prices, a time period that is relevant to the current situation should be used. Less correlation between data also generates a greater option value due to prices changing at varying rates when compared to each other. It is also beneficial to use time periods directly prior to the period that is being projected in order to account for any "intrinsic value" or value that is imbedded in the option at the beginning. The intrinsic value would be the difference in delivered basis between US Gulf and the minimum cost origin at time period 0.

For the time period sensitivities, there were two periods that were compared to the base case scenario in which the time period spanned from 1/7/2005 – 1/10/2020. The first sensitivity includes the time period from 1/1/2016 – 1/10/2020. This time period includes the past four years of prices and could be in line with current commodity markets. The specifications for this sensitivity are found in Table 5.5. above.

The other time period used is from 1/5/2018 – 1/10/2020 and is used to highlight the impact of more uncertainties in the market due to the tariffs. Though the tariffs were not enacted until March of 2018, the time period included the January and February of 2018 as well to include two full years. The other specifications for this sensitivity are also found in Table 5.5. above.

The results from running the time series basis batch fit and equations used are shown in Table 5.6. The table also shows the distribution, function, AIC and transformations made to the data. You can see that the distributions change for the US Gulf and PNW but only the functions changed for Brazil and Argentina. All data was transformed using first difference because the initial data, when tested using the Augmented Dickey-Fuller test, was not stationary.

Table 5.6. Soybean Time Series Basis Functions 1/1/2016 – 1/10/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Moving Average I	Moving Average I	Auto-Regressive Conditional Heteroskedastic	Moving Average I
Function:	RiskMA1(-0.003447, 3.0827, 0.066224, 0.3472)	RiskMA1(-0.01531, 3.8831, -0.38274, -1.9236)	RiskARCH1(0.041791, 32.283, 0.13936, 0.04655)	RiskMA1(0.0075054, 11.602, -0.28337, -0.69864)
AIC Score:	1062.6826	1162.3066	1350.2387	1629.3851
Transformation:	First Difference	First Difference	First Difference	First Difference

Table 5.7. below shows that the US Gulf and PNW have the highest correlation at 0.332. The South American origins (with data transformations) being the next most highly correlated (0.220). The table also shows that both US markets are not highly correlated with the South American origins.

Table 5.7. Soybean Basis Correlation with Transformed Data 1/1/2016 – 1/10/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed
US Gulf Transformed	1.000			
PNW Transformed	0.332	1.000		
Brazil Transformed	0.208	0.031	1.000	
Argentina Transformed	0.112	0.270	0.220	1.000

Table 5.8. below shows the results from the freight best fit equations for the time period from 1/1/2016 – 1/10/2020. This contains the distributions and functions that best fit the data, along with the AIC score and transformations. As previously mentioned, all freight data had the

first difference taken, and underwent a logarithmic transformation. These transformations were made because the data was not stationary, and the value had to remain positive.

Table 5.8. Soybean Freight Time Series Functions 1/1/2016 – 1/10/2020 (@Risk™)

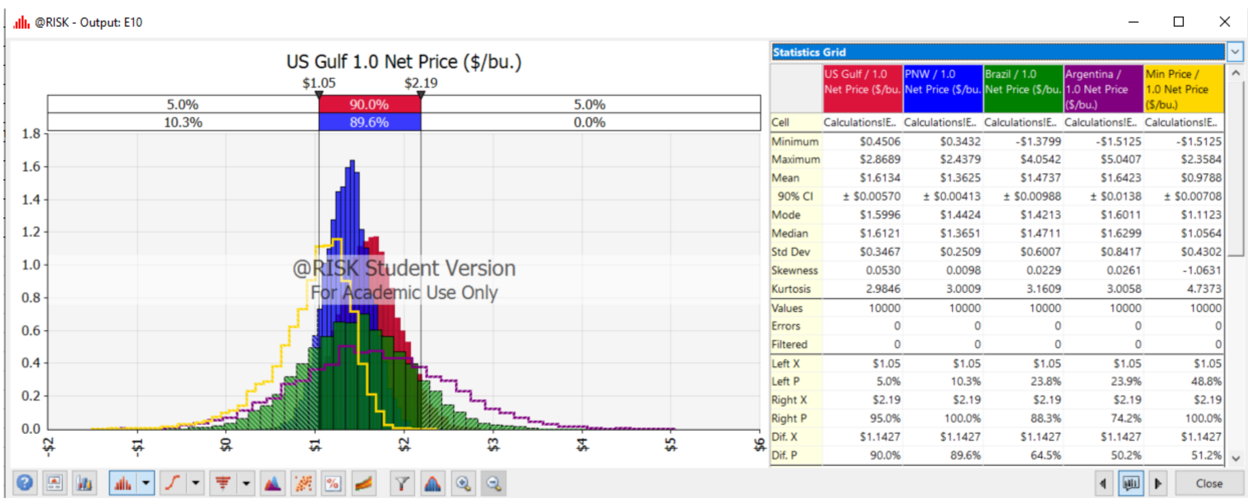
Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Moving Average I	Moving Average I	Moving Average I	Moving Average I
Function:	RiskMA1(	RiskMA1(	RiskMA1(	RiskMA1(
	0.0024622, 0.037983, 0.34685,	0.0020972, 0.03446, 0.31223,	0.0021757, 0.037998, 0.44471,	0.0017057, 0.03958, 0.40261,
	-0.047009)	-0.049363)	-0.041957)	-0.045174)
AIC Score:	-774.7228	-821.4027	-773.6874	-761.821
Transformation:	Logarithmic	Logarithmic	Logarithmic	Logarithmic
	First Difference	First Difference	First Difference	First Difference

Table 5.9. below shows the correlation between the transformed origin data. Like the full freight data set, the correlation between US Gulf and Brazil is the highest of any two origins (0.98). US Gulf is also more highly correlated with Argentina than PNW. This is likely due to the similarities in distanced traveled. PNW to China has a much shorter distance for the freight to travel. This leads to that freight price to be less responsive to changes in variable freight costs associated with distance traveled.

Table 5.9. Soybean Freight Correlation with Transformed Data 1/1/2016 – 1/10/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed
US Gulf Transformed	1.000			
PNW Transformed	0.859	1.000		
Brazil Transformed	0.979	0.839	1.000	
Argentina Transformed	0.917	0.795	0.960	1.000

The net price iterations are shown in Figure 5.3. below. US Gulf has the second highest mean net price ($1.61), only behind Argentina ($1.64) by $0.03. Brazil had the third highest ($1.47), followed by PNW with the lowest mean net price ($1.36). Much like the base case, Argentina had the lowest minimum (-$1.51) and the highest maximum ($5.04). Brazil followed with the second lowest minimum (-$1.38) and the second highest maximum ($4.05). Things varied slightly here because US Gulf had the highest minimum ($0.45) and the third lowest maximum ($2.87). PNW had the third lowest minimum ($0.34) and the lowest maximum ($2.44). Again, the PNW and US Gulf has the lower volatilities at $0.25 and $0.35 respectively. Brazil had a volatility of $0.60 and Argentina had the highest volatility at $0.84. This is also apparent visually when looking at the iterations in Figure 5.3. below. The US origins' iterations were a lot narrower than those of the South American origins.



	US Gulf / 1.0 Net Price ($/bu.	PNW / 1.0 Net Price ($/bu.	Brazil / 1.0 Net Price ($/bu.	Argentina / 1.0 Net Price ($/bu.)	Min Price / 1.0 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	$0.4506	$0.3432	-$1.3799	-$1.5125	-$1.5125
Maximum	$2.8689	$2.4379	$4.0542	$5.0407	$2.3584
Mean	$1.6134	$1.3625	$1.4737	$1.6423	$0.9788
90% CI	± $0.00570	± $0.00413	± $0.00988	± $0.0138	± $0.00708
Mode	$1.5996	$1.4424	$1.4213	$1.6011	$1.1123
Median	$1.6121	$1.3651	$1.4711	$1.6299	$1.0564
Std Dev	$0.3467	$0.2509	$0.6007	$0.8417	$0.4302
Skewness	0.0530	0.0098	0.0229	0.0261	-1.0631
Kurtosis	2.9846	3.0009	3.1609	3.0058	4.7373
Values	10000	10000	10000	10000	10000
Errors	0	0	0	0	0
Filtered	0	0	0	0	0
Left X	$1.05	$1.05	$1.05	$1.05	$1.05
Left P	5.0%	10.3%	23.8%	23.9%	48.8%
Right X	$2.19	$2.19	$2.19	$2.19	$2.19
Right P	95.0%	100.0%	88.3%	74.2%	100.0%
Dif. X	$1.1427	$1.1427	$1.1427	$1.1427	$1.1427
Dif. P	90.0%	89.6%	64.5%	50.2%	51.2%

Figure 5.3. Delivered Basis from Sensitivity 1.0 Simulation

The option value results for this simulation are shown in Figure 5.4. below. The results of this sensitivity are recorded in blue (1/1/2016 to 1/10/2020) while the results of the base case scenario are overlaid in red (1/7/2005 to 1/10/2020). The mean option value increased from $0.52 in the base case to $0.63 in sensitivity 1.0. The minimum value for both the sensitivity and base case are both $0.00. This is due to the option not having a negative value and only being at $0.00 when the US Gulf is the least cost origin. The minimum option value is generally $0.00 and cannot go negative. The maximum value for the sensitivity was $3.52 which is $0.77 higher than the base case ($2.75). They have similar volatilities with the sensitivity being slightly higher at $0.50 when compared to $0.47 in the base case.

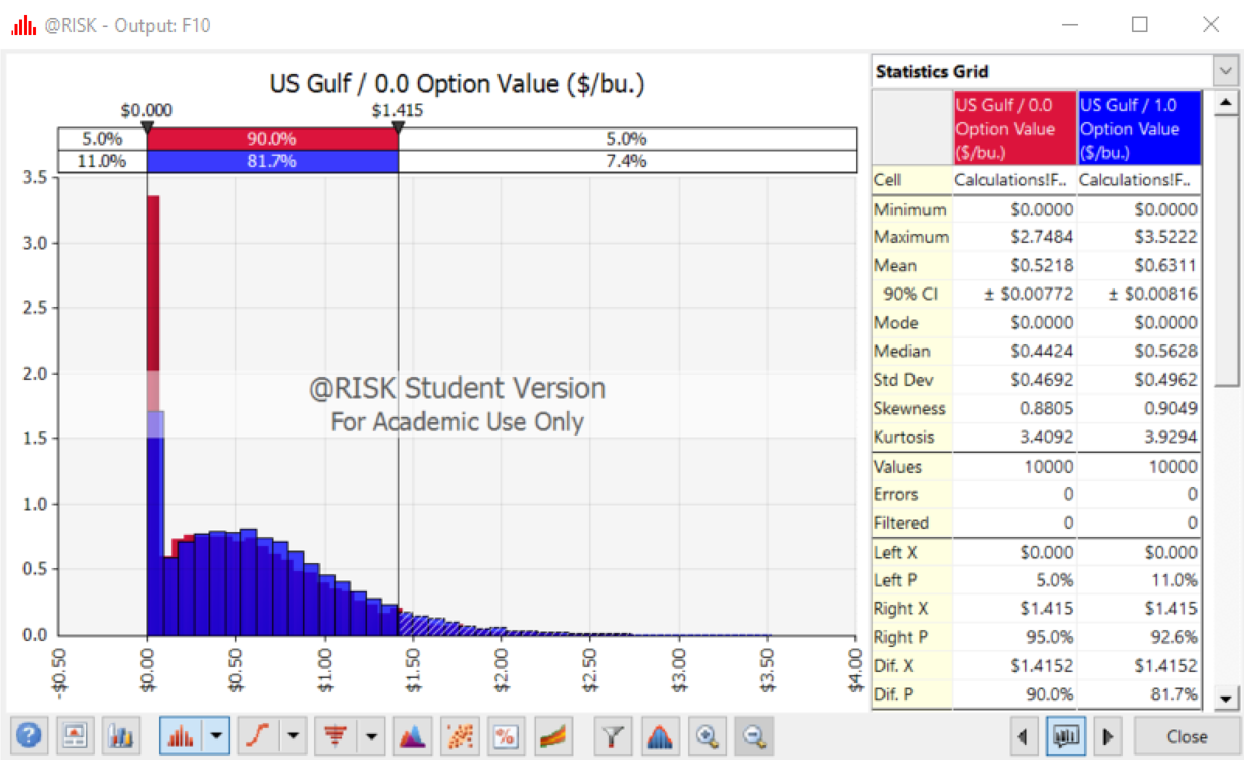


Figure 5.4. US Gulf Option Value Sensitivity 1.0 (blue) vs Base Case (0.0 in red)

Table 5.10. below are the results for the batch fit on the time period from 1/5/2018 – 1/10/2020 and includes the distributions, functions, AIC score, and Transformations. The data was tested for stationarity using the Augmented Dickey-Fuller test. The data was not stationary and so the first difference was taken to ensure stationarity.

Table 5.10. Soybean Basis Time Series Functions 1/5/2018 – 1/10/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Moving Average I	Moving Average I	Moving Average II	Auto-Regressive Conditional Heteroscedastic
Function:	RiskMA1(0.027019, 3.2292, 0.062993, 0.3187)	RiskMA1(-0.012248, 3.7991, -0.44576, -1.8637)	RiskMA2(-0.1025, 6.4024, 0.10742, 0.26094, 0.033359, 0.57612)	RiskARCH1(0.083209, 85.4, 0.33408, -0.65345)
AIC Score:	543.3944	580.2503	696.2465	791.601
Transformation:	First Difference	First Difference	First Difference	First Difference

Below is the correlation between the transformed data for all origins in data set with the time period from 1/5/2018 – 1/10/2020. The origin that is the most correlated with the US Gulf origin is the PNW (0.347) and the most highly correlated markets are the Brazil and Argentina origins (0.432). The transformed data in the US origins are less correlated with the transformed data in the South American origins. There is not very high correlation between any two origins in this data set with the data transformed.

Table 5.11. Soybean Basis Correlation with Transformed Data 1/5/2018 – 1/10/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed
US Gulf (Transformed)	1.000			
PNW (Transformed)	0.347	1.000		
Brazil (Transformed)	0.179	0.057	1.000	
Argentina (Transformed)	0.164	0.250	0.432	1.000

Table 5.12. below shows the results of the best fit on the freight data from 1/5/2018 to 1/10/2020. It shows the distributions, functions, AIC scores, and transformations. The data was not initially all stationary, so the first difference was taken. Additionally, freight values must be positive, so the data was transformed using the logarithmic transformation.

Table 5.12. Soybean Freight Time Series Functions 1/5/2018 – 1/10/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Moving Average I	Moving Average I	Moving Average I	Moving Average I
Function:	RiskMA1(-0.0020066, 0.031824, 0.44006, -0.037561)	RiskMA1(-0.0020836, 0.030768, 0.46395, -0.039945)	RiskMA1(-0.0022409, 0.034654, 0.42752, -0.040262)	RiskMA1(-0.0022184, 0.034395,0.42752, -0.040507)
AIC Score:	-426.1782	-431.1273	-407.7779	-409.0401
Transformation:	Logarithmic First Difference	Logarithmic First Difference	Logarithmic First Difference	Logarithmic First Difference

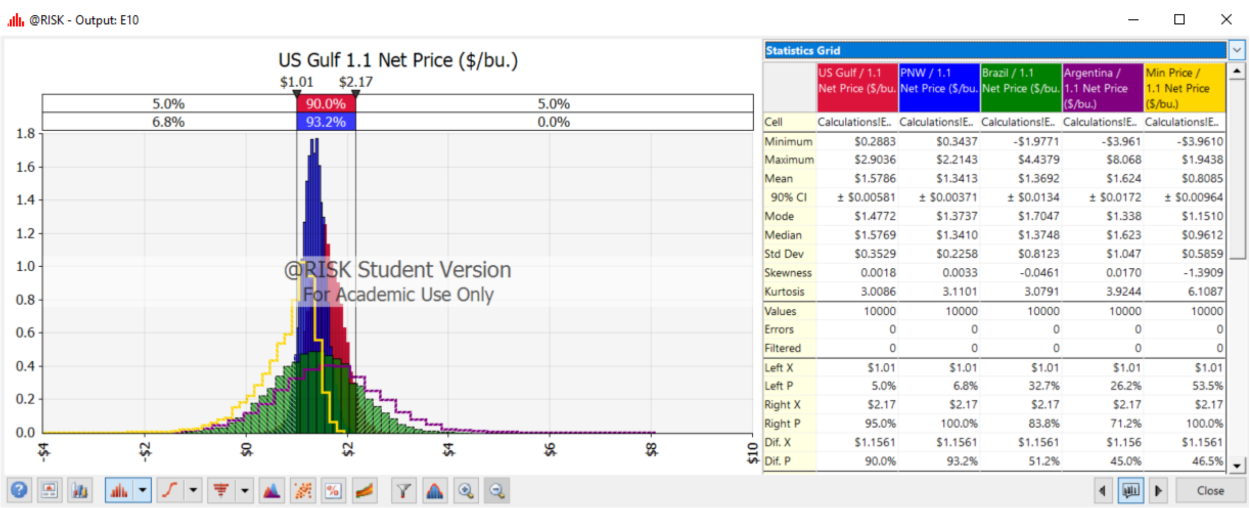
Table 5.13. below shows the correlation of the transformed freight data from 1/5/2018 to 1/10/2020. All the transformed data was highly correlated. US Gulf was slightly higher correlated with Brazil (0.999) and Argentina (0.999) than with PNW (0.944).

Table 5.13. Soybean Freight Correlation with Transformed Data 1/5/2018 – 1/10/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed
US Gulf (Transformed)	1.000			
PNW (Transformed)	0.944	1.000		
Brazil (Transformed)	0.999	0.938	1.000	
Argentina (Transformed)	0.999	0.940	1.000	1.000

The results of the iterations of net prices are found in Figure 5.5. below. The average net prices follow the same trend as the two prior scenarios. Argentina had the highest net price

($1.62), followed by US Gulf ($1.58), Brazil ($1.37) and PNW ($1.34). Argentina had the lowest minimum (-$3.96) and highest maximum ($8.07), followed by Brazil with a minimum of -$1.98 and a maximum of $4.44. USG had the next lowest minimum ($0.29) and the next highest maximum ($2.90). PNW had the highest minimum ($0.34) and the lowest maximum ($2.21). Again, PNW had the lowest volatility ($0.23), followed by USG ($0.35), Brazil ($0.81), and Argentina ($1.05). This is also apparent in Figure 5.5. below.



	US Gulf / 1.1 Net Price ($/bu.	PNW / 1.1 Net Price ($/bu.	Brazil / 1.1 Net Price ($/bu.	Argentina / 1.1 Net Price ($/bu.)	Min Price / 1.1 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	$0.2883	$0.3437	-$1.9771	-$3.961	-$3.9610
Maximum	$2.9036	$2.2143	$4.4379	$8.068	$1.9438
Mean	$1.5786	$1.3413	$1.3692	$1.624	$0.8085
90% CI	± $0.00581	± $0.00371	± $0.0134	± $0.0172	± $0.00964
Mode	$1.4772	$1.3737	$1.7047	$1.338	$1.1510
Median	$1.5769	$1.3410	$1.3748	$1.623	$0.9612
Std Dev	$0.3529	$0.2258	$0.8123	$1.047	$0.5859
Skewness	0.0018	0.0033	-0.0461	0.0170	-1.3909
Kurtosis	3.0086	3.1101	3.0791	3.9244	6.1087
Values	10000	10000	10000	10000	10000
Errors	0	0	0	0	0
Filtered	0	0	0	0	0
Left X	$1.01	$1.01	$1.01	$1.01	$1.01
Left P	5.0%	6.8%	32.7%	26.2%	53.5%
Right X	$2.17	$2.17	$2.17	$2.17	$2.17
Right P	95.0%	100.0%	83.8%	71.2%	100.0%
Dif. X	$1.1561	$1.1561	$1.1561	$1.156	$1.1561
Dif. P	90.0%	93.2%	51.2%	45.0%	46.5%

Figure 5.5. Delivered Basis from Sensitivity 1.1 Simulation

The option price results for this simulation are shown in Figure 5.6. The results of this sensitivity are shown in red (1/5/2018 to 1/10/2020) while the results of the base case scenario are overlaid in blue (1/7/2005 to 1/10/2020). The mean option value for sensitivity 1.1 was $0.76, which is the highest of any scenario this far. It is $0.13 higher than sensitivity 1.0 and $0.24 higher than the base case. This time period had a significant impact on the average price of the option. The minimum value for both the sensitivity and base case are both $0.00. This is due to the option not having a negative value and only being at $0.00 when the US Gulf is the least cost origin. The maximum value for the sensitivity was $5.39 which was again the highest of the three scenarios that were ran. Additionally, the standard deviation was $0.64 which is $0.17

higher than the base case. This means that there is greater volatility while using this time period for the price projections. The figure shows that there is more upside potential in this sensitivity than the base case.

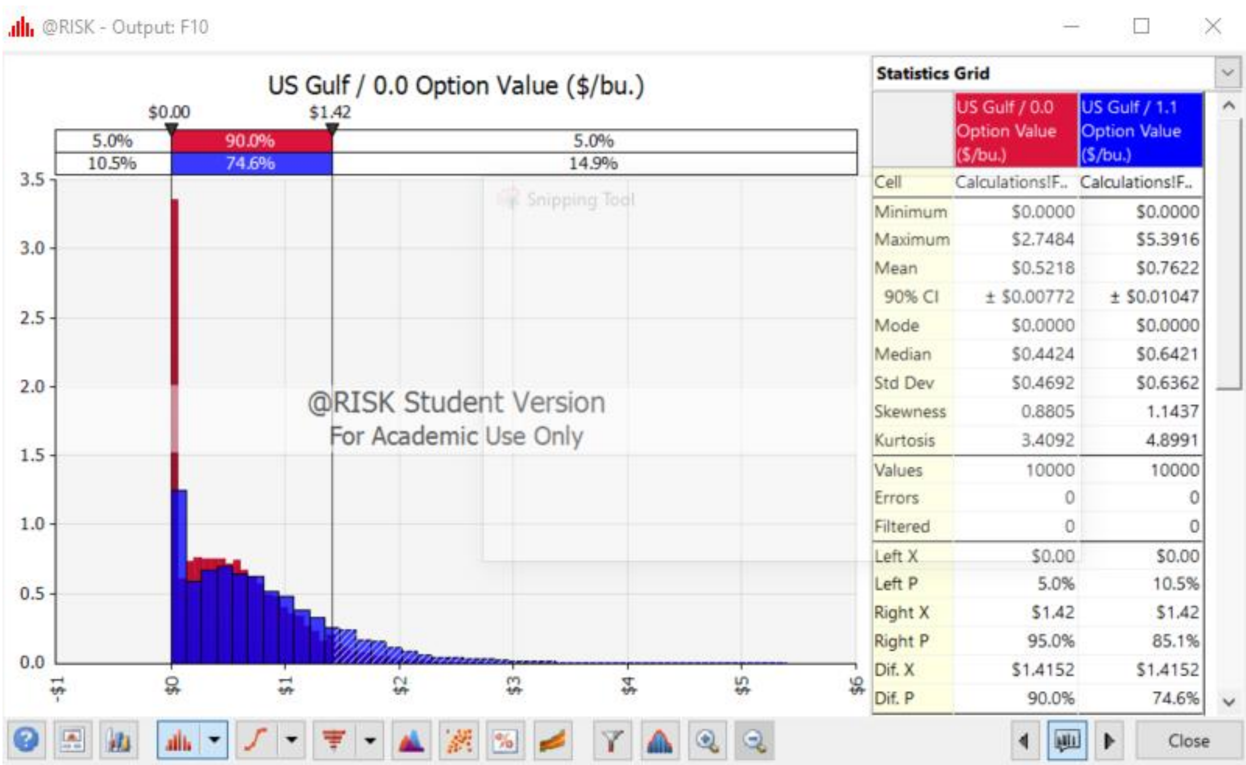


Figure 5.6. US Gulf Option Value Sensitivity 1.1 (blue) vs Base Case (0.0 in red)

Sensitivity 2 – Origins

Sensitivity 2 focuses on the origins that are included in the switching option. This sensitivity helps to illustrate the effect of having more options to switch to. Some commodity trading firms are only able to procure grain in certain origins. These firms are not able to capitalize on the spatial arbitrage opportunities that arise across more origins.

The first sensitivity only includes the two US origins (US Gulf and PNW). This illustrates a commodity trading firm that only can originate grain in the US Gulf and PNW, with no facilities in other countries. The next sensitivity included only US Gulf and Brazil. This sensitivity helps to illustrate the importance of being more spatially diverse with the ability to originate grain in other countries. There are increased differentials in grain prices when comparing two origins from different countries than two origins within the same country.

The time series batch fit basis and freight functions are the same as those used in the base case. The net price simulations for US Gulf and PNW along with the minimum price are found in Figure 5.7. The average price for US Gulf is higher ($1.50) than PNW ($1.38). This means that on average, there is value for US Gulf to have the option to switch to PNW. PNW had a lower minimum price (-$0.05) compared to US Gulf (-$0.03). US Gulf had a higher maximum ($3.28) than PNW ($2.60). US Gulf had a higher volatility ($0.44) than PNW ($0.33).

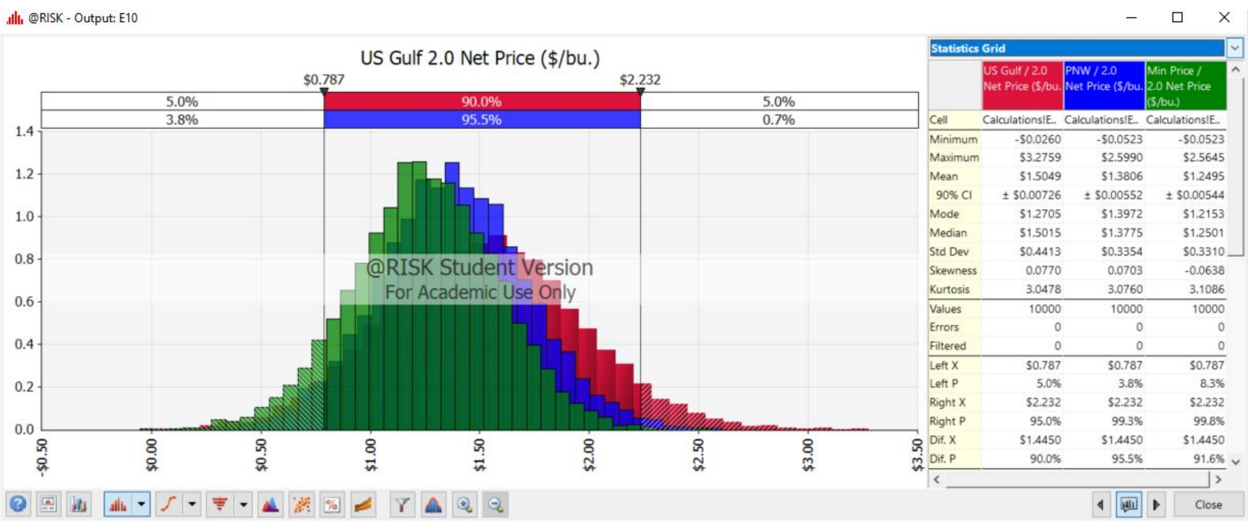


Figure 5.7. Delivered Basis from Sensitivity 2.0 Simulation

Having the option to originate grain from the PNW as an alternative to the US Gulf origin does result in some value, though not as much as in the base case where there are four origins. The average option value is $0.25 which is less than half that of the base case ($0.52). The minimum value of $0.00 occurred more often in this sensitivity. This is due to the value of $0.00 occurring when the US Gulf is the minimum of the two origins, compared to the minimum of four origins in the base case, which is less likely. It is more likely for the US Gulf origin to be the minimum origin with fewer origins. The maximum option value is $1.85 ($0.90 lower than the base case). The standard deviation is lower in this sensitivity too ($0.31 compared with $0.47). The value decreased significantly because there are less spatial arbitrage opportunities that arise between US Gulf and PNW than when Brazil and Argentina are included too. The base case also has more upside potential as show in Figure 5.8. below. There are less iterations above $0.50 in this sensitivity than the base case.

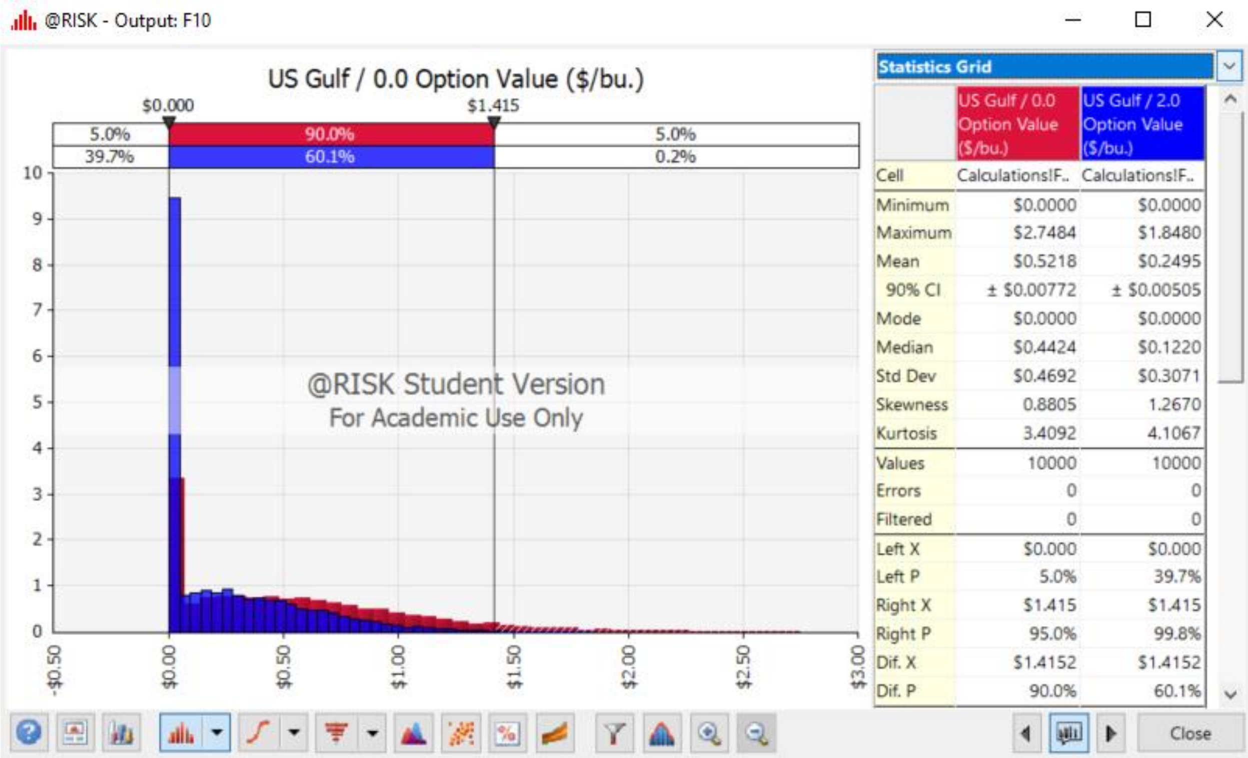


Figure 5.8. US Gulf Option Value Sensitivity 2.0 (red) vs Base Case (0.0 in blue)

Sensitivity 2.1 determines the option value when including only the US Gulf and Brazil origins. Again, the same basis and freight functions are used as the base case for projections in this sensitivity. The simulations for the net prices of US Gulf and Brazil are shown in Figure 5.9. US Gulf has a higher average net price ($1.50) than Brazil ($1.47). Brazil has a much greater range with a lower minimum (-$0.74) and higher maximum ($4.03), when compared with US Gulf (minimum of -$0.03 and maximum of $3.28). Brazil also had a significantly higher volatility with a standard deviation of $0.63 (compared to $0.44 for US Gulf).

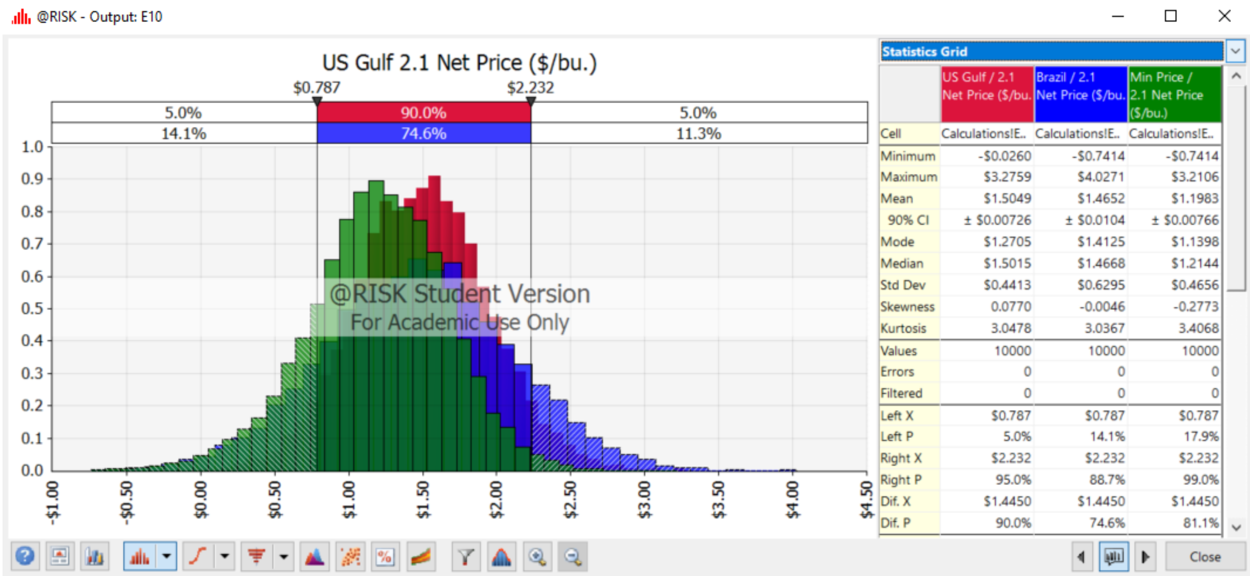


Figure 5.9. Delivered Basis from Sensitivity 2.1 Simulation

Like the results from sensitivity 2.0, sensitivity 2.1 results in an option value below that of the base case. This is not surprising as there are less origins than the base case. The average option value is $0.30 which is about $0.22 lower than the base case ($0.52), but about $0.05 higher than sensitivity 2.0 ($0.25). The minimum value at $0.00 is more common than the base case again. The maximum value is slightly higher than the base case ($2.89 compared with $2.75), and significantly higher than sensitivity 2.0 ($1.85). The volatility in this scenario and the base case were very similar and were $0.43 and $0.47, respectively. Results are shown in Figure 5.10. below.

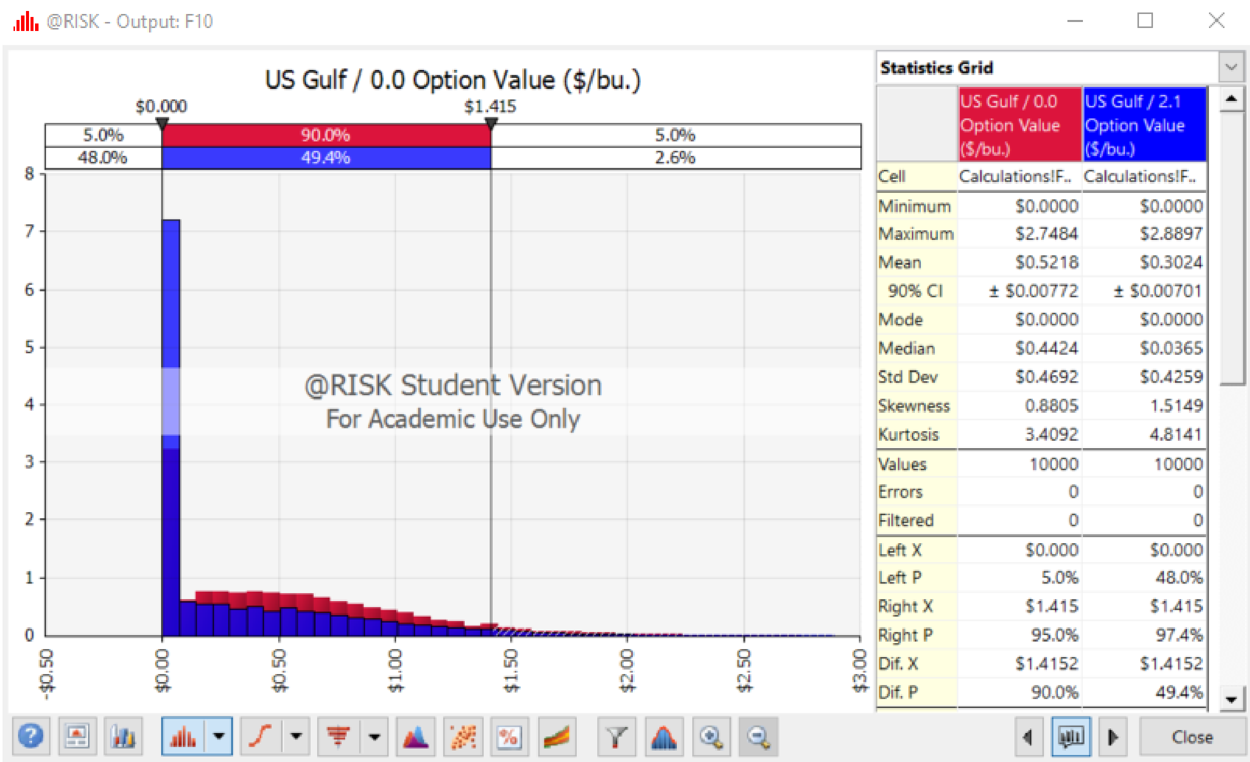


Figure 5.10. US Gulf Option Value Sensitivity 2.1 (blue) vs Base Case (0.0 in red)

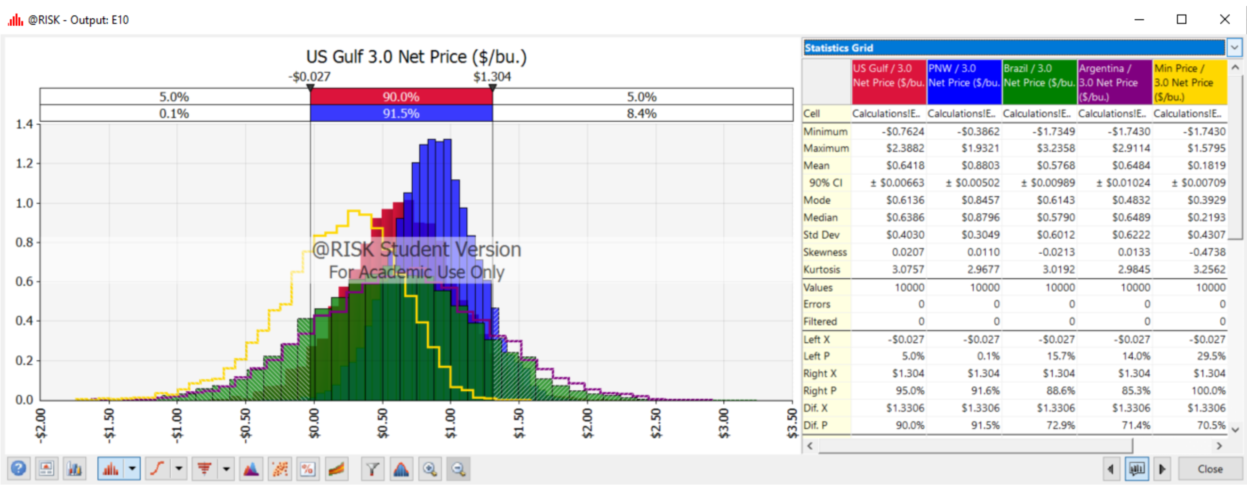
As expected, including the Brazil origin increases the value relative to only having the US origins. There is less correlation between the US Gulf and Brazil origin basis than the US Gulf and PNW origin basis, which leads to more option value due to more arbitrage opportunities.

Sensitivity 3 – No Ocean Freight

The 3rd sensitivity does not include ocean freight. The motivation behind this sensitivity is to illustrate the effect of the basis on the total value of the option. This option would also be important if the freight was not being paid by the seller of the grain. They would make their delivery decision strictly off the basis level at each origin and would be an equivalent to selling on a strictly FOB basis.

The simulation results for the basis is show in Figure 5.11. These iterations exclude ocean freight. PNW has the highest mean ($0.88), followed by Argentina ($0.65), US Gulf ($0.64), and

Brazil ($0.58). Argentina had the lowest minimum net price (-$1.74) which was followed closely by Brazil (-$1.73). US Gulf had the next lowest minimum (-$0.76) and PNW had the highest minimum (-$0.39). Brazil had the highest maximum value ($3.24), followed by Argentina ($2.91), US Gulf ($2.39), and PNW ($1.93). The most volatile origin with the highest standard deviation was Argentina ($0.65). This was followed closely by Brazil ($0.60) and then by US Gulf ($0.40) and PNW ($0.30).



	US Gulf / 3.0 Net Price ($/bu.	PNW / 3.0 Net Price ($/bu.	Brazil / 3.0 Net Price ($/bu.	Argentina / 3.0 Net Price ($/bu.)	Min Price / 3.0 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	-$0.7624	-$0.3862	-$1.7349	-$1.7430	-$1.7430
Maximum	$2.3882	$1.9321	$3.2358	$2.9114	$1.5795
Mean	$0.6418	$0.8803	$0.5768	$0.6484	$0.1819
90% CI	± $0.00663	± $0.00502	± $0.00989	± $0.01024	± $0.00709
Mode	$0.6136	$0.8457	$0.6143	$0.4832	$0.3929
Median	$0.6386	$0.8796	$0.5790	$0.6489	$0.2193
Std Dev	$0.4030	$0.3049	$0.6012	$0.6222	$0.4307
Skewness	0.0207	0.0110	-0.0213	0.0133	-0.4738
Kurtosis	3.0757	2.9677	3.0192	2.9845	3.2562
Values	10000	10000	10000	10000	10000
Errors	0	0	0	0	0
Filtered	0	0	0	0	0
Left X	-$0.027	-$0.027	-$0.027	-$0.027	-$0.027
Left P	5.0%	0.1%	15.7%	14.0%	29.5%
Right X	$1.304	$1.304	$1.304	$1.304	$1.304
Right P	95.0%	91.6%	88.6%	85.3%	100.0%
Dif. X	$1.3306	$1.3306	$1.3306	$1.3306	$1.3306
Dif. P	90.0%	91.5%	72.9%	71.4%	70.5%

Figure 5.11. Delivered Basis from Sensitivity 3.0 Simulation

The third sensitivity (3.0) includes only the difference in basis levels for the option value. The basis values are calculated using the same formulas as the base case scenario. This sensitivity resulted in similar results to the base case. The mean value of sensitivity 3.0 ($0.45) was $0.07 lower than the base case ($0.52). The minimum value was $0.00 in both cases. The maximum value for this sensitivity ($2.63) was only $0.06 lower than the base case ($2.75). The volatility was nearly identical for both cases with standard deviations at $0.46 and $0.47 for sensitivity 3.0 and the base case respectively. Results are shown in Figure 5.12. below.

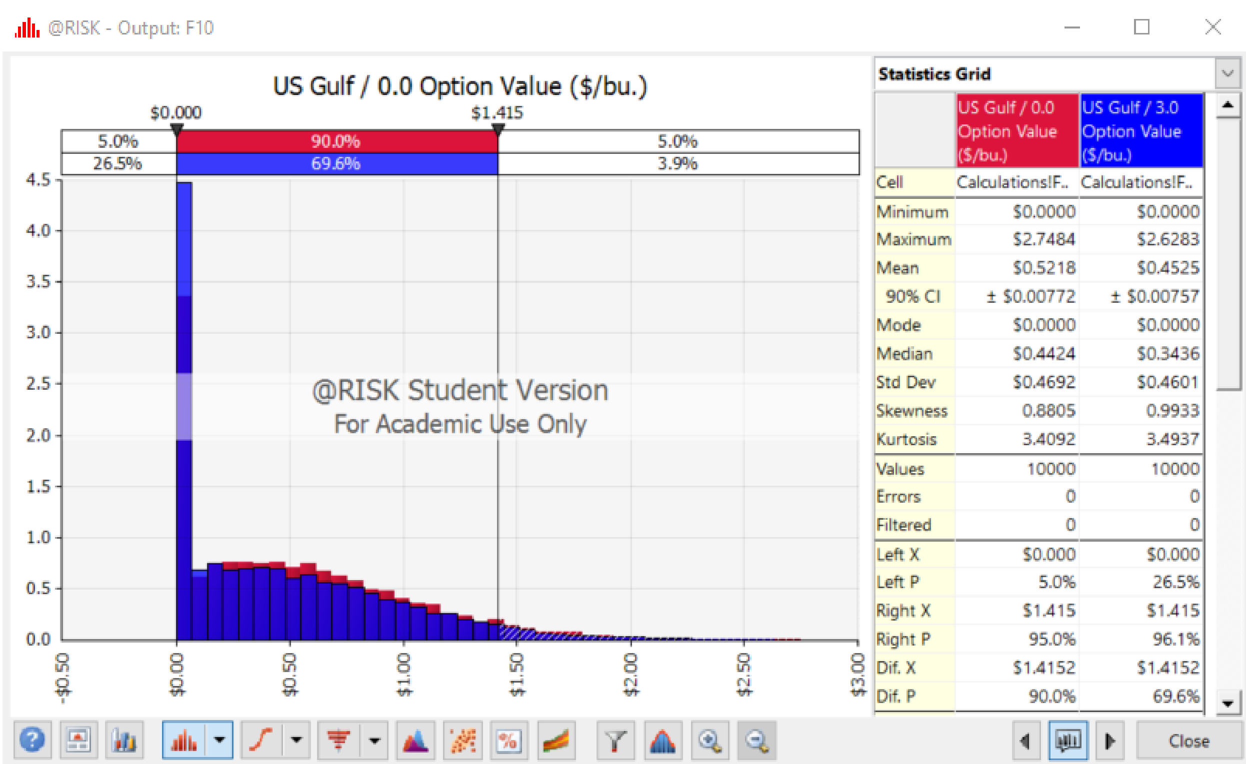


Figure 5.12. US Gulf Option Value Sensitivity 3.0 (blue) vs Base Case (0.0 in red)

Sensitivity 4 – Number of Periods Forward

The base case assumes 12 periods forward. Sensitivity 4 looks at the time value of the option. It determines the value of the option at 1-20 periods forward. Time is expected to increase the value of the option. This sensitivity also illustrates that if there is an exercise period that is close to the current period, it would not be as valuable. There is not as much potential for the prices to change and cause greater price differentials.

Using the advanced sensitivity analysis in sensitivity 4.0 results in an upward sloping option value. The further forward the exercise period is, the more valuable the option is. The sensitivity ran one period (week) forward has a significantly cheaper average option value at around $0.33, whereas the sensitivity ran at 20 periods forward has an average option value of nearly $0.60. The more time periods forward, the more time there is for prices to change, therefore increasing the volatility in the market. Closer to the current time period, there is less time for prices to change and diverge from each other.

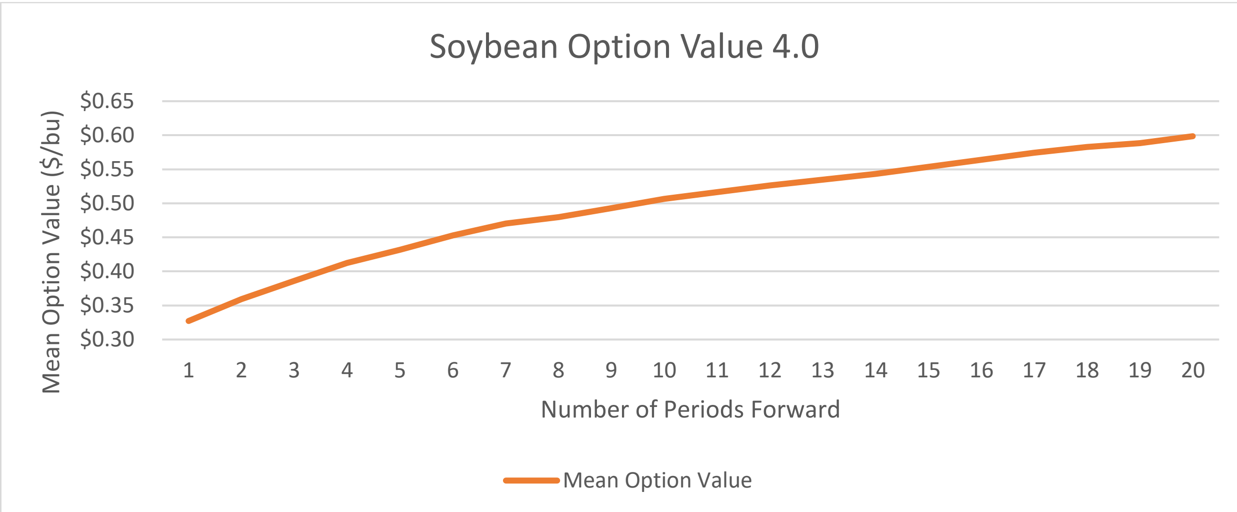


Figure 5.13. US Gulf Option Values from Sensitivity 4.0 Simulation

Sensitivity 5 – Risk Free Discount Rate

The final sensitivity illustrates a risk-free discount rate and how it would affect the option price. Because the basis values are weekly, the risk-free rates are adjusted to reflect weekly rates. The rate went from 0-12% annually, which was converted to weekly.

In sensitivity 5.0, changing the risk-free discount rate has very little effect on the option value. The value remained at $0.52 for each risk-free discount rate. Changing the risk-free discount rate from 0-12% has effectively no effect on the option value. This could partially be due to the need to convert the 0-12% to a weekly discount rate by dividing it by 52 (number of weeks in a year). The results of sensitivity 5.0 are shown in Figure 5.14. below.

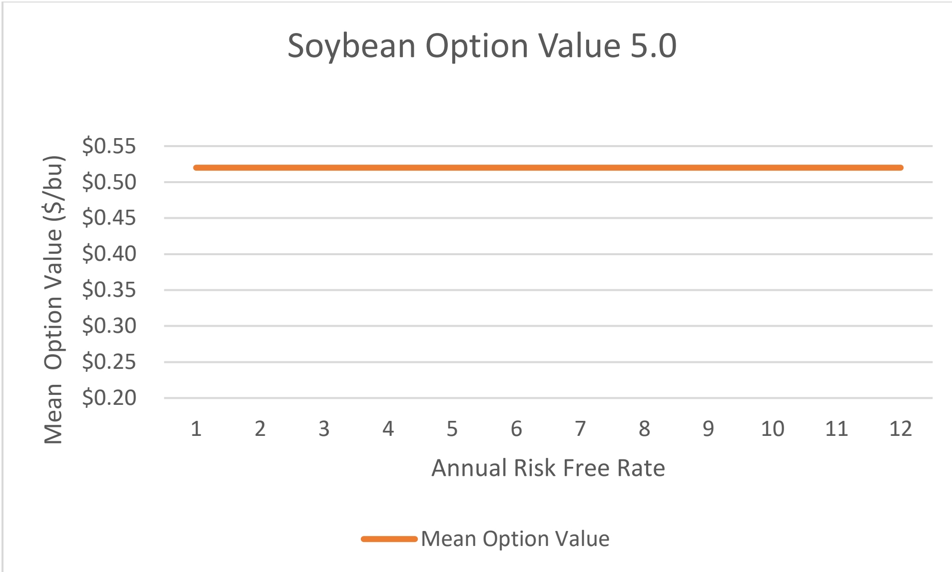


Figure 5.14. US Gulf Option Values from Sensitivity 5.0 Simulation

Other Options Types

In addition to the European type options, Asian and lookback options are valued as well. These other option types are calculated to determine how the value of the option would change if the terms of the contract were structured differently. The Asian option and the look back options are used to give an idea of what an American style equivalent would be by using the average, minimum, and maximum values. An Asian option would also be useful if the seller of grain wanted to mitigate risk up until the delivery period but was not concerned about upside potential. Asian options allow for some flexibility but avoid any major price differentials as the periods are averaged. It does not allow the seller of grain the ability to take advantage of large and favorable price swings.

The Asian option averages the minimum prices across the periods leading up to the expiration date (12 periods in this scenario). If the average price is lower than the projected price at period 12, there is value in the option. The results of the simulations are shown below in Figure 5.15. – Figure 5.17.

The Asian option results show an average value of $0.46 which is $0.06 lower than the base case. Both minimums were $0.00. The Asian option had a lower maximum value at $2.08 compared to $2.75 in the base case. The Asian option also had a lower volatility with a standard deviation of $0.39 compared to $0.47 in the base case. Asian options average the net price across all periods, so it makes sense that the values are less extreme than the base case that only accounts for prices at the end of the entire time period.

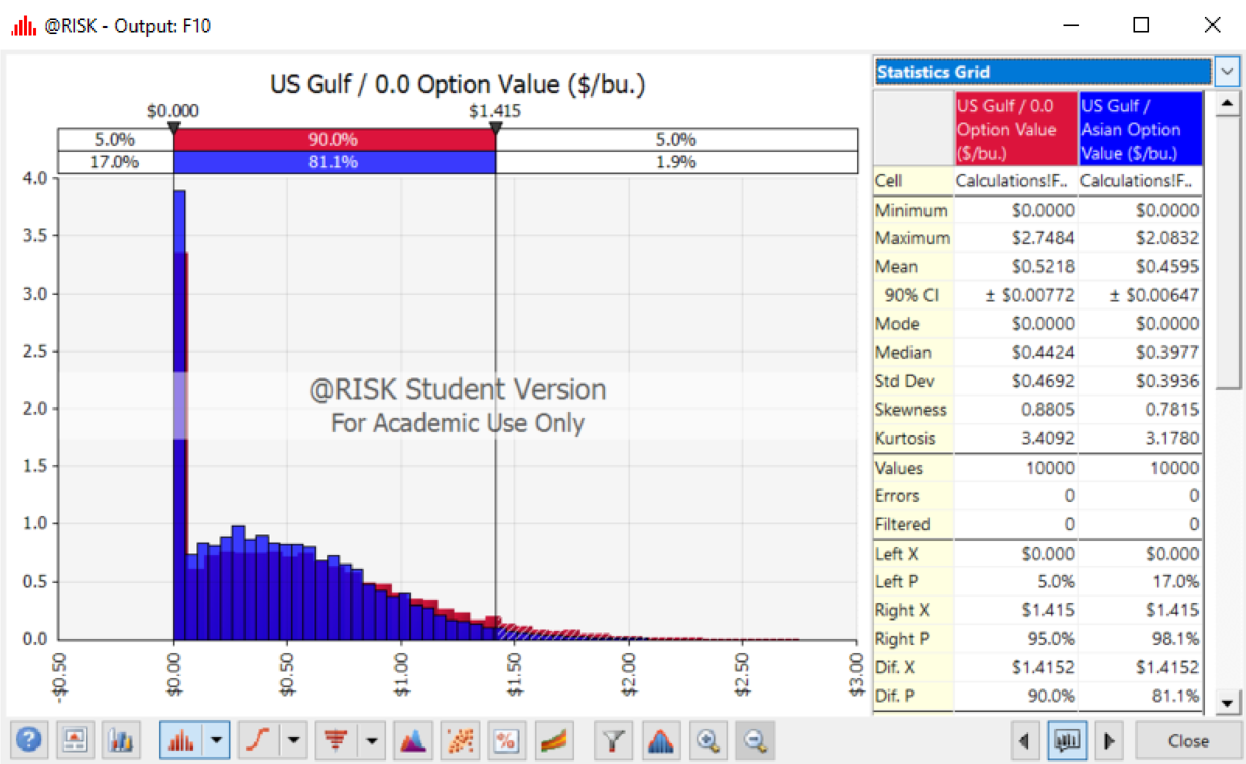


Figure 5.15. US Gulf Option Asian Option Value (blue) vs Base Case (0.0 in red)

The minimum lookback option results in the highest mean option value across all sensitivities, with a mean option value of $0.86. This is because the minimum lookback option allows the owner to take advantage of the absolute minimum price across all time periods leading up to the expiration period. The minimum values are both $0.00. The maximum option value is $0.73 higher than the base case ($3.47 vs $2.75). The simulation results in the lookback option value consistently trend higher than the European option. The volatility for both were very similar at $0.50 and $0.47 for the minimum lookback scenario and base case, respectively.

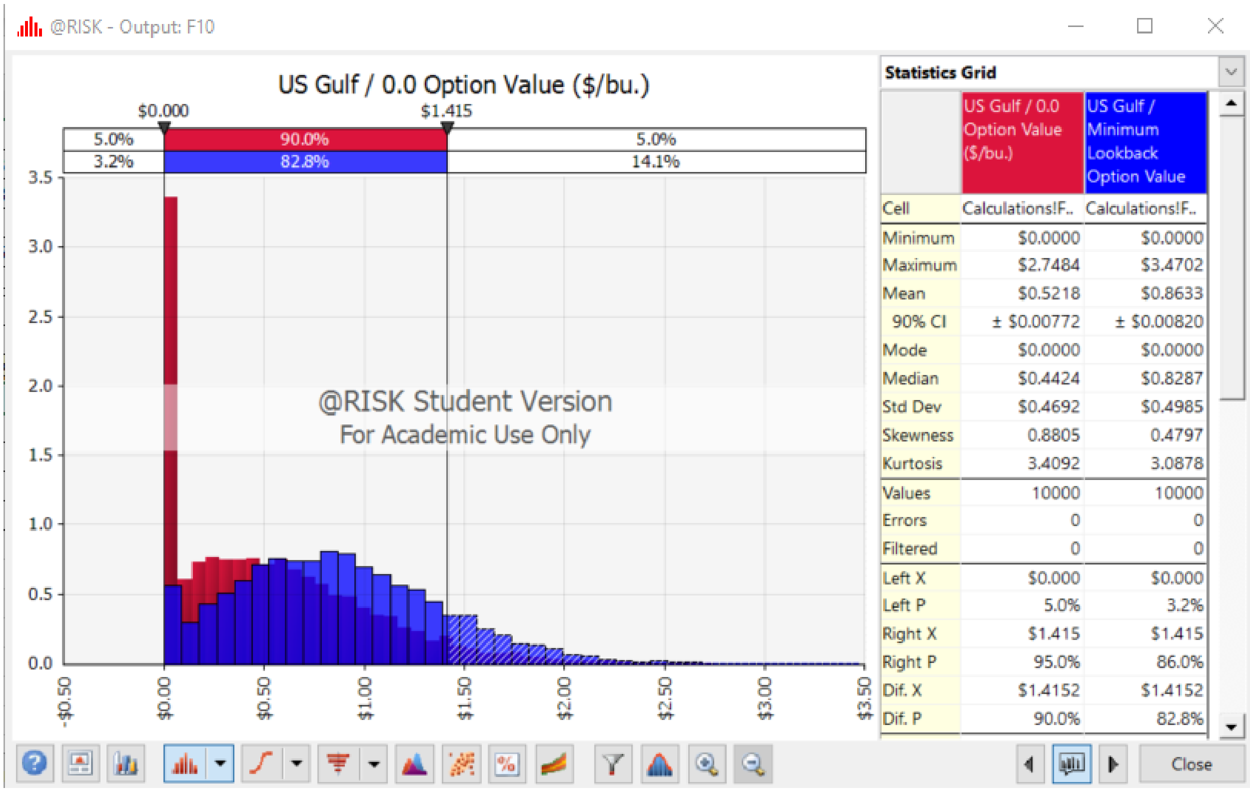


Figure 5.16. US Gulf Option Minimum Lookback Option Value (blue) vs Base Case (0.0 in red)

The maximum lookback option is determined off the maximum period value. Each period still uses the minimum origin price, but the maximum value amongst these periods is the price the holder of the option would originate the grain at. As expected, the mean option value is significantly lower than the base case ($0.18 vs $0.53). The minimum values are both $0.00 and the maximum option value is significantly lower than the European option ($1.84 vs $2.75). The volatility on this sensitivity is also much lower ($0.27) than the base case ($0.47).

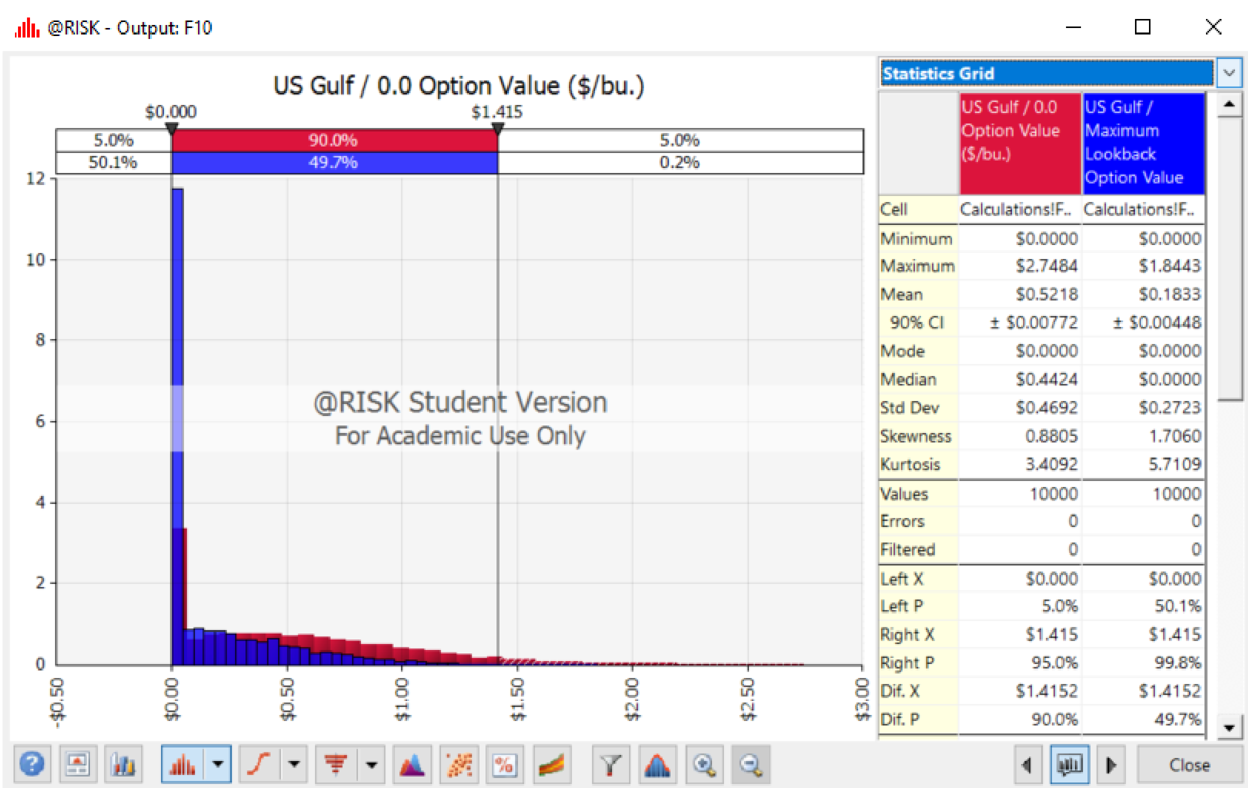


Figure 5.17. US Gulf Option Maximum Lookback Option Value (blue) vs Base Case (0.0 in red)

Summary

As shown by the results above and in Table 5.14. below, many of the parameters tested in sensitivities 1.0 to 3.0 influence the mean option price. Across the European option sensitivities, sensitivity 1.1 had the highest mean option value and the highest standard deviation. This is due to the lower basis correlation between origins than the base case. Additionally, the South American origins have higher basis volatility compared to the data from 1/1/2016 forward. The lowest priced option is sensitivity 2.0. This is because PNW is the only other origin to switch to. US Gulf and PNW basis are the two most highly correlated origins, which makes the option less valuable. Sensitivity 2.1, with only US Gulf and Brazil origins has slightly higher value due to lower correlation in the basis. Excluding freight (sensitivity 3.0) did not impact the option value significantly when compared with the other sensitivities. It only decreased the mean option value by $0.07.

Table 5.14. Soybean Results

Measure ($/bu.)	Base Case	Sensitivity 1.0	Sensitivity 1.1	Sensitivity 2.0	Sensitivity 2.1	Sensitivity 3.0
Sensitivity	N/A	2016-2020	2018-2020	US Origins	USG and BZ	No Freight
Mean	$ 0.52	$ 0.63	$ 0.76	$ 0.25	$ 0.30	$ 0.45
Standard Deviation	$ 0.47	$ 0.50	$ 0.64	$ 0.31	$ 0.43	$ 0.46
Likelihood of Min	18%	11%	11%	40%	48%	26%
Likelihood of Max	25%	29%	27%	60%	52%	15%

Note: Likelihood of min and max are for US Gulf origin when compared to other origins in the specific sensitivity

The other option types influenced the mean option price significantly. The Asian type option was around the same price as the base case. The lookback options were significantly different from the base case. The purpose of these non-European type options help to give an idea of what an American type option value would have. The Asian option would be if the manager exercised at a period that was average for the whole time period and the lookback options illustrate the best-case scenario (minimum lookback) and worst-case scenario (maximum lookback). The American type option value would be somewhere between the best and worst-case scenario.

Table 5.15. Other Soybean Option Results

Measure ($/bu.)	Base Case	Asian Option	Min Lookback Option	Max Lookback Option
Mean	$ 0.52	$ 0.46	$ 0.86	$ 0.18
Standard Deviation	$ 0.47	$ 0.39	$ 0.50	$ 0.27
Odds Above Option	82%	83%	97%	49%
Odds Below Option	18%	17%	3%	51%

Note: Odds above/below option are showing if what percentage of the simulations were in/out of the money, respectively.

Corn

Introduction: Corn

The corn section is be structured the same as the soybean section and is in the following order: Description of Data, Base Case Results, Sensitivity Analysis, Summary of Results, Interpretation of Results for Contracting Strategy, and Conclusion: Corn.

Description of Data

The origins that are used in the corn analysis are US Gulf (the base origin), PNW, Argentina, Brazil, and Ukraine for two sensitivities. All freight values are determined delivered to Japan. The base case time series batch fit distributions are shown in Table 5.16. below. The data was stationary, so no transformations were made. Ukraine is excluded from this batch fit due to missing data from 6/13/2008 – 9/22/2016. The Ukraine projected basis would be inaccurate because it would only be projecting using the period 9/23/2016 – 1/24/2020 and not the full time period like the other origins. The results of the batch fit are shown in Table 5.17. below.

Table 5.16. Corn Basis Time Series Functions 6/13/2008 – 1/24/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Auto-Regressive II	Auto-Regressive II	Auto-Regressive Moving Average	Auto-Regressive Moving Average
Function:	RiskAR2(26.37, 2.9217, 1.0285, -0.097444, 22.413, 22.413)	RiskAR2(20.975, 7.7279, 0.81126, 0.1419, 35.641, 35.549)	RiskARMA11(24.3, 7.2196, 0.92642, -0.24722, 31.668, 1.3433)	RiskARMA11(27.172,7.7217, 0.92343, -0.40317, 42.308, 2.9421)
AIC Score:	3032.3369	4213.9693	4138.447	4221.9143
Transformation:	None	None	None	None

Note: Ukraine was excluded due to unavailability of earlier data.

The correlation of the transformed data is shown in Table 5.17. below. There is not significant correlation amongst the transformed US Gulf origin data and any other origin, though Argentina has the highest correlation of the other origins (0.479). The most highly correlated origins (with data transformed) is the Brazil and Argentina origins (0.65).

Table 5.17. Corn Basis Correlation with Transformed Data 6/13/2008 – 1/24/2020

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.000			
PNW	0.272	1.000		
Brazil	0.274	0.318	1.000	
Argentina	0.479	0.267	0.650	1.000

The results of the batch fit for the freight data are found in 5.18 below. Like the soybean freight data, the data was not stationary as determined by the Augmented Dickey-Fuller test. The first difference of the data was used to ensure stationarity. The data also underwent a logarithmic transformation to ensure the data results stayed above 0 because ocean freight values are always positive.

Table 5.18. Corn Freight Time Series Functions 6/13/2008 – 1/24/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina
Distribution:	Moving Average II	Moving Average I	Moving Average II	Moving Average II
Function:	RiskMA2(	RiskMA1(	RiskMA2(	RiskMA2(
	-0.0019479, 0.042856, 0.36994, 0.0024533,	-0.0021458, 0.057475, -0.10038, 0.00801)	-0.0021745, 0.044896, 0.38626, 0.0075878,	-0.002218, 0.050027, 0.26686, 0.032967,
	-0.026236, 0.03375)		-0.029573, 0.03768)	-0.022848, 0.035335)
AIC Score:	-2098.8372	-1736.1402	-2038.4974	-1900.1251
Transformation:	Logarithmic	Logarithmic	Logarithmic	Logarithmic
	First Difference	First Difference	First Difference	First Difference

The correlation of the freight data from 6/13/2008 to 1/24/2020 is found in Table 5.19. below. US Gulf was and Brazil had the highest correlation (0.995). Brazil and Argentina had the next highest correlation (0.931). PNW was the least correlated with all origins ranging from 0.656 to 0.711.

Table 5.19. Corn Freight Correlation with Transformed Data 6/13/2008 – 1/24/2020

Correlation	US Gulf	PNW	Brazil	Argentina
US Gulf	1.000			
PNW	0.656	1.000		
Brazil	0.995	0.662	1.000	
Argentina	0.926	0.711	0.931	1.000

Table 5.20. below shows the corn base case and sensitivity specifications. This summarizes the specifications that were covered in Chapter 4.

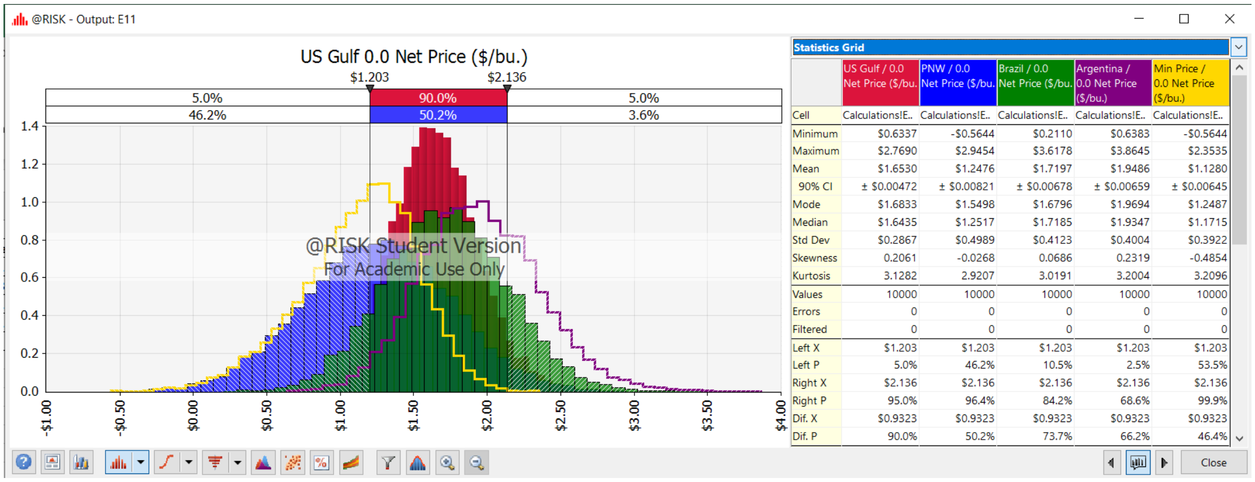
Table 5.20. Corn Sensitivity Specifications

Sensitivity	Time period	Origins Included	Ocean Freight	Periods Forward	Interest Rate
Base case	6/13/2008 – 1/24/2020	US Gulf, PNW, BRZ, ARG	Yes	12	0
Sensitivity 1.0	9/23/2016 – 1/24/2020	US Gulf, PNW, BRZ, ARG**	Yes**	12**	0**
Sensitivity 1.1	1/5/2018 – 1/24/2020	US Gulf, PNW, BRZ, ARG**	Yes**	12**	0**
Sensitivity 1.2	9/23/2016 – 1/24/2020	US Gulf, PNW, BRZ, ARG, UKR	Yes**	12**	0**
Sensitivity 1.3	1/5/2018 – 1/24/2020	US Gulf, PNW, BRZ, ARG, UKR	Yes**	12**	0**
Sensitivity 2.0	6/13/2008 – 1/24/2020**	US Gulf & PNW	Yes**	12**	0**
Sensitivity 2.1	6/13/2008 – 1/24/2020**	US Gulf & BRZ	Yes**	12**	0**
Sensitivity 3.0	6/13/2008 – 1/24/2020**	US Gulf, PNW, BRZ, ARG**	No	12**	0**
Sensitivity 4.0	6/13/2008 – 1/24/2020**	US Gulf, PNW, BRZ, ARG**	Yes**	1-20	0**
Sensitivity 5.0	6/13/2008 – 1/24/2020**	US Gulf, PNW, BRZ, ARG**	Yes**	12**	1-12% annually

** indicates same as base case

Base Case Results

The results of the simulations are shown in Figure 5.18. below. Each origin is shown in a different color, with yellow showing the statistics and results of the minimum price amongst all origins. Argentina has the highest mean net price ($1.95), followed by Brazil ($1.72), US Gulf ($1.65) and PNW ($1.25). PNW had the lowest minimum net price (-$0.56). Brazil had the next lowest minimum ($0.21). US Gulf and Argentina had very similar lowest minimum price at $0.63 and $0.64 respectively. Argentina had the highest maximum net price ($3.86), followed by Brazil ($3.62), PNW ($2.95) and US Gulf ($2.77). PNW had the most volatility with a standard deviation of $0.50. Brazil and Argentina followed with $0.41 and $0.40, respectively. US Gulf was the least volatile with a standard deviation of $0.29.



	US Gulf / 0.0 Net Price ($/bu.	PNW / 0.0 Net Price ($/bu.	Brazil / 0.0 Net Price ($/bu.	Argentina / 0.0 Net Price ($/bu.)	Min Price / 0.0 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	$0.6337	-$0.5644	$0.2110	$0.6383	-$0.5644
Maximum	$2.7690	$2.9454	$3.6178	$3.8645	$2.3535
Mean	$1.6530	$1.2476	$1.7197	$1.9486	$1.1280
90% CI	± $0.00472	± $0.00821	± $0.00678	± $0.00659	± $0.00645
Mode	$1.6833	$1.5498	$1.6796	$1.9694	$1.2487
Median	$1.6435	$1.2517	$1.7185	$1.9347	$1.1715
Std Dev	$0.2867	$0.4989	$0.4123	$0.4004	$0.3922
Skewness	0.2061	-0.0268	0.0686	0.2319	-0.4854
Kurtosis	3.1282	2.9207	3.0191	3.2004	3.2096
Values	10000	10000	10000	10000	10000
Errors	0	0	0	0	0
Filtered	0	0	0	0	0
Left X	$1.203	$1.203	$1.203	$1.203	$1.203
Left P	5.0%	46.2%	10.5%	2.5%	53.5%
Right X	$2.136	$2.136	$2.136	$2.136	$2.136
Right P	95.0%	96.4%	84.2%	68.6%	99.9%
Dif. X	$0.9323	$0.9323	$0.9323	$0.9323	$0.9323
Dif. P	90.0%	50.2%	73.7%	66.2%	46.4%

Figure 5.18. Delivered Basis from Base Case (0.0) Simulation

The results of the simulation for option price of the base case corn scenario are found in Figure 5.19. below. This is from the perspective of using US Gulf as the initial origin with the ability to switch to the other three origins. The mean option value was $0.51. The minimum option value is truncated at $0.00 because the option would not be exercised in the case where US Gulf was already the least cost origin. The maximum value across all iterations war $2.51. There is significant volatility as the standard deviation is $0.42.

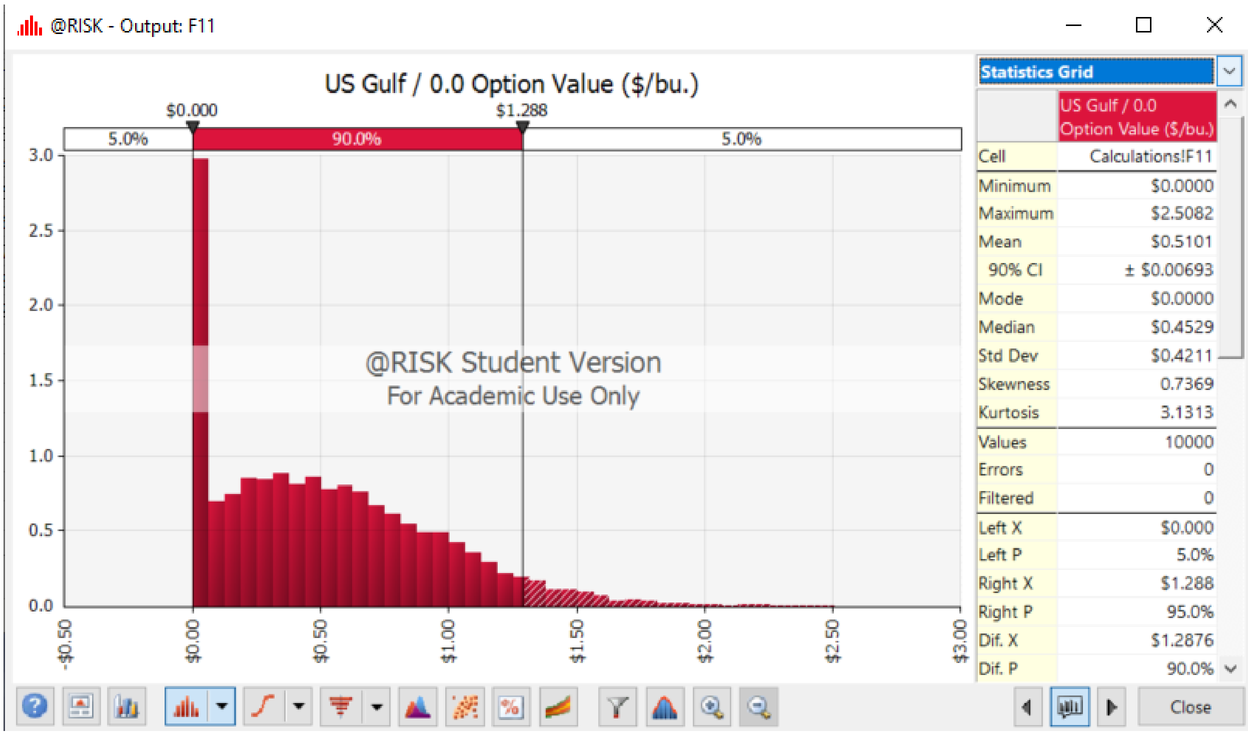


Figure 5.19. US Gulf Option Value from Base Case (0.0) Simulation

Sensitivity Analysis

Sensitivity 1 – Time Period

Sensitivity 1 illustrates how using different time periods and volatilities would affect the option value. The two time periods used for corn were 6/13/2008 – 1/24/2020 and 1/5/2018 – 1/24/2020. This first time period was chosen to illustrate the current and normal corn prices. It varies slightly to that of the soybean time period to include all the Ukraine data and allow for sensitivities with Ukraine included as an origin. The second time period sensitivity is the same as that of soybeans and was to illustrate the effect of more uncertainties in the markets due to tariffs and trade disputes.

The batch fit that was ran results are found in Table 5.21. The time period is adjusted for this sensitivity and so some of the origin distributions changed and all the origin functions changed. This batch fit also includes the Ukraine origin for one of the later sensitivities (sensitivity 1.2). Add data was adjusted by taking the first difference because the Augmented Dickey-Fuller test results indicated that not all of the data was stationary.

Table 5.21. Corn Time Series Basis Functions 9/23/2016 – 1/24/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina	Ukraine
Distribution:	Moving Average I	Auto-Regressive Conditional Heteroscedastic	Moving Average I	Moving Average I	Generalized Auto-Regressive Conditional Heteroskedastic
Function:	RiskMA1(-0.029564, 2.0571, 0.10344, 0.039379)	RiskARCH1(0.011614, 71.734, 0.14183, 0.091858)	RiskMA1(-0.081783, 4.2438, -0.16445, 0.57891)	RiskMA1(-0.018047, 3.9778, -0.12809, 0.20648)	RiskGARCH11(-0.013162, 0.9073, 0.40472, 0.68393,1.5919, 0)
AIC Score:	749.3212	1252.8645	995.5672	973.2962	1060.5317
Transformation:	First Difference	First Difference	First Difference	First Difference	First Difference

The correlation of the transformed data shows that the most correlated origin with the US Gulf is the PNW, though not by much. The two most highly correlated origins were Brazil and PNW. Keep in mind, all the data went through transformations in this case. Table 5.22. below shows the correlation matrix of the transformed data.

Table 5.22. Corn Correlation with Transformed Data 9/23/2016 – 1/24/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed	Ukraine Transformed
US Gulf (Transformed)	1.000				
PNW (Transformed)	0.085	1.000			
Brazil (Transformed)	0.060	0.147	1.000		
Argentina (Transformed)	0.080	0.018	0.122	1.000	
Ukraine (Transformed)	0.071	0.178	-0.026	0.148	1.000

The batch fit results of the time series freight data from 9/23/2016 to 1/24/2020 are found in Table 5.23. below. Again, this includes Ukraine as well, though it is not used until a later sensitivity. The freight data over this time period was not stationary, so the first difference was taken. Additionally, freight data must be positive, so a logarithmic transformation was also made. Moving Average I was the distribution chosen for all origins.

Table 5.23. Corn Time Series Freight Functions 9/23/2016 – 1/24/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina	Ukraine
Distribution:	Moving Average I	Moving Average I	Moving Average I	Moving Average I	Moving Average I
Function:	RiskMA1(0.0012575, 0.034627, 0.46043, -0.032054)	RiskMA1(-0.00016166, 0.033811, 0.33442, -0.035662)	RiskMA1(0.00080093, 0.036311, 0.43381, -0.033821)	RiskMA1(0.00078309, 0.035963, 0.44028, -0.033734)	RiskMA1(0.0016641, 0.07195, -0.39604, 0.0072256)
AIC Score:	-680.8045	-684.5245	-655.0827	-657.5953	-422.0918
Transformation:	Logarithmic	Logarithmic	Logarithmic	Logarithmic	Logarithmic
	First Difference	First Difference	First Difference	First Difference	First Difference

The correlations of the transformed freight from 9/23/2016 to 1/24/2020 are found in Table 5.24. below. US Gulf was most highly correlated with Brazil and Argentina (0.982). The highest correlation was between Brazil and Argentina, which reported a 1.00 correlation. Ukraine was not highly correlated with any other origin.

Table 5.24. Corn Correlation with Transformed Data 9/23/2016 – 1/24/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed	Ukraine Transformed
US Gulf (Transformed)	1.000				
PNW (Transformed)	0.762	1.000			
Brazil (Transformed)	0.982	0.783	1.000		
Argentina (Transformed)	0.982	0.784	1.000	1.000	
Ukraine (Transformed)	0.375	0.390	0.393	0.391	1.000

The net price (basis + ocean freight) iterations for each origin, along with the minimum price origin are shown in Figure 5.20. below. Each origin is shown in a different color, with yellow showing the statistics and results of the minimum price amongst all origins. Argentina has the highest mean net price ($2.21), followed by Brazil ($1.84), US Gulf ($1.61) and PNW ($1.41). PNW had the lowest minimum net price (-$2.18) and the highest maximum net price ($4.57). Brazil had the next lowest minimum ($0.43), followed by US Gulf ($0.53), and lastly Argentina ($0.87). Argentina followed PNW having the second highest maximum ($3.76). Brazil had the next highest maximum ($3.33) and US Gulf had the lowest maximum ($2.75). PNW had over double the volatility of any other origin with a standard deviation of $0.79. Brazil and Argentina followed, both with a standard deviation of $0.37. US Gulf had the least volatility with a standard deviation of $0.27.

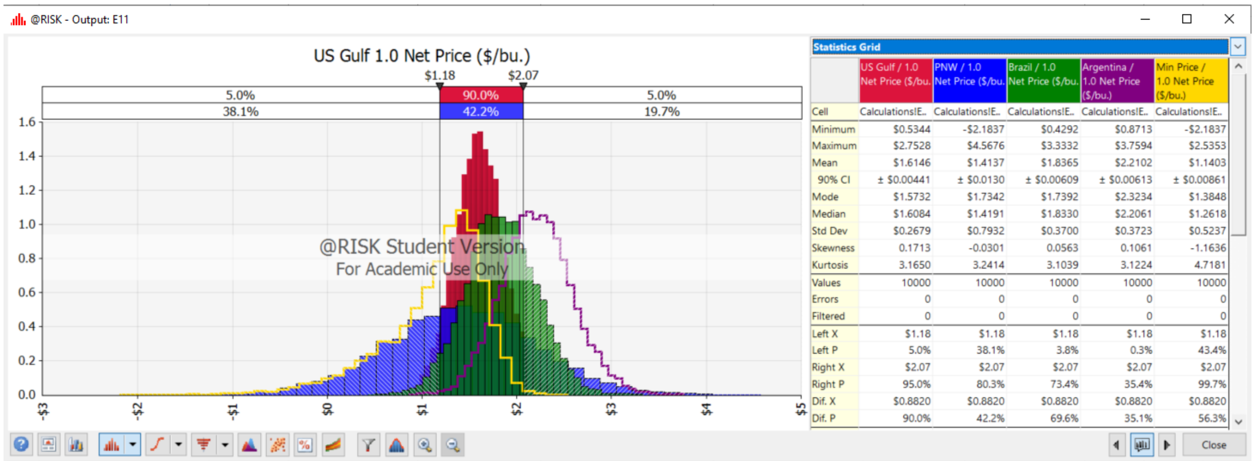


Figure 5.20. Delivered Basis from Sensitivity 1.0 Simulation

The option value of sensitivity is shown in blue with the base case shown in red. Sensitivity 1.0 has a slightly lower mean option value ($0.47) than the base case ($0.51). Both have a minimum value of $0.00, but this sensitivity has a higher maximum option value ($4.04) which is significantly higher than the base case ($2.51). The standard deviation of sensitivity 1.0 is higher as well ($0.55 compared to $0.42).

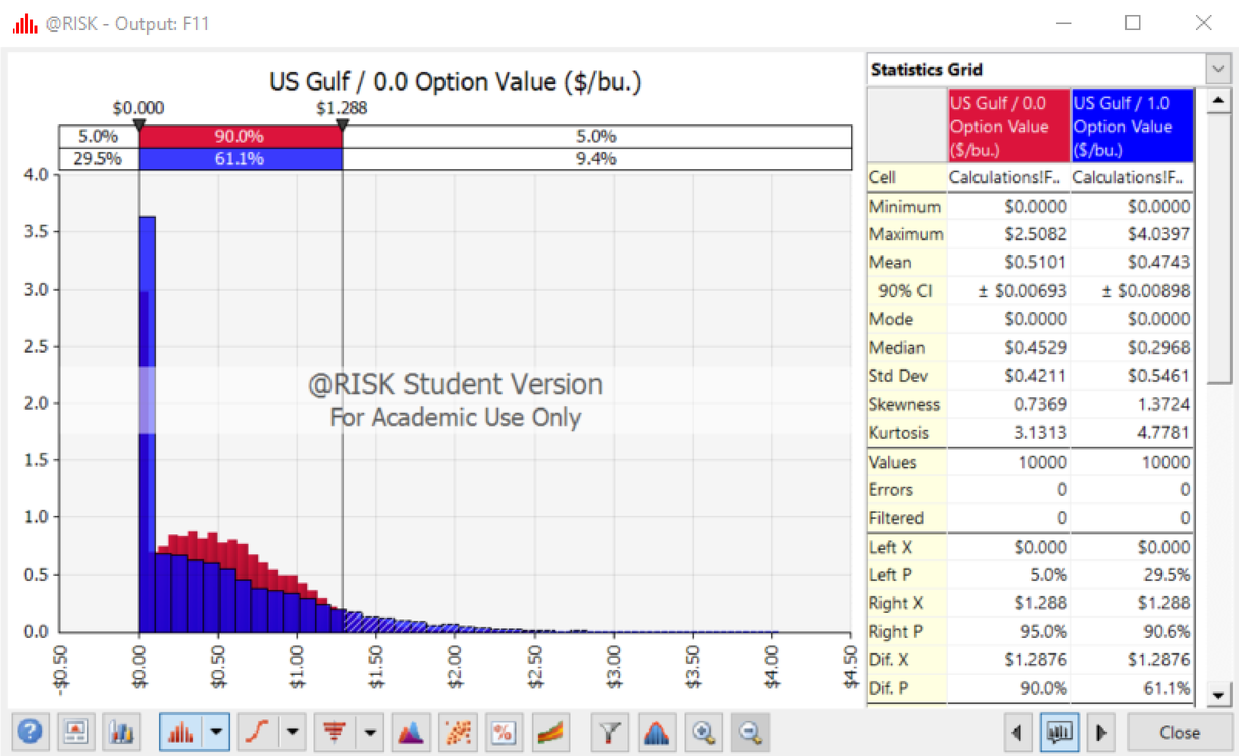


Figure 5.21. US Gulf Option Value Sensitivity 1.0 (blue) vs Base Case (0.0 in red)

The results of the batch fit of the data from 1/5/2018 to 1/24/2020 are shown in Table 5.25. The data was again adjusted because it was deemed nonstationary by the Augmented Dicey-Fuller test. Ukraine is included in the batch fit for this time period as well, though not used in this sensitivity.

Table 5.25. Corn Time Series Basis Functions 1/5/2018 – 1/24/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina	Ukraine
Distribution:	Moving Average I	Moving Average II	Moving Average I	Moving Average I	Auto-Regressive Conditional Heteroskedastic
Function:	RiskMA1(-0.024038, 2.1245, 0.115, 0.037217)	RiskMA2(-0.0025755, 9.4171, -0.77933, -0.25715, 4.6478, 4.8688)	RiskMA1(-0.024959, 3.5674, -0.35562, 0.99249)	RiskMA1(0.078312, 3.9078, -0.16634, 0.16164)	RiskARCH1(-0.012809, 34.54, 0.29517, 1.5919)
AIC Score:	464.898	797.8178	573.3254	596.3865	704.5501
Transformation:	First Difference	First Difference	First Difference	First Difference	First Difference

The transformed US Gulf data is most highly correlated with the transformed Argentina data. The transformed Brazil and Argentina data are the most highly correlated of any two origins.

Table 5.26. Corn Correlation with Transformed Data 1/5/2018 – 1/24/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed	Ukraine Transformed
US Gulf Transformed	1.000				
PNW Transformed	0.078	1.000			
Brazil Transformed	-0.020	0.258	1.000		
Argentina Transformed	0.141	0.012	0.163	1.000	
Ukraine Transformed	0.006	0.228	-0.066	0.162	1.000

The results of the corn freight batch fit for the time period from 1/5/2018 to 1/24/2020 are shown in Table 5.27. below. The data tested was not all stationary, so the first difference was taken to ensure stationarity. Because it is freight data and freight data must remain positive, a logarithmic transformation was made too.

Table 5.27. Corn Time Series Freight Functions 1/5/2018 – 1/24/2020 (@Risk™)

Parameter	US Gulf	PNW	Brazil	Argentina	Ukraine
Distribution:	Moving Average I	Moving Average I	Moving Average I	Moving Average I	Moving Average II
Function:	RiskMA1(	RiskMA1(	RiskMA1(	RiskMA1(	RiskMA2(
	-0.0018117, 0.030292, 0.45697, -0.029825)	-0.0025934, 0.034262, 0.33324, -0.033705)	-0.002051, 0.033485, 0.43464, -0.031866)	-0.0020388, 0.033274, 0.43464, -0.031546)	-0.00036417, 0.02807, 0.60107, 0.34417,0.0029487,0.010185)
AIC Score:	-445.0902	-418.2184	-423.9655	-425.1469	-454.9635
Transformation:	Logarithmic	Logarithmic	Logarithmic	Logarithmic	Logarithmic
	First Difference	First Difference	First Difference	First Difference	First Difference

The correlation of the freight data for this time period is found in Table 5.28. below. US Gulf, Brazil, and Argentina all have 1.00 or nearly 1.00 correlation. PNW had a correlation of 0.77 with US Gulf and slightly lower for Brazil (0.768) and Argentina (0.766). Ukraine was the least correlated of any origin, but had a correlation around 0.55 for Brazil, Argentina, and US Gulf.

Table 5.28. Corn Correlation with Transformed Data 1/5/2018 – 1/24/2020

Correlation	US Gulf Transformed	PNW Transformed	Brazil Transformed	Argentina Transformed	Ukraine Transformed
US Gulf Transformed	1.000				
PNW Transformed	0.770	1.000			
Brazil Transformed	0.999	0.768	1.000		
Argentina Transformed	0.999	0.766	1.000	1.000	
Ukraine Transformed	0.548	0.487	0.553	0.552	1.000

The results of the simulation are found in Figure 5.22. below. They indicate that Argentina has the highest mean net price ($2.20), followed by Brazil ($1.81), US Gulf ($1.57), and PNW ($1.25). PNW had the lowest minimum net price ($0.37), followed by US Gulf

($0.72), Brazil ($0.89), and Argentina ($0.99). Argentina had the highest maximum net price ($3.55) which was significantly higher than Brazil ($2.88), US Gulf ($2.56), and PNW ($2.34). Argentina had a higher volatility ($0.34), when compare to Brazil ($0.27), PNW ($0.26), and US Gulf ($0.26) which were all very similar.

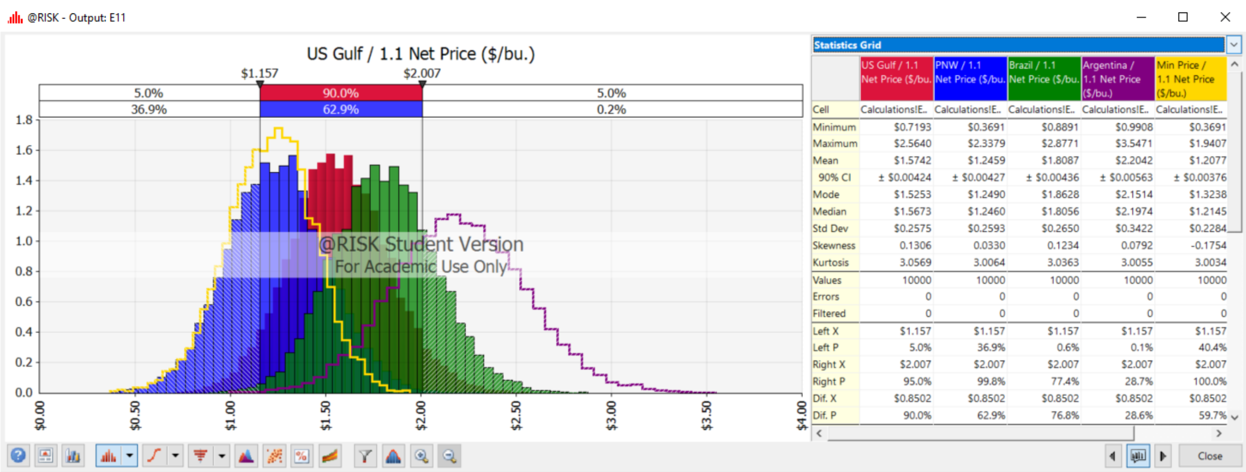


Figure 5.22. Delivered Basis from Sensitivity 1.1 Simulation

The option value of sensitivity 1.1 is significantly lower than the option value of the base case ($0.40 compared to $0.51). The maximum value is also nearly half of the base case maximum option value ($1.68 compared to $2.51). The standard deviation (volatility) is also significantly lower ($0.32 compared to $0.42).

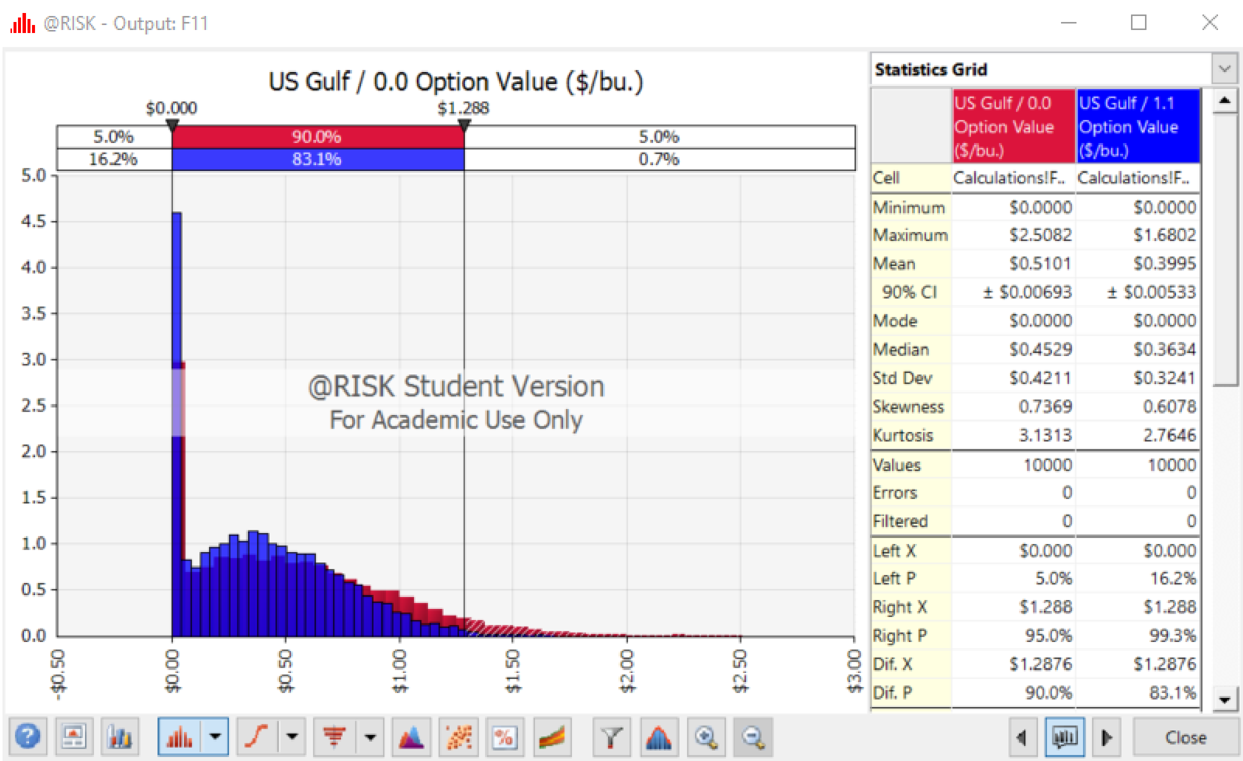


Figure 5.23. US Gulf Option Value Sensitivity 1.1 (blue) vs Base Case (0.0 in red)

Sensitivities Including Ukraine

Sensitivities 1.2 and 1.3 include Ukraine as a fifth origin, using the same time periods as sensitivity 1.0 and 1.1. The sensitivities are run the same as the first two sensitivities.

Figure 5.24. below shows the net price iterations for sensitivity 1.2. The average net prices for the origins are the same as sensitivity 1.0, but with the addition of Ukraine, with a mean net price of $1.95, which is the second highest. Ukraine has the second lowest minimum net price ($1.00) and the highest maximum net price ($4.80). Ukraine was the second most volatile, with a standard deviation of $0.52.

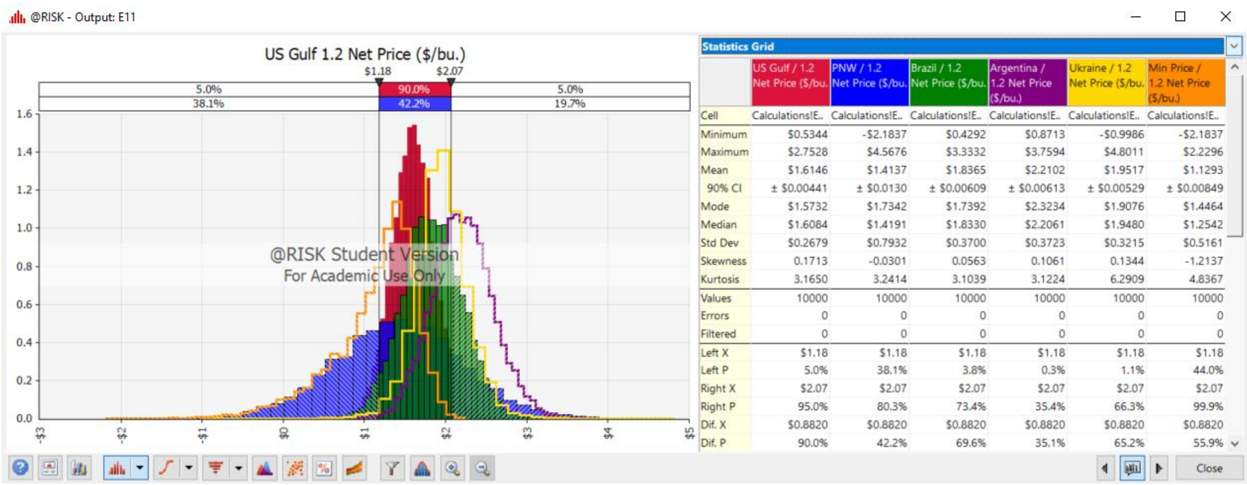


Figure 5.24. Delivered Basis from Sensitivity 1.2 Simulation

When including Ukraine as an additional origin, there was very little change in average option price and increased by about $0.01 from sensitivity 1.0 to 1.2. This illustrates that the addition of a Ukrainian origin does not increase the option value by a significant amount. This because Ukraine rarely has the least cost origin. The minimum value in both cases is $0.00. The maximum value is greater for sensitivity 1.2 ($4.60) than sensitivity 1.0 ($4.04). When looking at the figure, both graphs have very similar trends. The standard deviations are nearly identical at $0.54 (sensitivity 1.2) and $0.55 (sensitivity 1.0). There are less occurrences of $0.00 option value in sensitivity 1.2 than 1.0.

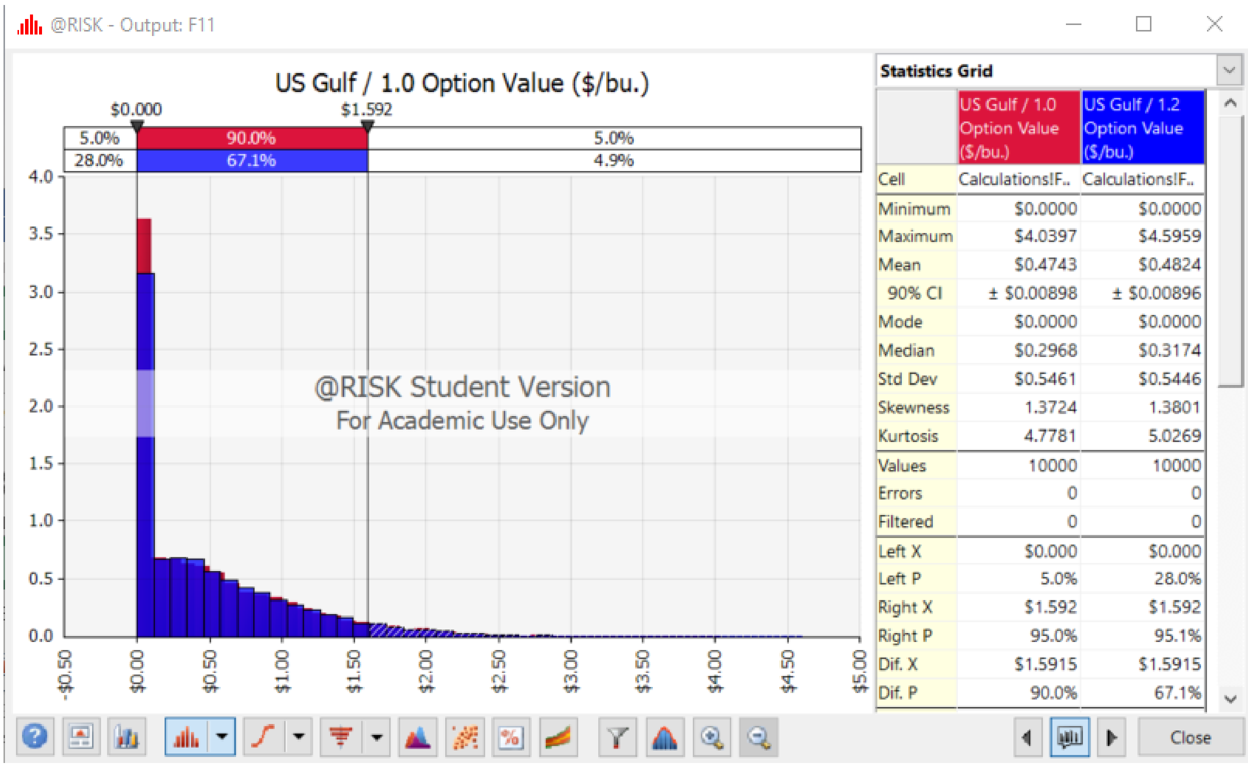
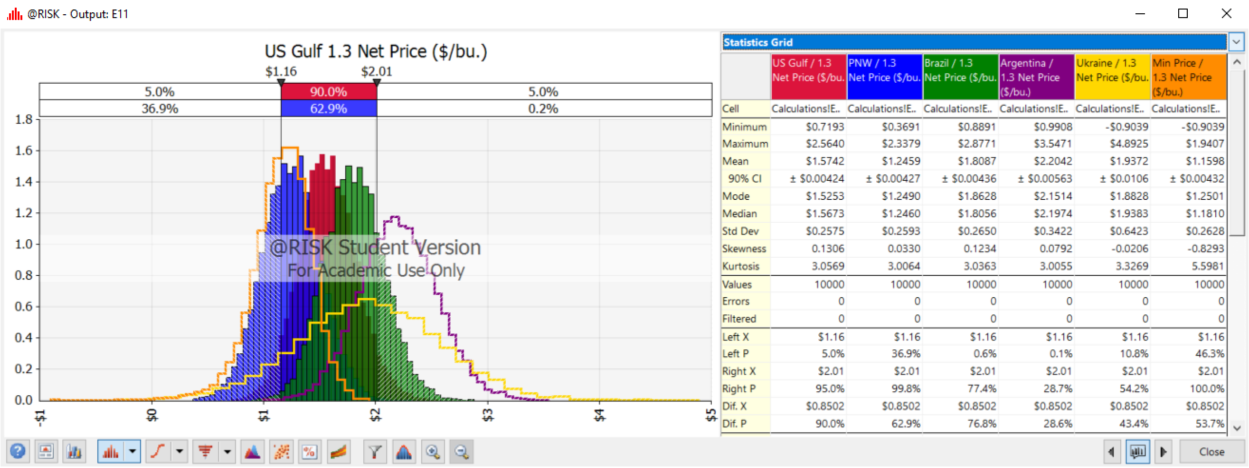


Figure 5.25. US Gulf Option Value Sensitivity 1.2 (blue) vs Sensitivity 1.0 (1.0 in red)

The net price results for sensitivity 1.3 are found below in Figure 5.26. The statistics for US Gulf, PNW, Brazil, and Argentina are the same as sensitivity 1.1. Ukraine has the second highest mean option value ($1.94). Ukraine also had the lowest minimum (-$0.90) and highest maximum ($4.89). The volatility or standard deviation was the highest of all origins as well ($0.64).



	US Gulf / 1.3 Net Price ($/bu.	PNW / 1.3 Net Price ($/bu.	Brazil / 1.3 Net Price ($/bu.	Argentina / 1.3 Net Price ($/bu.)	Ukraine / 1.3 Net Price ($/bu.	Min Price / 1.3 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	$0.7193	$0.3691	$0.8891	$0.9908	-$0.9039	-$0.9039
Maximum	$2.5640	$2.3379	$2.8771	$3.5471	$4.8925	$1.9407
Mean	$1.5742	$1.2459	$1.8087	$2.2042	$1.9372	$1.1598
90% CI	± $0.00424	± $0.00427	± $0.00436	± $0.00563	± $0.0106	± $0.00432
Mode	$1.5253	$1.2490	$1.8628	$2.1514	$1.8828	$1.2501
Median	$1.5673	$1.2460	$1.8056	$2.1974	$1.9383	$1.1810
Std Dev	$0.2575	$0.2593	$0.2650	$0.3422	$0.6423	$0.2628
Skewness	0.1306	0.0330	0.1234	0.0792	-0.0206	-0.8293
Kurtosis	3.0569	3.0064	3.0363	3.0055	3.3269	5.5981
Values	10000	10000	10000	10000	10000	10000
Errors	0	0	0	0	0	0
Filtered	0	0	0	0	0	0
Left X	$1.16	$1.16	$1.16	$1.16	$1.16	$1.16
Left P	5.0%	36.9%	0.6%	0.1%	10.8%	46.3%
Right X	$2.01	$2.01	$2.01	$2.01	$2.01	$2.01
Right P	95.0%	99.8%	77.4%	28.7%	54.2%	100.0%
Dif. X	$0.8502	$0.8502	$0.8502	$0.8502	$0.8502	$0.8502
Dif. P	90.0%	62.9%	76.8%	28.6%	43.4%	53.7%

Figure 5.26. Delivered Basis from Sensitivity 1.3 Simulation

The mean option value increased by about $0.02 when including Ukraine as a fifth origin from $0.39 to $0.41. The minimum value for both was $0.00. The maximum value increased from $1.68 (sensitivity 1.1) to $2.43 (sensitivity 1.3). Again, the standard deviation was nearly unchanged going from $0.32 to $0.33. The graph overlay shows that the iterations were very similar. The sensitivity including Ukraine (sensitivity 1.3) had less occurrences of $0.00.

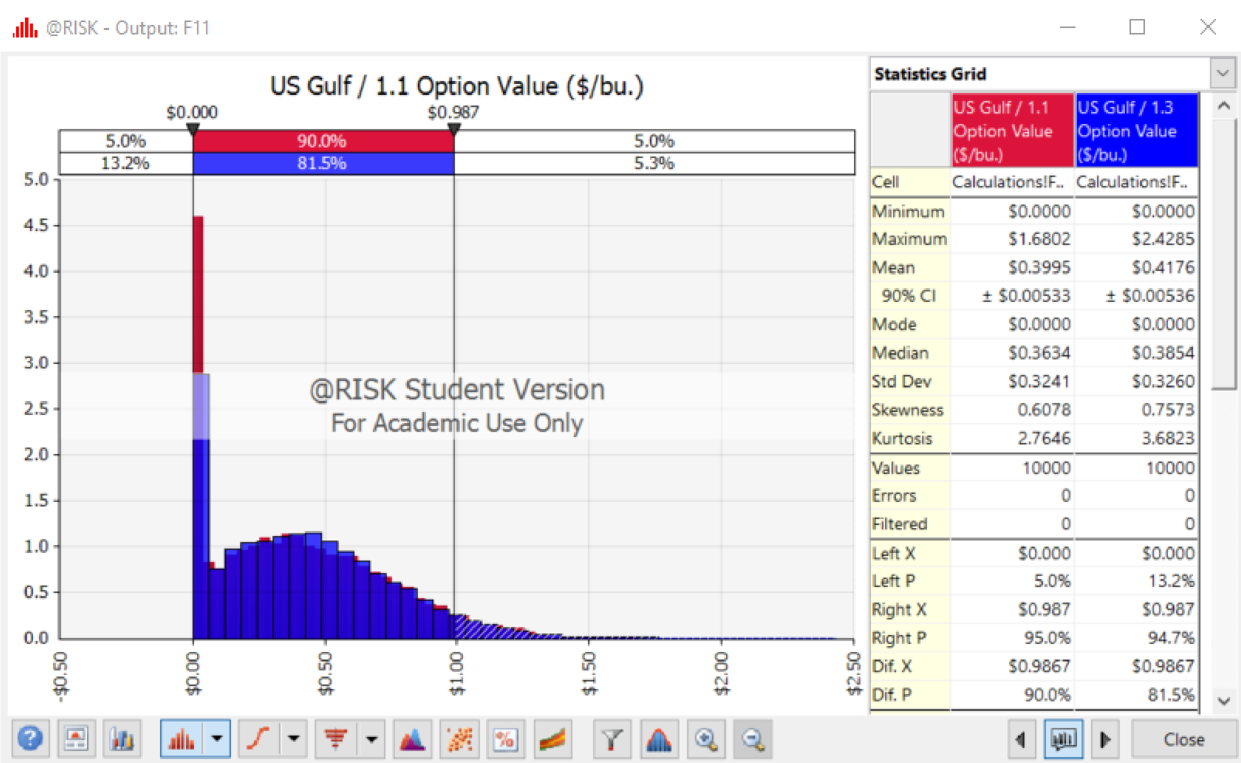


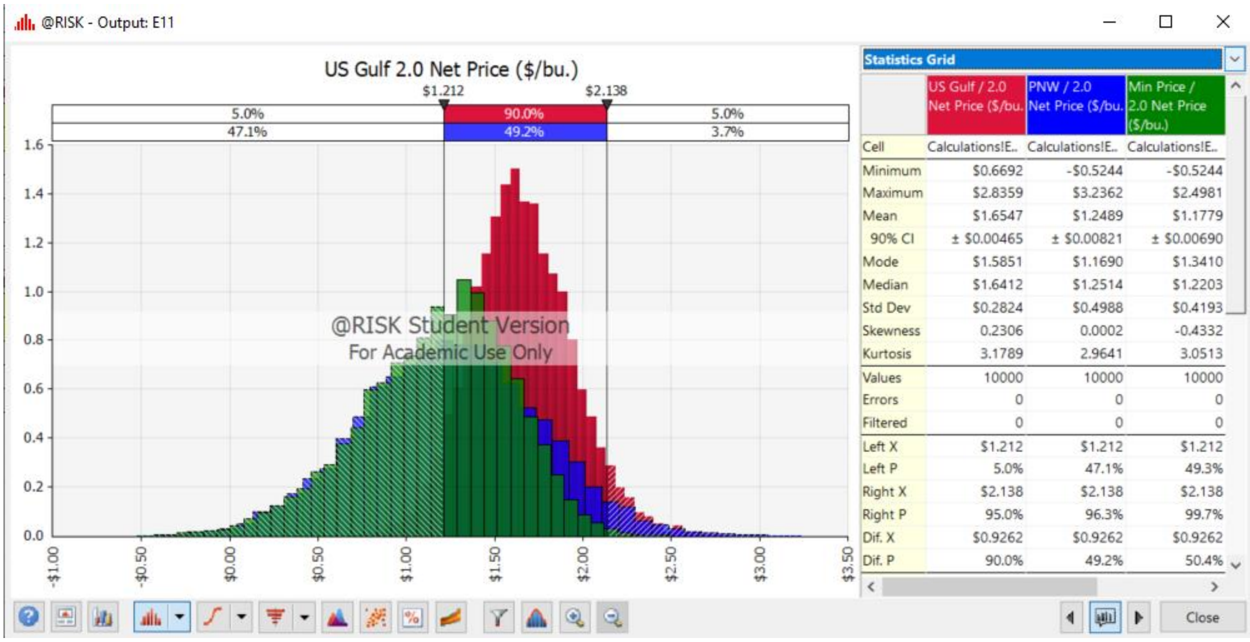
Figure 5.27. US Gulf Option Value Sensitivity 1.3 (blue) vs Sensitivity 1.1 (1.1 in red)

Adjusting the time period does have a significant effect on the average option price. The average option value decreased by $0.07 without including Ukraine (sensitivity 1.0 to 1.1) and decreased by $0.06 when including Ukraine (sensitivity 1.2 to 1.3). The minimum value remained at $0.00 for all scenarios. The longer time periods had higher maximum option values while excluding and including Ukraine. The longer time period had higher standard deviations, but the addition of the Ukraine origin had little effect on it.

Sensitivity 2 – Origins

Sensitivity 2 compares the results of differences in different combinations of origins. These sensitivities were used to determine the option value for commodity trading firms that do not have the ability to originate from all four origins that are used in the base case. Only the two US origins are used in the first sensitivity. This is done to illustrate a commodity trading firm with the ability to originate in the two US origins but are unable to utilize the South American origins. The second origin sensitivity illustrates how the value of the option is changed when including only the Brazil origin. The value is expected to be much higher than the first sensitivity because there are more spatial arbitrage opportunities that arise from more spatially diverse origins.

The functions used are the same as the base case. The results are found in Figure 5.28. below. US Gulf had the higher mean net price ($1.65) than PNW ($1.25). PNW had a much lower minimum net price (-$0.52) and higher maximum ($3.24) than US Gulf ($0.67 and $2.84 respectively). PNW also had nearly double the standard deviation ($0.50 vs $0.28).



	US Gulf / 2.0 Net Price ($/bu.	PNW / 2.0 Net Price ($/bu.	Min Price / 2.0 Net Price ($/bu.)
Cell	Calculations!E..	Calculations!E..	Calculations!E..
Minimum	$0.6692	-$0.5244	-$0.5244
Maximum	$2.8359	$3.2362	$2.4981
Mean	$1.6547	$1.2489	$1.1779
90% CI	± $0.00465	± $0.00821	± $0.00690
Mode	$1.5851	$1.1690	$1.3410
Median	$1.6412	$1.2514	$1.2203
Std Dev	$0.2824	$0.4988	$0.4193
Skewness	0.2306	0.0002	-0.4332
Kurtosis	3.1789	2.9641	3.0513
Values	10000	10000	10000
Errors	0	0	0
Filtered	0	0	0
Left X	$1.212	$1.212	$1.212
Left P	5.0%	47.1%	49.3%
Right X	$2.138	$2.138	$2.138
Right P	95.0%	96.3%	99.7%
Dif. X	$0.9262	$0.9262	$0.9262
Dif. P	90.0%	49.2%	50.4%

Figure 5.28. Delivered Basis from Sensitivity 2.0 Simulation

The option value decreases slightly from the base case. The average option value is about $0.04 lower than the base case. Less origins to procure grain in, leads to less spatial arbitrage opportunities and decreases the option value. The minimum option values were the same ($0.00) and the maximum option values were very similar at $2.51 and $2.55 for sensitivity 2.0 and the base case scenario, respectively. Sensitivity 2.0 ($0.45) had a slightly higher standard deviation than the base case ($0.42).

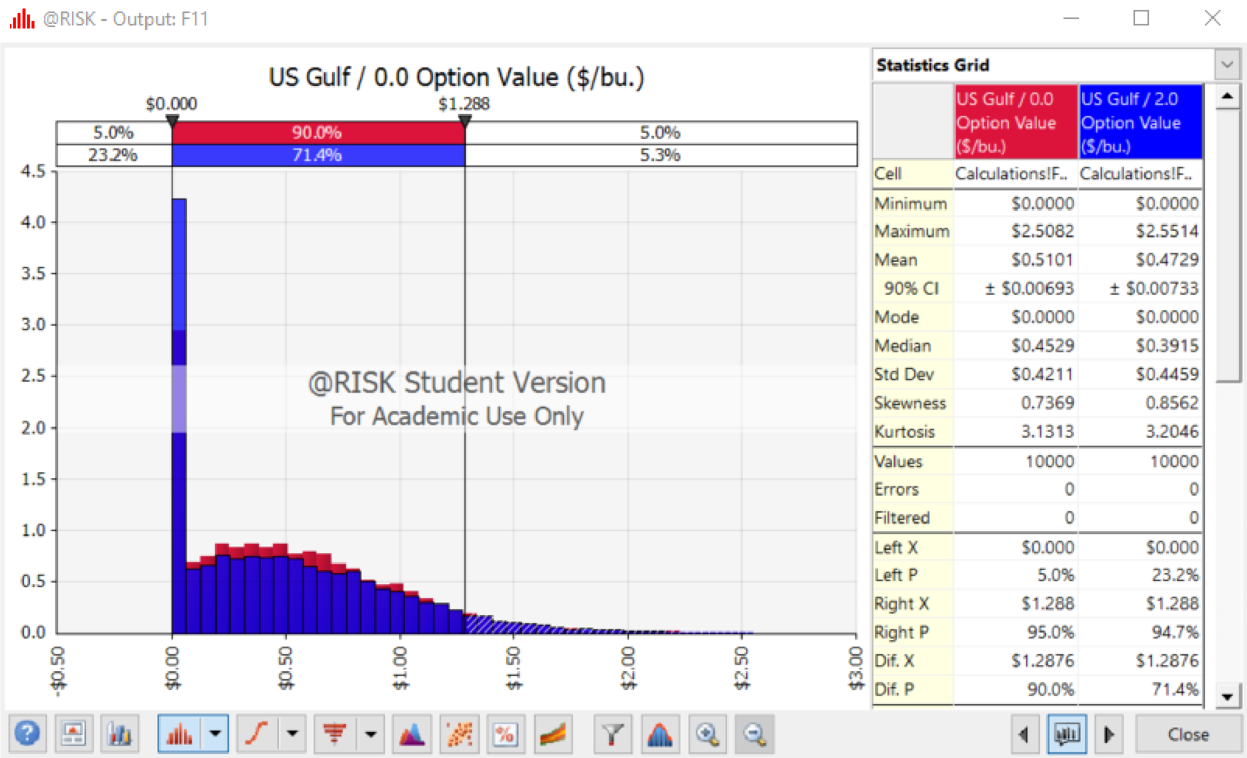


Figure 5.29. US Gulf Option Value Sensitivity 2.0 (blue) vs Base Case (0.0 in red)

Sensitivity 2.1 observes how the value of the option is affected when only US Gulf and Brazil origins are used. Again, the same functions were the same as the base case. The results of the net price simulations are found in Figure 5.30. below. Brazil had a higher average net price ($1.72) when compared to US Gulf ($1.65). Brazil had a lower minimum net price ($0.27) and a higher maximum price ($3.38) than US Gulf ($0.67 and $2.84 respectively). Brazil also had a higher standard deviation ($0.42) than US Gulf ($0.28).

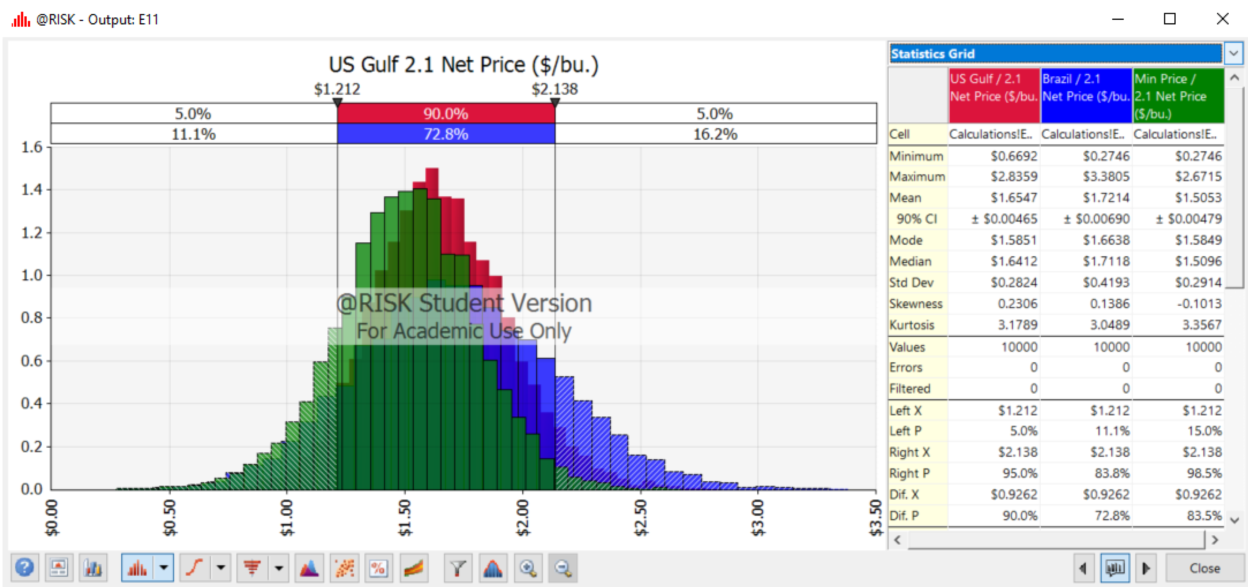


Figure 5.30. Delivered Basis from Sensitivity 2.1 Simulation

As expected, the average option value decreases significantly when compared with the base case. It decreased from $0.51 to $0.15 from the base case to sensitivity 2.1. The minimum option value was the same in both cases. The maximum option value decreased $0.75 from $2.51 (base case) to $1.86 (sensitivity 2.1). The standard deviation decreased from $0.42 to $0.24 from the base case to sensitivity 2.1.

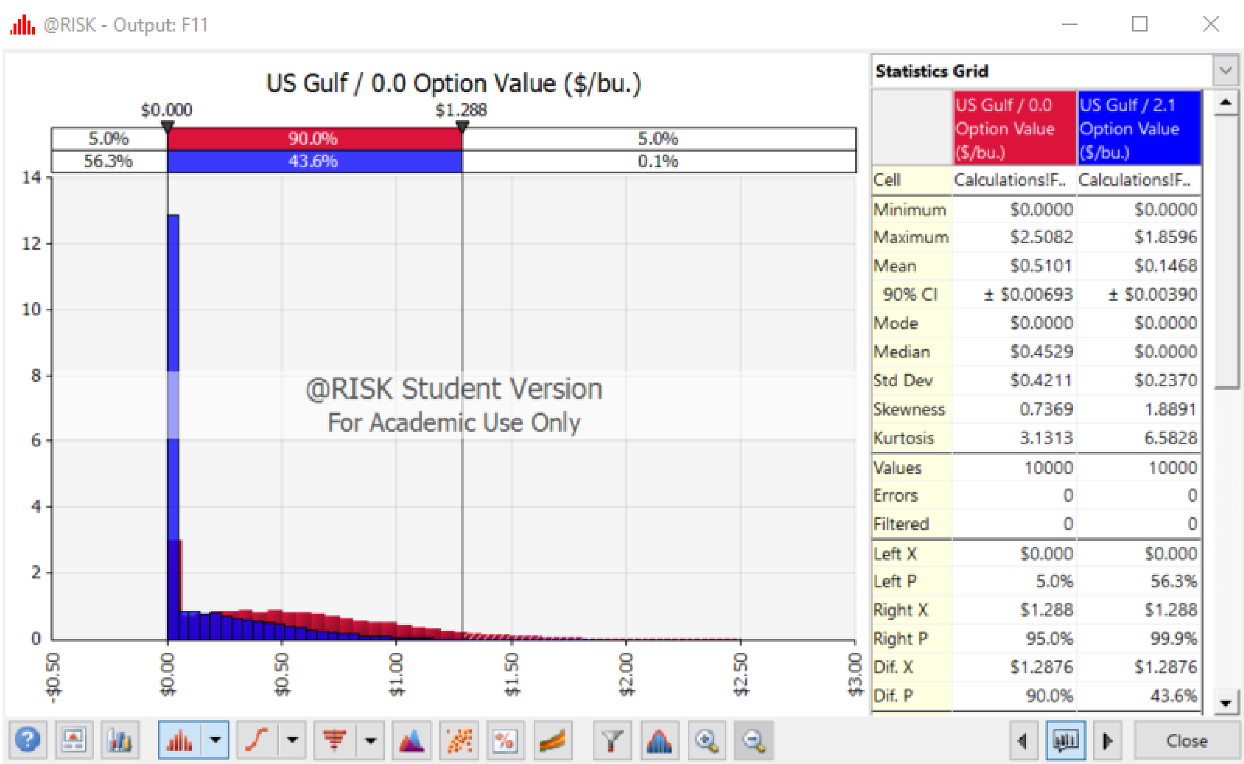


Figure 5.31. US Gulf Option Value Sensitivity 2.1 (blue) vs Base Case (0.0 in red)

Sensitivity 3 – No Ocean Freight

Sensitivity 3 eliminates ocean freight from the net price, so only considers the basis level. This would illustrate a scenario where the seller of the grain is not in charge of paying for the freight or FOB rate. The freight would be excluded, and the call option would be on only the basis.

The net price simulation results are shown in Figure 5.32. Argentina had the highest average net price ($0.83). PNW had the next highest average net price ($0.75), followed by Brazil ($0.69), and US Gulf ($0.63). PNW had the lowest minimum net price (-$0.87), followed by Brazil (-$0.61), and US Gulf (-$0.13). PNW had the highest maximum net price ($2.52), with Argentina ($1.93) and Brazil ($1.91) at very similar levels. US Gulf had the lowest maximum net price ($1.31). PNW was the most volatile with a standard deviation of $0.49. Brazil and

Argentina were very similar at $0.35 and $0.31, respectively. US Gulf was the least volatile at $0.19.

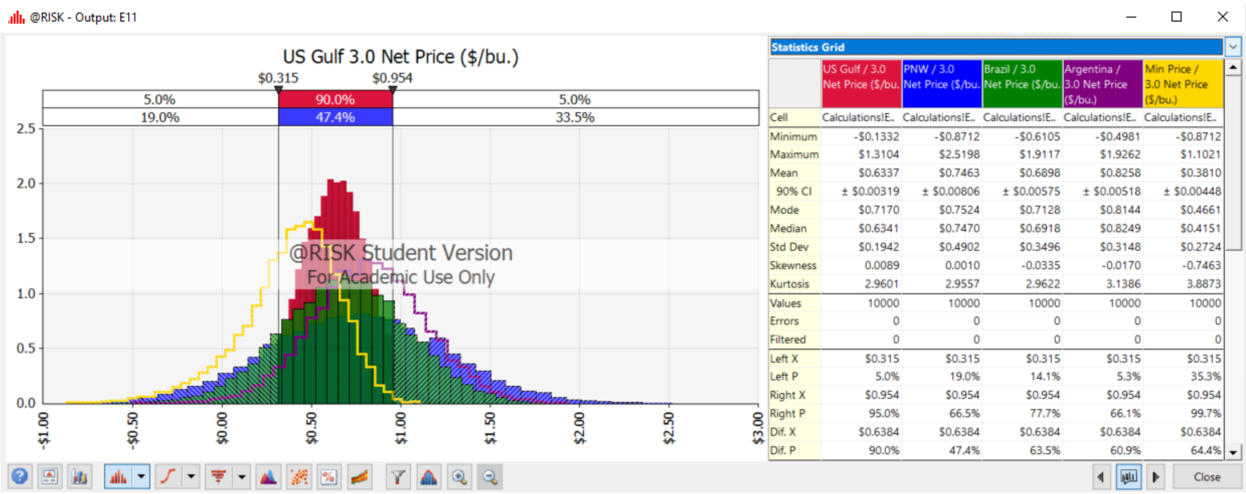


Figure 5.32. Delivered Basis from Sensitivity 3.0 Simulation

The simulation result for the option value is found in Figure 5.33. below. The average option value for this sensitivity is half of that of the base case ($0.25 vs $0.51). The minimum option value is $0.00 for both scenarios. The maximum option value is significantly lower in sensitivity 3.0 ($1.75) than the base case ($2.51). Sensitivity 3.0 also had a significantly lower standard deviation ($0.27) than the base case ($0.42).

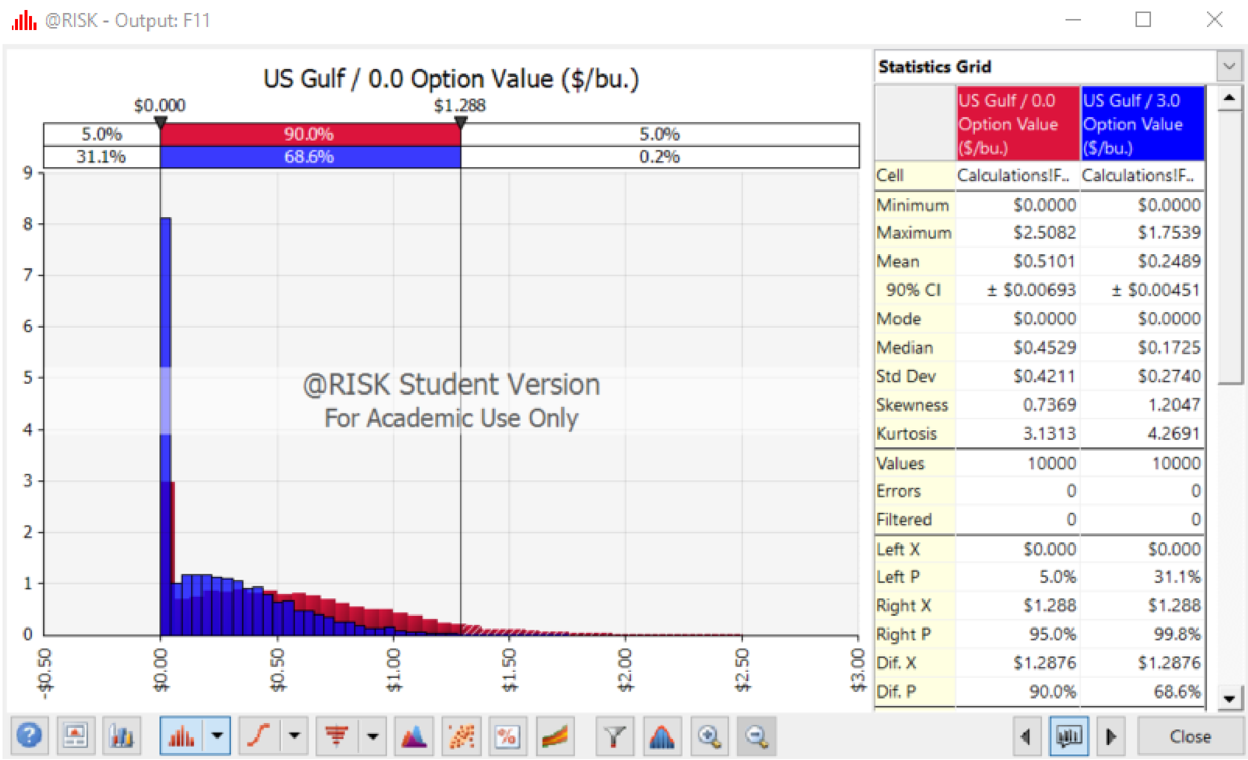


Figure 5.33. US Gulf Option Value Sensitivity 3.0 (blue) vs Base Case (0.0 in red)

Sensitivity 4 – Number of Periods Forward

Sensitivity 4 analyzes how adjusting the time period affects the average option value. The value at each period from 1 to 20 periods forward is calculated. The motivation behind this sensitivity is to determine the effect of time on the option value. It is expected that an increase in time results in an increase in option value. There is expected to be a positive correlation between time and option value. Periods that are less far forward are expected to have less value so a commodity trading firm may be less likely to engage in the shorter-term options because there is less upside potential.

As expected, the option value increases as the number of time periods increases. This is due to the increase in volatility and a greater chance that the prices divert from the initial price more. From the mean price at period 1 to the mean price at period 20, the option price almost triples going from $0.24 to $0.69. The option price goes up by about $0.0225 for each 1 period increase. This illustrates the time value of the option. Figure 5.34. shows the path that the mean option value follows as the number of time periods increases.

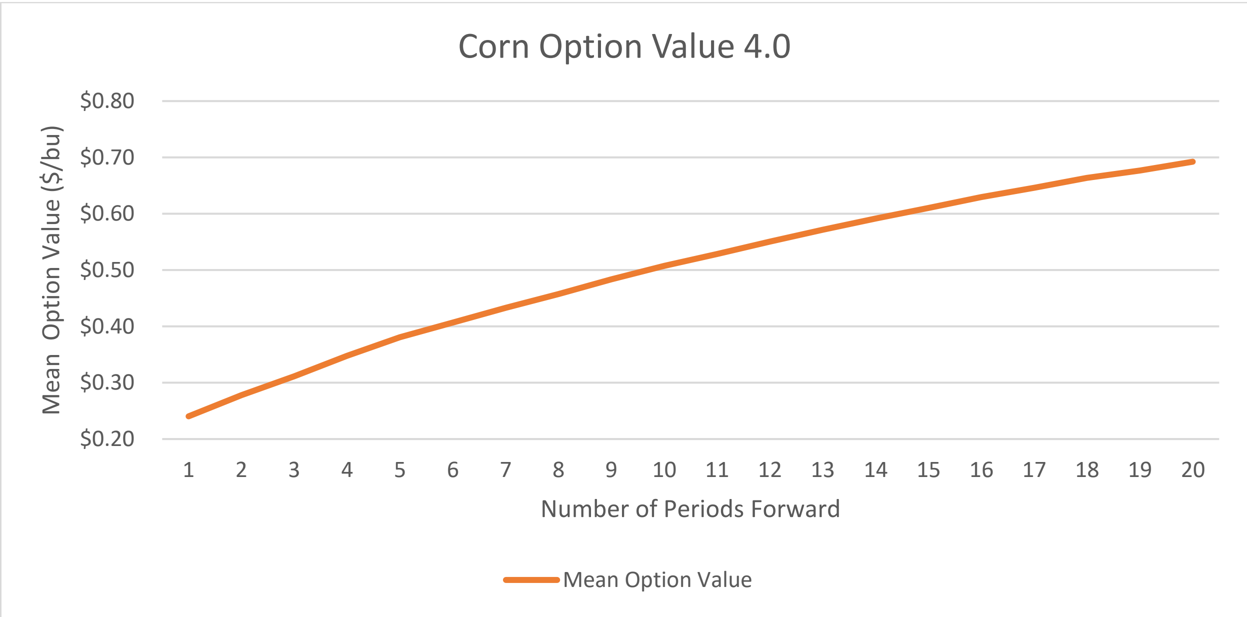


Figure 5.34. US Gulf Option Values Sensitivity 4.0

Sensitivity 5 – Risk Free Discount Rate

The final sensitivity determines the effect of adjusting the risk-free discount rate. The rate are yearly rates that are adjusted to weekly rates when calculating the option value. This sensitivity is done to determine if a risk-free discount rate should be included in the option calculations. It is to determine at what level the discount rate will affect the option value.

Figure 5.35. shows the effect of increasing the yearly risk-free discount rate from 0% to 12%. The figure shows that the discount rate has little, if any, effect on the mean option price. At each level, the mean option value remains at $0.51. This is likely due to the rates need to be adjusted to weekly discount rates. Because of this, the increases of even up to 12% yearly results in a weekly risk-free discount rate of 0.23% weekly over the 12 weeks. This results in a cumulative discount rate of 2.77% over the entire period observed. For the discount rate to

become significant, the number of periods out would have to increase substantially, or the risk-free discount rate would have to increase to unrealistic levels.

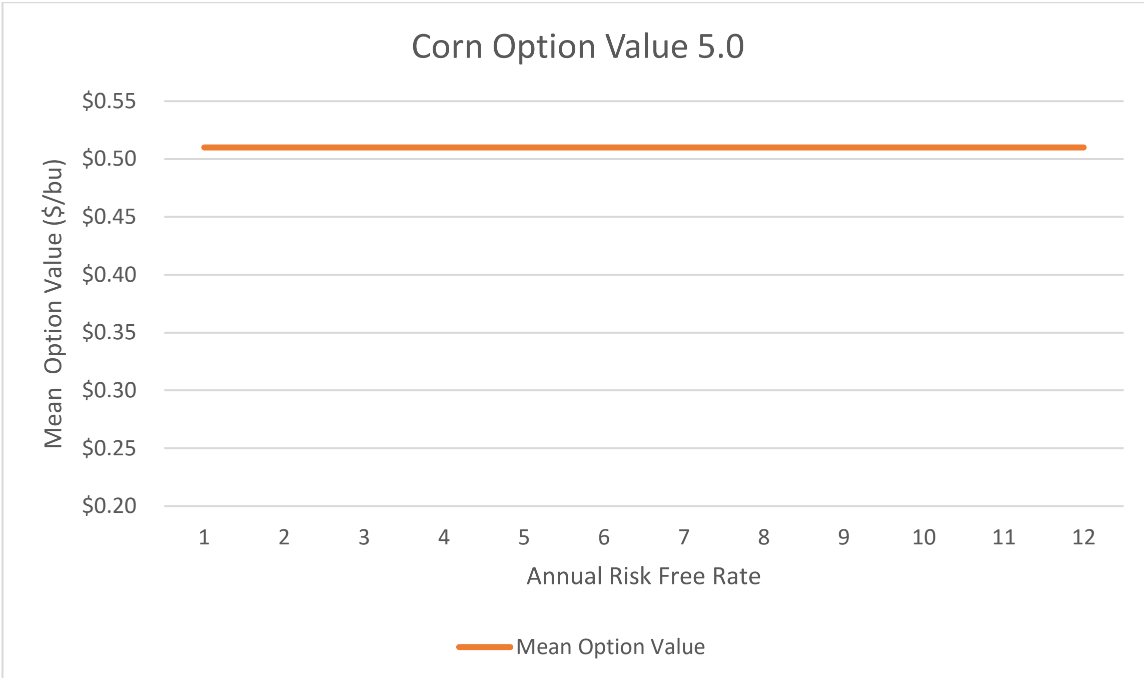


Figure 5.35. US Gulf Option Values Sensitivity 5.0

Other Option Specifications

Asian and lookback options are calculated in addition to the sensitivities. These are calculated to determine the effects of the structure of the contract has on the option price. The Asian option eliminates the higher potential value by averaging the periods. An increase or decrease in basis will have less of an affect because the value is averaged over time. The lookback options serve as a best and wort case scenario for the option pricing. They set the boundaries for the option values.

These options are also calculated using the same dataset as the base case scenario. The Asian option price is calculated by taking the average of the minimum prices across the time periods leading up to the expiration date. The lookback options are calculated off the minimum and maximum of all the minimum period prices, respectively. The results of these simulations are shown below in Figure 5.36. – Figure 5.38.

When simulating the Asian option, the mean option value was $0.42, or $0.09 lower than the base case ($0.51). The minimum option values were $0.00. The maximum option value for the Asian option ($2.44) was slightly lower than the base case ($2.51). The Asian option had a standard deviation ($0.33) that was $0.11 lower than the base case ($0.42).

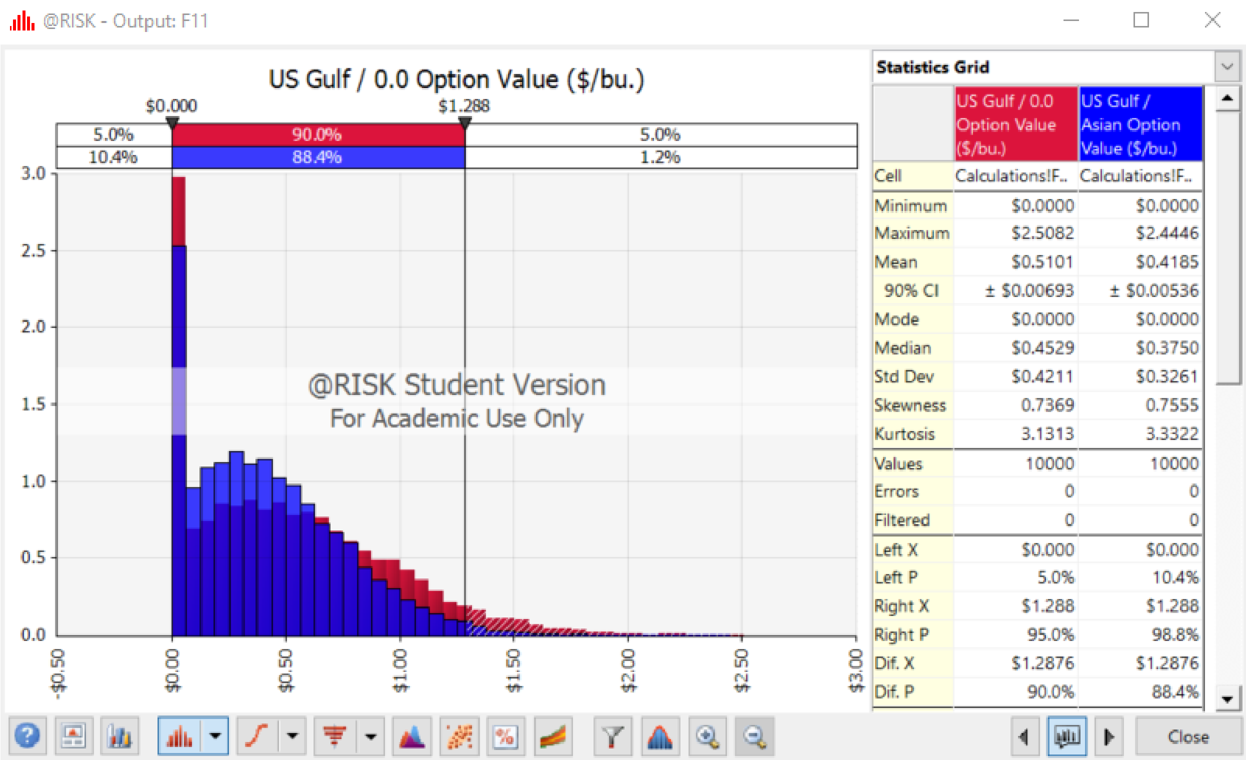


Figure 5.36. US Gulf Asian Option Value (blue) vs Base Case (0.0 in red)

The simulation results for the minimum lookback option indicate that the average option value for the minimum lookback option ($0.74) is significantly higher than the base case ($0.51). The minimum values are both $0.00. The maximum option value for the minimum lookback option ($2.62) is $0.11 higher than the base case ($2.51). The standard deviations were very similar at $0.41 and $0.42 for the minimum lookback option and base case respectively.

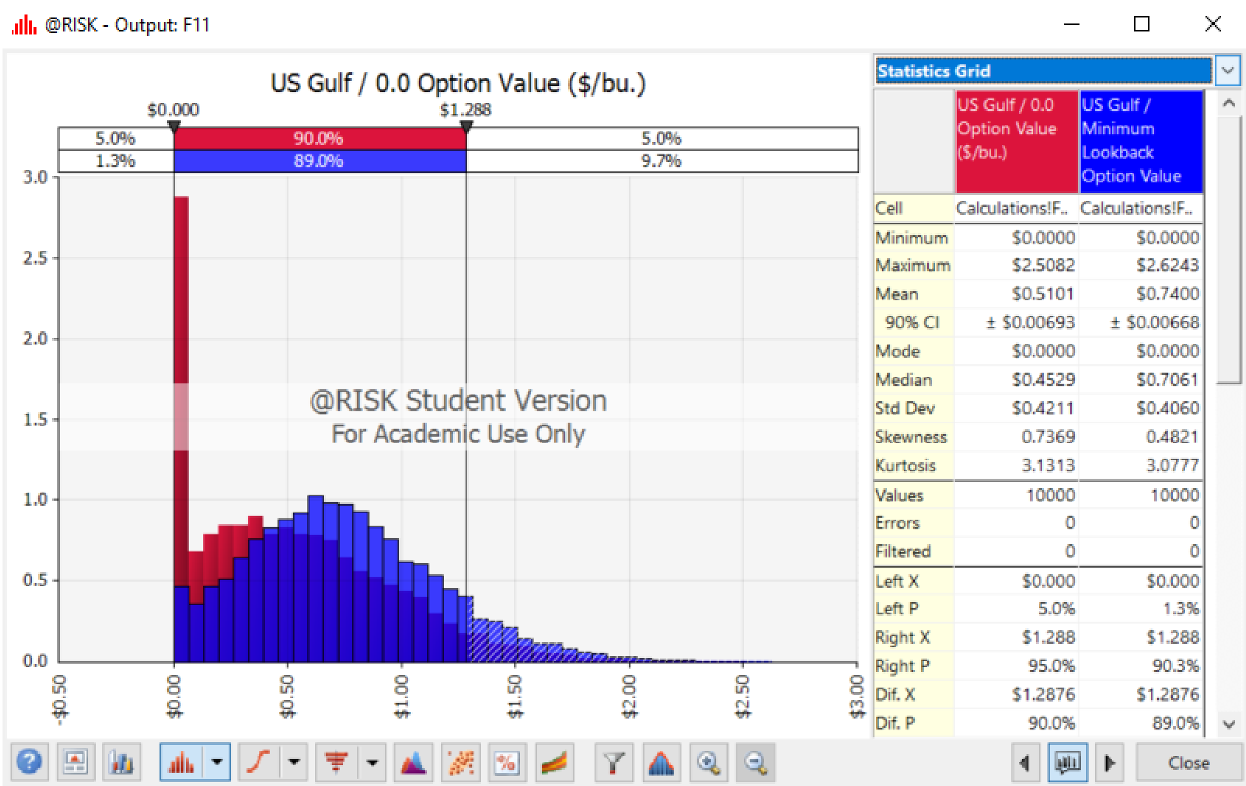


Figure 5.37. US Gulf Minimum Lookback Option Value (blue) vs Base Case (0.0 in red)

The results of the maximum lookback option are found in Figure 5.38. below. The mean option value for the maximum lookback option was the lowest of any mean option value at only $0.08. This is less than 20% of the base case mean option value ($0.51). The minimum option value was $0.00. The maximum option value for the maximum lookback option ($2.25) was $0.26 lower than the base case ($2.51).

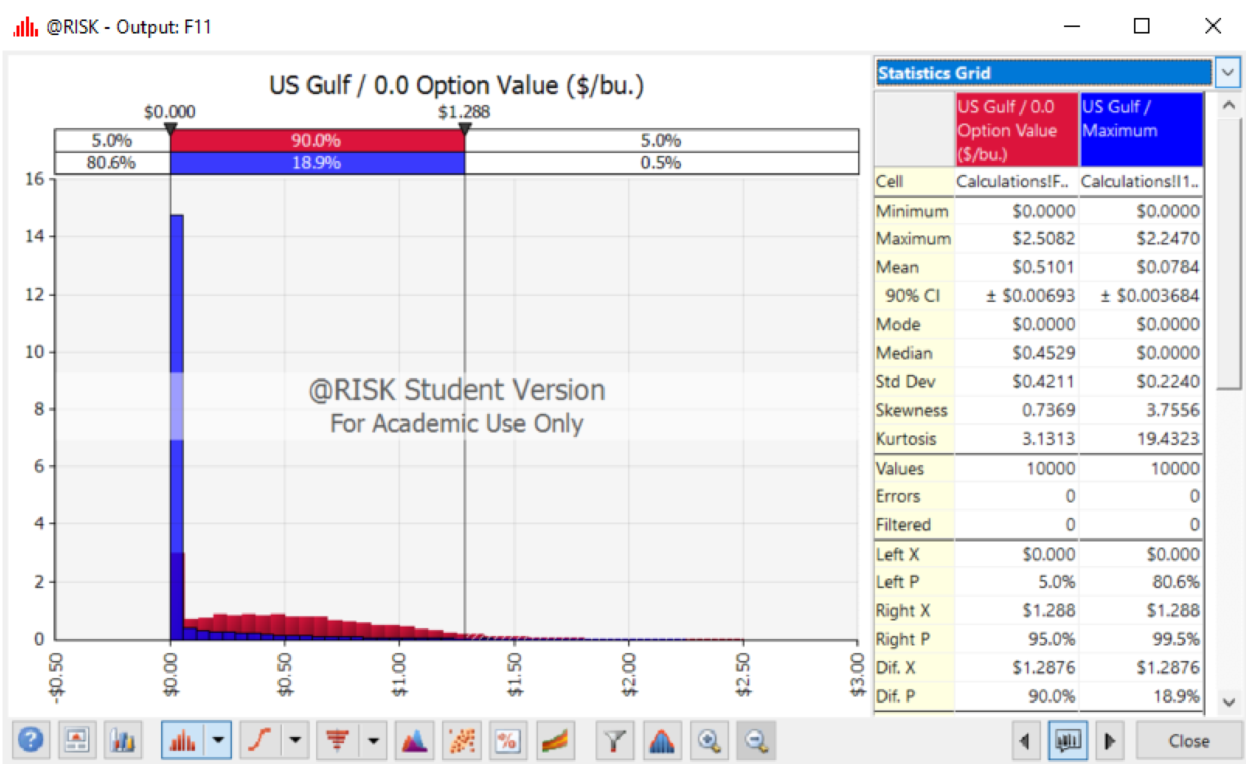


Figure 5.38. US Gulf Maximum Lookback Option Value (blue) vs Base Case (0.0 in red)

Summary

Table 5.29. show the results of the above simulations from sensitivities 1.0 to 3.0. It helps to show how the mean option price change during each sensitivity. The base case has the highest mean of all European corn option models that were ran. It was not significantly higher than most of the other sensitivities. The lowest mean option value was in sensitivity 2.1. This limits the option to two origins. This significantly takes away from the option value. This sensitivity has value less than half of the time because US Gulf is the minimum cost origin more than not. Excluding freight had a significant effect on the mean corn option price. It was less than half of the mean option value of the base case.

Table 5.29. Corn Results

Measure ($/bu.)	Base Case	Sens. 1.0	Sens. 1.1	Sens. 1.2	Sens. 1.3	Sens. 2.0	Sens. 2.1	Sens. 3.0
Mean	$ 0.51	$ 0.47	$ 0.40	$ 0.48	$ 0.42	$ 0.47	$ 0.15	$ 0.25
Standard Deviation	$ 0.42	$ 0.55	$ 0.32	$ 0.54	$ 0.33	$ 0.45	$ 0.24	$ 0.27
Likelihood of Min	14%	30%	16%	27%	13%	23%	56%	31%
Likelihood of Max	14%	4%	3%	2%	2%	77%	44%	9%

The other option types had strong influence on the mean option value when compared to the base case. The Asian type option was slightly lower than the base case. The minimum and maximum lookback options were significantly different from the base case. The non-European type options help to set the bounds and give an idea of what an American type option would be valued at. The minimum lookback option illustrates the best-case scenario for an American type option. The maximum lookback option illustrates the worst-case scenario for an American type option. The Asian type option is similar to the average of the American type option. The American type option would be valued somewhere between the minimum and maximum lookback option and would be somewhere near the value of the Asian type option.

Table 5.30. Other Option Results

Measure ($/bu.)	Base Case	Asian Option	Min Lookback Option	Max Lookback Option
Mean	$ 0.51	$ 0.42	$ 0.74	$ 0.08
Standard Deviation	$ 0.42	$ 0.33	$ 0.41	$ 0.22
Odds Above Option	86%	89%	99%	58%
Odds Below Option	14%	11%	0%	42%

Interpretation of Results for Contracting Strategy

This thesis analyzes the switching type option from a profitability aspect and is used to determine the additional value that is gained by having the option to switch origins. Switching options can also be useful in scenarios where the seller of grain is unable to ship grain out of a specific origin as explained in some of the examples in Chapter 2. Additionally, switching options are useful in managing grain stock at multiple origins. Strategic management of grain inventory is crucial in commodity trading firms, and proper implementations of switching options could be useful in aiding in managing grain inventories. These are some examples of reasons a commodity trading firm would engage in a switching option other than for increased profitability.

Though switching options are not generally incorporated into grain contracts currently, switching origins is practiced throughout the grain industry. In the case of the switching options that are used today, there is not often a set premium charged. Rather than paying a premium, it is negotiated into the pricing of the contracts. An example using the soybean base case mean option value, the buyer of the option would not pay the $0.52/bu., but rather, the grain would be discounted by that amount. Rather than getting paid a basis of $3.00/bu., the seller would receive $2.48/bu.

The various sensitivities can change the interpretation of the option. The first sensitivity is used to illustrate that using different periods of data with different levels of volatility impact the option price. It is important to select a time period that would accurately reflect the current prices. Another example is sensitivity 2 which restricts the origins would be useful for commodity trading firms without all four origins to switch between. Commodity trading firms with only US Origins would result in less value, so would pay less in premiums to switch between the two origins when compared to commodity trading firms with the ability to switch between four origins. Sensitivity 3 illustrates the option value without the inclusion of ocean freight or a FOB option value. This model is used to illustrate a scenario in which the seller of the grain does not pay for the freight to deliver the grain to the destination. The option value is driven strictly off the basis.

Another example would be the 4th sensitivity. Commodity trading firms could determine which time period would be the best. Further forward contracts have higher premiums but could result in more profit it the price moves more favorably. There is also more risk in this because the seller of grain would take a greater discount (pay higher premium) in order to have the option to switch further out. Sensitivity 5 shows that for any period under 12 periods forward, discount rates do not need to be included in the option value calculation. Periods over 12 periods forward would need to be analyzed on a case by case basis to determine if it is necessary to include in the model for pricing the option.

The non-European option types such as the Asian and lookback type options help to give an idea of where an American type option value would be. The American type option was not modeled in this thesis for reason covered in previous chapters. The lookback options help to set the upper and lower bounds for American type option value and the Asian option helps to set the average price. The American type option value would be somewhere between the minimum and maximum lookback option value and would be close to the Asian option value.

Strategic Interpretation of Options in Export Contracts

The premium that the seller of the grain would pay would likely be imbedded in the price of the grain and be negotiated between the buyer and seller of the grain. The mean option values that were calculated in this thesis provide an estimation of the value of the option. The base case scenarios for soybeans and corn were surprisingly very similar at $0.52 and $0.51, respectively. The value of the option changes depending on the time period used, origin access, inclusion or exclusion of freight, and time periods forward.

The premium would only be a percentage of the mean option value and is known as the sharing parameter. The premium is represented in Formula 9. γ represents the sharing parameter which is a percentage of the mean option value. This scenario examines a sharing parameter from 25-100%. in 25% intervals and represents the portion of the option value that the buyer of the option would pay for the premium.

$$Premium = OptionValue * \gamma \tag{9}$$

After knowing the premium, the profitability can be determined. The option is profitable if the difference between the base origin (US Gulf) and the minimum price origin is greater than the option premium. The profit would be any amount that is left over. Formula 10 shows the calculation for profitability. The sharing parameter would be negotiated between the seller and buyer of the grain.

$$Profit = (USGulfNetPrice + Premium) - MinNetPrice \tag{10}$$

Profitability percentage is the percent of time that the option is profitable. The profitability is dependent on what premium is determine (Formula 9) and if the option is profitable (Formula 10). The profitability percentage was calculated at different γ values ranging from 25-100% at 25% intervals. The percentage is how much of the average option value that the seller of the grain (“buyer” of the option) would pay or forgo to have the ability to switch origins. The premium would be paid or discounted to the buyer of the grain (“seller” of the option). The profitability percentages along with loss percentage were calculated of 10,000 iterations that were ran in the base case model. The results for soybeans are shown in Table 5.31. below.

Table 5.31. Soybean Profit/Loss Probability

γ (% of option value)	Option Premium	Profit %	Loss %
100%	$0.52	45%	55%
75%	$0.39	55%	45%
50%	$0.26	65%	35%
25%	$0.13	74%	26%

The cheaper the option premium, the higher the profit percentage is. If the option is sold for 50% of the average option value, the seller of the grain profits over 2/3rds of the time. The seller of the grain would profit 50% of the time if the option premium were somewhere between $0.52 and $0.39. If the option premium were only 25% of the mean option value, the seller of the grain would profit every 3 of 4 times. In all cases, the maximum loss that would be incurred is when US Gulf is the least cost origin. The loss incurred in these situations is only the premium paid so is $0.52, $0.39, $0.26, and $0.13, respectively. The results of the corn profitability percentage are found in Table 5.32. below.

Table 5.32. Corn Profit/Loss Probability

γ (% of option value)	Option Premium	Profit %	Loss %
100%	$0.51	44%	56%
75%	$0.38	55%	45%
50%	$0.26	67%	33%
25%	$0.13	77%	23%

As the option value decreases, the profitability percentage increases. Somewhere between $0.38 and $0.26, there is a 50/50% chance of profit or loss on the premium paid. When the price gets lowered to $0.26, there is a 66% chance of profit, or about two in every three times. The maximum loss that can be incurred is the premium paid, so this would depend on the agreed upon value of the option. The seller of the grain would only lose the premium paid if there was not value in switching away from the US Gulf origin.

Conclusion

There is value in switching options that is derived from spatial arbitrage opportunities that arise within commodity markets. Unexpectedly, the base case of soybeans and corn had a very similar value. The time period used affected soybeans and corn differently, soybeans option value increased with the shorter time periods and corn option value decreased with the shorter time period. This is due to the differences in volatility and correlations between origin basis and freight data. Both were affected by decreasing the number of origins to switch between. Corn was less responsive while including only US origins, but both decreased significantly when only including US Gulf and Brazil for origins. PNW corn was more consistently the least cost origin, so that is why the value remained strong in corn sensitivity 2.0. Excluding freight in soybeans had little effect on the price of the option value. This did not hold true for corn though, the value decreased significantly. The explanation for that is likely linked to the percentage of the net price that is derived in the basis vs freight for soybeans vs corn. A greater percentage of the net price for corn is derived from the freight than for soybeans. Excluding the freight decreases the value by decreasing net price and arbitrage opportunities.

The non-European option results are similar relative to each other in both soybeans and corn. The minimum lookback is the highest valued option, the maximum lookback option is the lowest valued option, and the Asian option is in between the two other option values. They behaved similarly in comparison to the base case European option too because the Asian option was slightly under the base case option value. The minimum lookback was higher, and the maximum lookback was lower than the base case.

Switching options are a great tool to have and use especially when working within a geographically diverse commodity trading firm. Different commodity trading firms may use switching options for different purposes and the model used to determine the option value will vary based on the commodity trading firm being analyzed. Different types can also be implemented based on what the commodity trading firm's goal is. Switching options add to the flexibility of a commodity trading firm and can also generate higher profits with favorable price swings in commodity prices.

CHAPTER 6: SUMMARY AND DISCUSSION

Summary of Problem

Access to multiple origins can be viewed as a switching type real option that allows the seller of grain the ability to ship grain from any origin, they have access to. The ability to ship from any origin would be granted by the buyer of the grain for an agreed upon price or implied in the transaction price. This application of the switching option would be compared to a long call option, where the "strike price" would be the minimum cost origin. Firms with access to more origins can ship out of more locations which leads to greater amounts of spatial arbitrage opportunities. The value of this switching option can be evaluated using real option analysis. In this thesis, real option analysis has been used to determine the value of switching options in soybean and corn markets. The purpose of this thesis is to develop a model that determines the real option value of a switching option from the perspective of a commodity trading firm.

Procedures

Chapter 2 provided a background on spatial arbitrage and gave examples of previous studies that address switching options. This was useful in developing background for addressing the problem in this thesis. Chapter 3 developed analytical framework of the procedures of real option analysis used in this thesis.

The methodology developed by Johansen (2013) helps to develop the origin type switching option by illustrating the value that is generated off spatial diverse assets in the international grain market. This same process is used with real option models developed in Bullock (2020). This model incorporates Monte Carlo Simulation with the Bestfit™ program within Palisade's @Risk™ software. The simulation runs multiple iterations to allow the values to converge on a mean given the distributions chosen.

Results

Chapter 5 illustrates the value of an origin type switching option. Chapter 5 includes calculating the option value of soybeans and corn. Each commodity has its own base case scenario and similar sets of sensitivities to determine the effects of changing different inputs.

Soybeans

The base case for soybeans is derived off data from the full period from 2005 to 2020. It is from the perspective of a firm based out of the U.S. Gulf with locations in PNW, Brazil, and Argentina. The base case includes freight and analyzes the option 12 periods forward. There is no risk-free discount rate included in the base case. The average option value of the base case scenario is $0.52 per bushel.

Sensitivities were conducted changed the period used, origins included, FOB prices, shifting periods forward, and adjusting the risk-free discount rate. There were also sensitivities that are useful in setting the bounds for an American type option. Some of the sensitivities had a significant impact on the option value, whereas others did not show much of an effect. In general, the shorter periods have higher option values. This is due to shifting correlations and volatilities. Reducing the number of origins had a negative effect on the option value, and in both cases for soybeans, result in an option value at or around half of the base case option value. The removal of freight from the calculation had little effect on the option value in soybeans, though did decrease slightly.

The option value increases as the number of periods forward increases. Adjusting the risk-free discount rate did not have a significant effect on the option value. Additionally, the non-European options were used to illustrate the upper and lower bound as well as an average bound for an American type option. The bounds were about 150% and 50% of the mean option value in the base case. The average (Asian option) was slightly lower than the base case.

Corn

The corn base case covered a period from 2008 to 2020. It is also from the same perspective as the soybean scenario: U.S. Gulf origin, with the ability to switch to PNW, Brazil, or Argentina. This also includes freight and is done 12 periods forward. There is no risk-free discount rate in the corn base case either. The base case for corn resulted in a very similar value to soybeans with an average value of $0.51.

The sensitivities for corn are very similar to those in soybeans. The first couple used different periods within the full time period. Additionally, sensitivities were simulated while adjusting the origins that the firm can switch between. Another sensitivity uses FOB values that exclude freight. Other sensitivities look at the effects of adjusting the number of periods forward and risk-free discount rate. The final sensitivities serve the purpose of giving the bounds of an American type option.

An increase in volatility had positive impact on the value of the option as shown when comparing sensitivities 1.0 and 1.1 in both soybeans and corn. Volatility increases from sensitivity 1.0 to 1.1 in soybeans. The value also increases. In corn, the volatility decreases from sensitivity 1.0 to 1.1, along with value. Origin correlation has the opposite effect, the lower the correlation, the higher the value. This is illustrated when comparing the base case with sensitivities 1.0 and 1.1 in soybeans and the base case with sensitivity 1.0 in corn. The value of the soybean option increases when the correlation decreases from the base case to sensitivity 1.0 and 1.1. The correlation increases from the base case to sensitivity 1.0 in corn, while the value decreases.

Changing the period has the opposite effect on corn than it does with soybeans. In both corn sensitivities, the option value decreases. The change was not as big as with soybeans either. Decreasing origins has mixed results in corn. On sensitivity is hardly affects and the other decreases significantly. When ocean freight is not included, the value of the option changes significantly and decreases by over 50%. The number of periods forward has the same effect on corn as it does on soybeans, the further forward the period is, the more valuable the option is. Risk-free discount rate has almost negligible effects on the option value.

The Asian and lookback options that help set the bounds for the American option have very similar results to those in soybeans. The upper bound is about 150% the base case. The lower bound is just under 50% of the base case and the Asian option was slightly lower than the base case. The American type option would be valued somewhere between the two lookback options.

Generalizations

There is great value in origin switching options. Commodity trading firms with access to multiple origins have the potential to engage in these options through negotiating with the grain buyer. It is a useful tool that geographically diverse commodity trading firms have in their bucket of tools that can be extremely useful. It is useful for profitability and strategic grain management. The value of the option is due to the correlation among origins. The less correlation there was, the more valuable the option. Additionally, increasing the number of origins had a positive impact on option value in most cases. These were both true for soybeans and corn. It was illustrated when shifting the periods used and shifting the origins to switch between.

Implications

The implications of this are for the private sector. It is a tool that can be used for geographically diverse firms that have multiple origins. The value of the option is increased with less correlation among origins and by increasing the number of origins. The option value is a starting point for negotiating the premium between the buyer and seller of grain. The agreed upon value can be negotiated into the price paid, and not necessarily in the traditional sense of a premium paid. If the price paid was negotiated into the price of the grain, it would be explicit. If there was an actual transaction for the option, it would be considered an implicit premium. An explicit premium is more commonly seen today but is ultimately agreed upon by both parties.

The commodity trading firm could include any combination of available origins that they have access to. Additionally, it could also be used in situations where the firm is only concerned with FOB values. It could be used on a local level as well for firms with multiple interior elevator locations. It is an overall very versatile tool that can help commodity trading firms with multiple locations that are geographically diverse.

Contributions

Currently, origin switching options are not common. They are more often viewed as an explicit price that is negotiated into the price of the contract than an implicit premium paid. They are not formally referred to as a switching option but are more commonly known as an optional origin contract. There are other studies that introduce other implications of switching options, more predominately switching options in flexible facilities (Pinto et al., 2007; Dockendorf and Paxon, 2013). Other studies on switching options focus on origin type switching options and determine the value of the physical assets (Johansen, 2013; Johansen and Wilson, 2018). This thesis analyzes a similar problem but is used to determine the value that would be assigned to switching option. It is useful to determine the value of having the ability to switch between origins and discusses how the profitability percentage changes as the premium changes.

Future Research

This thesis provides a framework that has many applications in future research in switching option valuation using real option analysis. This research can used and built upon through other applications that includes:

- This research can be built upon by using the same framework in other commodities. Many large commodity trading firms handle large amounts of the different varieties of wheats where this same framework could be used. It could also be adapted and applied to other agricultural goods or the energy industry.
- The framework could also be used to develop switching options involving other origins that were not included in this thesis. The origins used are specific to the company that wishes to engage in the switching option. This would also need to be discussed with the buyer of the grain as well to ensure they are ok with the optional origin clause.
- An alternative base origin could be used. This thesis uses U.S. Gulf as the initial origin, with the ability to switch between the other origins. The value of the option would change if a different base origin were used. This is because the value of the option is derived from the difference between the base origin and the least cost origin.

A couple of areas that could be improved or extended would be:

- Extension to find a more definitive American type option value rather than just the bounds. Some firms may prefer to engage in a switching option with an American type exercise option over a European type exercise option.

- Incorporation of value changes due to tariffs and embargos. This is increasingly important given the current international grain complex.
- Determine the most appropriate time period to use for the data. This thesis tests multiple periods for each commodity, but it does not determine which value would be more appropriate given the current situation.

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