INTERMARKET TRADING STRATEGIES AND RISK

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ABSTRACT

The purpose of this thesis is to research methods that will be used to discover the profitability and risk of spatially arbitraging soybeans. A portfolio is used to analyze trading strategies, and the dependence measures is critical when simulating all of the variables. The dependence measures will aid in selecting the appropriate assets for the portfolio. The profits and risks for each asset will be analyzed and an optimization procedure will weigh the assets appropriately in bushels. Strategizing has become very important for merchandisers, because of the added risk associated with trading commodities. The results indicate that spatial arbitrage profits exist, but each origin does not always spatial arbitrage opportunities. These trades carries a great deal of risk as a firm becomes more vertically integrated.

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CHAPTER 1. STATEMENT OF PROBLEM

Introduction

The agriculture industry has seen many changes, including increased volatility in the futures price, basis price, and transportation costs. Commodity traders have to analyze many variables to find a profitable trading strategy. Where to buy, through what port to sell, and by what mode of transportation are decisions that reduce the portfolio's risk. Transportation, grain inventory, etc. need to be planned in advance to effectively arbitrage. "Arbitrage" is a term that refers to the ability to profit from mispriced assets. The profitability that comes from the trading strategy is called spatial arbitrage. Country elevators, the Pacific Northwest Port (PNW), and the U.S Gulf Port (USG) should all differ in basis price equal to transfer costs. Traders can spatial arbitrage grain that differs in price more than the transfer costs between the origins, ports, or any other location that is buying/selling grain. Traders keeps markets integrated, and markets that become less correlated are quickly arbitraged back to an efficient market place (Baulch, 1997).

The purpose of this thesis is to research develop a model to analyze spatial arbitrage profitability, and intermarket relationships between ports and origins. A portfolio is used to analyze trading strategies, and the dependence measures are critical when simulating all the variables. The dependence measures aid in selecting the appropriate assets for the portfolio. The profits and risks for each asset are analyzed, and an optimization procedure weighs the assets appropriately in bushels. Strategizing has become very important for merchandisers because of the added risk associated with trading commodities. The behavior of the basis and transportation is seasonal; however, they have become more volatile. With this added risk, there should be increased spatial arbitrage opportunities, or higher profits, but risk and profits do not always move in tandem. It is widely thought that investors would adjust their portfolio if they could achieve the same profits with lower risk (Markowitz, 1952). This problem is the focus of this research. There are commodity traders who have a portfolio of assets to move soybeans from origin to destination, but traders would like to create a portfolio that has the greatest profit with a limited amount of risk.

In 2004, soybeans had a high degree of risk, but in 2005-2007, deviation from the mean was about $.10/bu. Then, in 2008, the risk increased to $.20/bu, increasing further to $.30/bu in 2009 (Wilson and Dahl, 2011). There could be many factors causing the added volatility at the origin and destination basis. Some of these influential factors are discussed briefly in this chapter but can be found in greater detail in Wilson and Dahl (2011).

Spatial Arbitrage

Spatial arbitrage is the opportunity to capitalize on missed price markets. Spatial arbitrage is a profitable opportunity that exists when the price difference between two spatial, distanced locations varies more than transfer costs (Baulch, 1997). Hence, the major variables impacting the decision to arbitrage are the transfer costs as well as the origin and destination basis. Policies, bottlenecks, geography, and lack of information are barriers between markets. Arbitrage is the mechanism that allows markets to become efficient and integrated. Barriers between the markets restrict the arbitrager’s ability to profit from inefficiencies. There would be a poor allocation of resources if the arbitrage mechanism failed.

The Borenstein and Kellogg (2012) found that existing spatial arbitrage opportunities could not be captured due to bottlenecks in the supply chain. The exporting pipeline from Cushing, Oklahoma, was at capacity, which restricts arbitragers. The global oil market price tended to be greater than the West Texas Intermediate (WTI) price at Cushing, Oklahoma. The small transfer costs from Cushing, Oklahoma, to the U.S gulf ports gave arbitragers a large profit opportunity. The risk associated with the trade were minimal because the fluctuation in transfer cost was nil and because the WTI and global oil prices were spread positively. By arbitraging the price spread between WTI and global oil, the net price should only differ by transfer costs.

(Wilson, 2012) found that the Panama Canal is at capacity. The Panama Canal is expanding to handle larger ships that produce greater economies of scale for ocean shippers. During this expansion period, (Wilson, 2012) found that there was less traffic moving through the canal and a greater shipping demand for the PNW. A bottleneck at the canal and the increased toll fees could be contributing to the shift of grain flow towards the PNW. Spatial arbitrage between the PNW and USG seems like a short-term battle because of the expansion at the Panama Canal, but as the global population continues to grow, the need to enhance our transportation system becomes a top priority.

Spatial arbitrage opportunities in the oil industry could be the same as the spatial arbitrage opportunities for soybeans. Bottleneck at the canal could also be causing the ocean rate spreads found in (Wilson and Dahl, 2011), which creates larger spreads between the PNW and USG basis. When missed priced assets are found, they become arbitraged away quickly. In some cases, the bottleneck is not discovered or expanded, so the spatial arbitrage is never earned. The bottleneck found in the oil industry has not been expanded yet, so the oil refineries in the Midwest are capitalizing on cheap crude oil due to excess supply. The inefficient U.S. market would minimally reduce the welfare of global oil consumers (Borenstein and Kellogg, 2012). However, oil refiners in the U.S. Midwest gain a competitive advantage over other U.S oil refiners.

Somewhere along the agriculture supply chain, businesses are earning economic profits similar to Midwest oil refineries. The Market Integration section will discuss factors that cause barriers to markets which lead to less-integrated markets.

Change to the Basis

The basis at each location depends largely on the cost of transporting the commodity from the origin to destination. Origin basis also depends on local supply and demand. Intermarket demand from feedlots and bio-fuel plants affects the basis between geographically separated locations, but through arbitrage, the difference equals the transfer costs unless there are barriers between markets.

Rail, barge, and ocean shipping have become more volatile, greatly impacting volatility of the basis at every location. The origin basis along the Mississippi River is stronger than the Dakotas because of the ease of shipping with a less-expensive transportation mode. The soybeans produced along the Mississippi River are higher quality than ones from the Dakotas, which results in a higher basis.

The quality of the soybean crop also has a large effect on the destination basis. There is a noticeable difference in soybean oil and test weight between northern soybean-production states and southern states (Wilson, 2012). Quality differences between the Dakotas and states along the Mississippi River could be a contributing factor to the large spread for the destination basis price. Soybean prices currently exclude premiums/discounts, so the destination basis could reflect the quality difference. Asian countries are willing to pay a premium for soybeans shipped from the USG because of the significant difference in soybean quality.

There are origins that will almost always ship to the PNW, but other origins (farther east) can be undecided about which direction their grain will flow. The origins that are undecided about their grains' directional flow will be pulled towards the direction offering the greatest net price. The boundary for whether the grain will ship west or east changes depending on multiple variables, and a majority of these variables have become more volatile.

Other variables that significantly impact the origin basis are ocean-rate spreads, outstanding export sales, concentration in the grain-handling industry, measures of railcars late, the ratio of grain stocks to storage capacity, futures prices, and varying measures of futures and destination spreads (Wilson and Dahl, 2011). The significance for transportation costs was indicated earlier, and the changes in that industry are explained in greater detail in the Changes in Transportation section.

At the origin, operating margins have a small influence on the basis, but in recent years, facilities have a higher operating margin due to the increased volatility in market variables. Facilities have to put up a substantial capital in their margin account and suffer some opportunity costs. The PNW and USG basis spreads have increased in recent years due to the amplified volatility in the shipping industry, which is mostly caused by the oil market. The destination basis has also become more volatile due to the seasonality of soybean demand and the transportation spread from China. The increased soybean demand from Asian countries also creates a large spread between PNW and USG.

Changes in Transportation

The volatility regarding transportation rates has increased for rail, barge, and ocean shipping. Of the three transportation modes, the volatility for ocean rates has increased the most (Wilson and Dahl, 2011).

Overall, the railroad industry has become more efficient over the years. The primary railcar market has the lowest amount of risk, but the secondary railcar market is more volatile

(Wilson and Dahl, 2011). The railroads realizes greater economies of scale due to larger railcars as well as faster loading and unloading at the origin and destination. Grain handlers also realize the benefit of a more efficient rail system. Grain handlers realize economies of scale when shipping greater distances because their fixed costs for transporting grain decrease with distance. The costs of transporting, in some cases, increase at a decreasing rate or are non-linear. The non-linearity can be seen with all transportation modes.

Efficiency payments are made to shuttle facilities and terminals if they can load/unload a shuttle train within a specified time period. Efficiency payments are incentives for new grain-handling facilities to load shuttle trains which increase the railcar turnaround. These adoptions from the railroad industry and grain-handling firms have made transporting by rail more competitive with other modes of transportation (Wilson and Dahl, 2011).

The costs of shipping via barge have also increased for soybeans and corn (Wilson and Dahl, 2011). Seasonality plays a key role in the cost of shipping; after the soybean and corn harvest, barges are high in demand (Miljkovic, et al., 2000). A reason for the increased barge rates in recent years could be due to more corn production. An acre of corn can produce five times the yield of soybeans, so more barges are needed to move the larger quantity of grain due to higher export demands. Oil prices along with barge supply and demand are key determinant of barge rates.

> All three modes used to transport ethanol—rail, barge, and truck—are at or near capacity. Total rail freight is forecast to increase from 1,879 million tons in 2002 to 3,525 million tons by the year 2035, an increase of nearly 88 percent. Federal Highway Administration projects truck freight to almost double from 2002 to 2020, and driver shortages are projected to reach 219,000 by 2015. (Denicoff, 2007)

When goods and services reach their capacity levels, there becomes a shortage in supply, and then, the volatility and the price in those industries tend to increase.

Finally, ocean rates have also seen an increasing trend (Hummels, 2007). The increased price of oil has a significant effect on ocean rates. There has been a larger ocean-rates spread for shipping from the USG or PNW. This spread is largely due to the competition for shipping from other industries. The Panama Canal has reached its capacity, driving up the costs of shipping from the USG.

Shifts in Supply and Demand

China's demand for soybeans is far greater than what was expected in the past few years. China's middle class has been growing, demanding more meat production and, alternatively, increasing China's soybean demand.

> China's soybean consumption outpaced the increase in domestic production during the last 25 years mainly because of increases in consumption of soybean oil and meal induced by income and population growth, particularly in large urban areas. In 2003/04, according to USDA estimates, soybean consumption in China reached more than 34.4 million metric tons, four times the volume in 1980. In response to the rapid growth in demand, China now imports about half of its total soybean consumption. China's soybean imports accounted for about one-third of world soybean imports in 2003. (Tuan, et al., 2004)

The U.S transportation infrastructure and the Panama Canal were unprepared for the growth of China's middle class. The main reason for the growth in exports at the PNW as well as the spread in the basis between the PNW and USG.

Other shifts in the supply and demand are due to the increase of bio-fuels. In the past few years, the United States has increased the use of bio-fuels, which has increased the acres for corn production. Since 2005, the United States had plans to increase its bio-fuel production from 4 billion gallons a year (bgy) in 2006 to 7.5 bgy in 2012. (Denicoff, 2007) predicted that, by 2016, ethanol production would reach 15 billion gallons. With the planned increase in bio-fuel production, the USDA projected that U.S. farmers would shift soybean acres to corn acres. Corn production was planned to increase from 13.05 billion bushels in 2007 to 14.5 billion bushels in 2016 (Denicoff, 2007).

All these changes in agriculture affect the basis at the origins and destinations. There has been an increase in volatility at every aspect of the agriculture industry's supply chain. In most cases, the end user suffers from the grain industry's volatility because value-added products tend to have sticky prices. Sticky prices at the retail level are due to the costs of adjusting the finished goods' price. These sticky prices will significantly reduce the volatility from the raw-material market, making business more risky at the retail level. Farmers and elevators also have a difficult time managing the industry's added volatility. Commodity traders are typically great at reducing the risk by hedging with the futures market. Commodity traders handle large volumes of soybeans, and it is critical to reduce as much risk as possible. Both commodity traders and farmers are susceptible to changes in the basis. In the past, the basis was more predictable, but volatility in the shipping industry has altered that seasonality.

Problem Statement

A commodity trader's strategy was straightforward before the added volatility for all modes of transportation, which then also affects the basis values at the origin and destination. A majority of the soybeans were shipped through the U.S. gulf ports in the past (Wilson, 2012) because of the cheap transportation provided by the Mississippi River. Since 2002-2004, there have been some major changes in shipment flows for soybeans (Wilson, 2012). As indicated earlier, the basis spread between the USG and PNW has grown. The increasing spread indicates a shift in the flow of grain from the Midwest.

This added risk in trading commodities needs a method to manage and capitalize on these new shifts in grain trading, so this study will focus on managing the added risk as well as capturing the most profitable spatial-arbitrage opportunity. There has been a significant increase in the basis risk for soybeans during the last eight years (Wilson and Dahl, 2011). The standard deviation for soybean basis values has reached a new norm of $.20-.$30/bu, and new, profitable opportunities arise with this added variability (Wilson and Dahl, 2011). A trading strategy needs to be developed to capture the most profitable trades.

Spatial-arbitrage opportunities may exist because of the increased PNW and USG spread and the added volatility. The variables should be highly correlated within the portfolio, and the basis values between the ports should always be in equilibrium. The origin basis should equal the destination basis minus transfer costs. However, demands from these ports have become more volatile, and the ocean rate volatility has increased (Wilson and Dahl, 2011). The added volatility makes it more difficult for markets to stay integrated.

Arbitrage opportunities may also exist between ports and origins because of the increased competition in certain geographical regions. Storage capacity has become tighter due to traders holding onto their long positions. The volatility and the current value of the futures price have increased the costs for business across the supply chain. More volatility for rail, barge, and ocean rates has increased the transportation costs and made those assets more risky. The research conducted for this paper focuses on creating a trading strategy for commodity traders who are trading soybeans from the origin to the destination and then expanding internationally.

Objectives

The agriculture industry has seen many changes and has become more risky in the process. The shipment of soybean flow has shifted towards the PNW. This thesis uses the most recent methodology from similar research problems to answer the questions. There are two major objectives for the thesis. The first one is to analyze the intermarket relationships in the soybean market. The second objective is to discover the origins that generate, on average, the greatest spatial-arbitrage profit and probability of occurrence. Determining where the greatest spatial-arbitrage profit occurs and how often spatial-arbitrage opportunities exist provides information for a company that is interested in merchandising soybeans. The merchandising company would be able to determine where to place country elevators. The most important theory is dependence measures because the input used for our simulation's optimization model needs to hold the correct relationships between variables.

A portfolio is created where a trader owns origins with soybeans or buying soybeans from origins located strategically so a firm can optimally transfer grain at least cost and risk to gain the largest amount of profit. Most literature about trading strategies and spatial arbitrage uses parametric modeling. Pearson linear correlation is one of the dependence measures used in this thesis, for simplicity, and is considered more of a parametric model. The most recent methodology used for market integration is a non-parametric model. The shift to non-parametric modeling in market integration research, such as (Goodwin, et al., 2011) is not surprising due to the non-linearity of market relationships. The dependency measure used by (Goodwin, et al., 2011) is copula. Copula is the other dependency measure that will be used for this thesis, and it is much more complex. Copula is used heavily in the finance and insurance industry. Copula provides a methodology with the fewest assumptions about the distributions and the correlation between assets in the portfolio.

This research hopes to clarify the reasons for the shifts in market boundaries, and the increasing flow of soybeans to the PNW while finding the trading strategy that maximizes returns with a limited amount of risk. (Wilson and Dahl, 2011) found that there has been a shift in the flow of grain for soybeans.

Hypothesis

The trading strategy developed for the data's time period suggests that more origins located in southern states will trade towards the PNW because it provides a greater return for the risk. This shift in grain flow could be due the discovery of spatial arbitrage for soybeans. The Panama Canal has reached its capacity (Wilson, 2012), which forms a bottleneck. The bottleneck at the Panama Canal is similar to the problems in Cushing, Oklahoma, that were reported by (Borenstein and Kellogg, 2012), and on top of the bottleneck, there are higher-quality yields from southern soybean-producing states.

Organization

Chapter 2 discusses the literature related to the research of this thesis. The literature review consists of literature about the Law of One Price, Arbitrage, Market Integration, Portfolio Theory, and Trading Strategies. The methodology of the research is reviewed in Chapter 3, and this chapter consists of the theory of price discovery, basis theory, the theory of competitive intermarket prices, and the law of one price in relation to this thesis topic. Chapter 4 discusses the empirical model and the data used for this research. Next is a discussion about dependence measures, such as Pearson linear correlation, rank correlation, and tail dependence measures.

Within the Copula section, the background of copula, basic copula, and copula families are explained in great detail. The final section touches on simulation procedures. Chapter 5 explains the copula results and their significance in great detail. The chapter begins with the results of the basis case, and the following sections cover the sensitivity results. Copula and Normal Risk Constrained Optimization is compared in the results. Normal Risk Constrained Optimization is deemed appropriate because of the assumption made on the marginal distributions and its dependency measure. Chapter 6 discusses the conclusions drawn from the results and the implications for the agriculture industry.

CHAPTER 2. BACKGROUND AND RELATED LITERATURE

Introduction

The agriculture industry has seen many changes in recent years, and the biggest change is volatility. Market-price volatility makes business much more risky. Another important change is the increasing spread between the Pacific Northwest basis and the U.S. Gulf basis. This increasing spread between PNW and USG is similar to the larger spread between WTI oil and Brent crude oil. (Borenstein and Kellogg, 2012) discovered that arbitrage opportunities existed, but they were constrained by bottlenecks in the oil supply-chain. The spread for soybeans between two ports may be due to both transportation costs and quality issues. Japan buys no soybeans from the PNW port because there is a noticeable difference in protein and oil content, hence Japan is willing to pay a .35 $/bu premium for higher-quality soybeans (Wilson, 2012). Volatility in the soybean basis makes it more difficult for markets to be integrated in the short run. If markets become less integrated, it opens the door for spatial-arbitrage opportunities. The Market Integration section highlights other factors that lead to arbitrage opportunities or poorly integrated markets.

A portfolio is created where a trader owns origins with soybeans or buying soybeans from origins located strategically so a firm can optimally transfer grain at least cost and risk to gain the largest amount of profit. Based on the profits and risk, we can decide where to buy and sell soybeans. The portfolio's assets are highly correlated with each other; however, that correlation may be non-linear. The cost of transportation has an effect on the basis. However, many industries use the same modes of transportation. During soybean harvest, the transportation costs should be more correlated with the basis values because transportation is at such a high demand.

The literature review tells the story about how spatial arbitrages effect market relationships and new methods to analyze market relationships. Most literature regarding arbitrage has been about market relationships or price transmission. Two markets with homogeneous products should move in a one-to-one relationship. If these markets fail to move in a one-to-one relationship, then a risky arbitrage opportunity would exist. Arbitragers would be able to hedge their price risk with the use of a derivative for certain commodities. There are still risks involved with the basis, transportation costs, and quality aspects. Homogeneous products, such as soybeans, which are in a freely functioning market should efficiently transmit prices from market to market so that the differences between markets are transfer costs. That being said, there should be no profitable arbitrage opportunities. Efficient markets are abiding by the law of one price (LOP) because of arbitrage.

Some economists think that a freely functioning market should efficiently link prices across regional markets, but if markets are not freely functioning, arbitrage opportunities arise. In early studies about market transmission, economists discovered that the law of one price is not completely accurate, meaning that prices do not move in an exact one-to-one manner. Isard (1977), Protopapadakis and Stoll (2012), Thursby et al. (1986), and Ardeni (1989) did not completely agree with LOP. Those researchers found an LOP failure in the short and long runs using parametric techniques in many commodities because of sticky prices.

Recent literature, such as (Goodwin, et al., 2011) was not in complete opposition to LOP. The empirical evidence in the literature about market integration found that lags for adjusting prices between markets can tend to be longer than expected. The most recent literature illustrated that LOP is relevant in the long run. Parametric and non-parametric techniques were used to support LOP The first technique used to support the long-run LOP was co-integration

(Engle and Granger, 1987). The co-integration technique was transformed into a threshold times series model which allowed for non-liner modeling. The most recent technique used a copula based model, which is a non-parametric model, and this technique found evidence to support LOP (Goodwin, et al., 2011).

Researchers studying market integration concentrated on finding whether two markets adjust prices accordingly to achieve equilibrium LOP. Included in this literature review is literature on Efficiency Frontier regarding ways to measure return gains with minimal risk. Other studies, such as trading strategies, are included in the literature review and have not had much attention in market integration. The literature regarding trading strategies and arbitrage is my research contribution. Previous literature that is explained further in this thesis' literature review is Arbitrage, Law of One Price, Market Integration, Portfolio Theory, and Trading Strategies.

Arbitrage

Arbitrage can happen in all marketplaces. Arbitrage is the process that shifts markets from inefficiency to efficiency. An arbitrager searches for mispriced goods and tries to make a profit from the market inefficiencies. Arbitrage can be found in spatially mispriced, tangible goods, or it can be discovered in mispriced intangible assets, such as options. Tangible assets, such as soybeans, are spatially arbitraged in this thesis.

Market integration, the law of one price, and arbitrage are all closely related topics. A common concern for the market-integration, law-of-one-price, and arbitrage literature is transfer costs. The public does not know what a firm transfer costs are because business transactions between merchandisers and transportation companies are private information. These unobservable costs make it difficult to put an accurate value on spatial arbitrage, whether a market is abiding by the law of one price, or if the markets are truly integrated. A majority of the methodology developed to test market-integration and arbitrage opportunity checks for the probability of market efficiency or a market relationship.

Threshold autoregression is a technique that is used to achieve estimated results on the return to arbitrage. There are many costs associated with spatially arbitraging commodities. As a researcher, some of these costs are available publicly, but knowing exactly what a commodity trader pays for transportation is unlikely. There are many other direct costs, such as loading/unloading, insurance, and storage, associated with a trade.

Arbitrage is the process that makes the law-of-one-price theory possible. Arbitrage is the force applied by arbitragers to keep markets integrated and to follow the law of one price. Arbitrage does not work perfectly and, in most cases, carries a large amount of risk (Shleifer and Vishny, 1997). In some cases, arbitragers do not attempt to arbitrage a market due to the amount of risk involved. Therefore, the market remains inefficient until the risk is matched with the return. As market prices spread farther apart, it takes an additional amount of capital to converge them back to an equilibrium price, and the markets could continue to spread. If the markets continue to diverge, more capital is needed, and more risk is involved in the transfer. Arbitragers are keen traders and investors. Like a rational investor, if arbitragers can gain the same profit with a lower amount of risk, they trade those assets compared to a more risky trade (Ali, et al., 2003).

The spread between the PNW and the USG is diverging. This increased spread is similar to the arbitrage opportunities seen in (Borenstein and Kellogg, 2012) study. Grain commodity traders are already investing capital in the physical commodity, but they need to find a strategy that limits their risk and maximizes spatial-arbitrage profits.

The study done by (Borenstein and Kellogg, 2012) about the increasing spread between the (WTI) oil price and Brent crude oil is highly related to the objective for this thesis. Oil has different grades, but in reality, they should have similar prices through arbitrage. Before oil fracking in North Dakota and Canada, the WTI and Brent crude oil had small price spreads (Borenstein and Kellogg, 2012).

The increase in North Dakota oil production overwhelmed the export pipeline from Cushing, Oklahoma, where the WTI oil price is derived. The excess supply at Cushing lowered the WTI oil price, which represents an arbitrage opportunity for selling more to the export market. This arbitrage opportunity remained due to constraints in the supply chain. Oil refineries in the upper Midwest benefited from the lower WTI oil price (Borenstein and Kellogg, 2012). Midwest refineries produced a product at the lower WTI oil price. The study about the oil industry discovered that the constraint in the supply chain caused a spatial-arbitrage opportunity, but the study was more concerned about the effect of Midwest fuel prices. This study used an ordinary least squares (OLS) model to regress price changes in crude oil and Midwest fuels prices.

China has gone through a great economic transition since 1988. China is interested in how integrated its commodity marketplace is compared to historical market integration across a time period of great policy changes (Park, et al., 2002). Many factors can inhibit market efficiency. Infrastructure bottlenecks, managerial incentive reforms, and production-specialization policies are all contributing factors that affect market integration (Park, et al., 2002). In the research of Park et al (2012) used a parity-bounds model that follows Baulch (1997) and Sexton et al. (1991), which was extend from (Spiller and Huang, 1986).

The goal of research about China's market integration is to understand whether the lack of integration, if any, is related to failed arbitrage, autarky, or trade-flow switching. The parity-bounds model is a useful tool to discover the source of failed integration. China would like to understand if the failed arbitrage is from barriers between marketplaces or if commodity traders are still learning how to arbitrage. Autarky is when price differences are greater than the transfer costs between markets. Trade-flow switching may be due to successful arbitrage, which would allow other markets to seem less integrated when there is trade-flow switching. Researchers using conventional market-integration tests would assume less market integration due to trade-flow switching.

A study about international market integration for gold from 1890 to 1908 (Clark, 1984) is similar to the previous review studies (Park, et al., 2002; Borenstein and Kellogg, 2012). A very noticeable similarity between those research papers is the barriers between markets. From 1890 to 1908, there was a noticeable flow of gold to an unprofitable location. Researchers thought that it was the government interaction that caused the unprofitable flow. Market exchange rates and the official exchange rates could fluctuate within a certain bandwidth. The bandwidth is associated with the cost of shipping gold; sometimes, the rate difference was greater than the bandwidth. Once the bandwidth passes the "gold points," arbitragers participate in the marketplace (Clark, 1984). Arbitragers' participation in the market limits the monetary authorities' discretionary power over the nation's money supply (Clark, 1984). However, there were times that either the Bank of England or the U.S. Treasury possessed discretionary powers to promote gold imports and ban gold exports. These barriers created by government policy would lead to market inefficiencies and unprofitable trades.

A major concern in the (Clark, 1984) study was the estimation of transfer costs. As noted earlier, these costs are not all available and could bias the profitable opportunities upwards. Other gold-trading costs are opportunity costs. There could be a significant amount of capital involved in buying and moving gold, and researchers used time and interest rate as the opportunity costs. The interest rate worked against the arbitragers' profit with the amount of time required to ship gold across the Atlantic Ocean. The interest rate is the main factor inhibiting a profitable trade. A majority of the other risks could be hedged using forward contracts.

Law of One Price

The law of one price is a theory that was discovered many years ago. The law of one price would have failed, even in the early years of trade, due to the inefficiency of arbitrage. Arbitragers would still be trying to discover the process of arbitrage, which would lead to inefficient markets. Price-discovery information would only exist between traders and would be very private. Price discovery would be happening, literally, as commodity traders negotiated their price; the relay of that price would have occurred very slowly. Slow market movements limits the opportunities for arbitragers, hence the failure of the law of one price. There would be almost no volatility because the prices would not change until commodity traders met to negotiate.

Society has become more sophisticated, and a lot has changed in the business of exchanging goods. Tools have been created to speed up price discovery and information sharing. The futures market is where most commodities achieve price discovery, and it takes place in a matter of seconds. There are factors such as exchange rates, transfer costs, homogeneous products that are slightly differentiated due to quality, and many other variables that determine the price of goods between markets. The volatility of commodity prices has increased substantially in recent years, and the time to relay these price changes happens instantaneously.

It seems as if price discovery and timing for relaying the price information have become so fast that price adjustments between integrated markets have become sticky in the very short run. There has been much controversy in the market-integration literature that started by disagreeing with LOP completely and evolved to new techniques for calculating market integration that agreed with LOP in the long run.

(Isard, 1977) was one of the first to disagree with LOP. His research on apparel and paper products discovered that, from 1969 through 1977, prices were fairly constant. Empirical evidence found that prices have been heavily influenced by the exchange rate, and paper and apparel moved towards their initial level after the price change. (Isard, 1977) tested the price indexes for several commodities and found that the exchange rate was a significant independent variable that affects the currency price of close, substitutable products from different countries. In his research, Isard used regression analysis to confirm his results. Isard concluded that the exchange rate causes short-run price changes that persist for several years. By this conclusion, Isard was able to prove, with his empirical results, that the LOP was violated for these commodities between countries.

(Protopapadakis and Stoll, 2012) used commodities from different countries that are traded on the futures market. This research used individual commodities, rather than price indices, giving more true estimates of market integration. Coffee, sugar, soybean meal, and wheat were more likely to veer from LOP in the short run, but the LOP validity holds in the long run (Protopapadakis and Stoll, 2012). Arbitrage opportunities arose in the short run, allowing prices to converge back to one price in the long run.

(Ardeni, 1989) disagreed with previous empirical analysis (Isard, 1977; Protopapadakis and Stoll 2012; Thursby et al., 1986) about market integration. (Ardeni, 1989) disagreed with most empirical work done prior to 1989 because researchers failed to take times-series data into account. If previous research did take times-series data into account, when previous researchers transformed these variables by first differences or correcting for serial correlation. (Plosser and Schwert, 1978) found that first differencing is not a solution to nonstationarity. First differencing may transform the variable to stationary data, but it alters the data enough to bias the empirical results. Ardeni (1989) used co-integration approach to test the long-run relationship between variables that are nonstationary without imposing restrictions on short-run dynamics. He used the unit root test and the co-integration test for a group of commodities from four countries. Ardeni (1989) found no support for LOP with his empirical results in the short run or the long run.

Some previous literature actually supports LOP. As pointed out that most early empirical analysis was flawed because they failed to account for nonstationarity in the data sets. Non-stationarity times-series data is unpredictable, occasionally observations in the data set veer off from the rest of the data points randomly, and this would lead previous analysis inaccurate.

Co-integration techniques were created by (Engle and Granger, 1987), and were used to support LOP in the long run. The research in (Ardeni, 1989) was still able to reject LOP in the long run using co-integration techniques. There was support of the LOP in (Buongiorno and Uusivuori, 1992) study in the long-run for pulp and paper commodities. (Buongiorno and Uusivuori, 1992) they used (Engle and Granger, 1987) co-integration techniques for their empirical analysis.

The problem with co-integration techniques and other parametric techniques is that they assume that market relationships are linear. However, market relationships may be non-linear due to seasonality and the changing of transfer costs (Park, et al., 2007). This research used a threshold co-integration approach to test natural-gas markets. Researchers found non-linear price adjustments in seven different gas markets. The non-liner price adjustments were due to season, geographical location, and the local market's supply and demand. Developing threshold co-integration models that account for non-liner price adjustments have helped support the LOP in the long run and have helped measure price adjustments in the short run.

The most recent model for measuring market integration utilizes a copula. Copulas use joint distribution of prices that are separated by space and is applied to weekly data. Copulas have been used more abundantly in the finance industry as a tool in risk management. (Goodwin, et al., 2011) is the first to use a copula-based model to test non-linear, spatial-arbitrage relationships. (Goodwin, et al., 2011) found that large market adjustments occur when there are large price differences. The copula based model found similar results to the co-integration models have found in past literature.

The literature on LOP has agreed that market are efficient in the long-run but not in the short-run. Early literature has failed in analyzing market integration because the arbitrage opportunities in the short run are quickly unprofitable and lead to a long-run, intermarket equilibrium price.

Market Integration

Market integration is very similar to the LOP, but researchers are now interested in determining what markets are less integrated due to outside influences. (Vollrath and Hallahan, 2006) wrote about market integration between the livestock markets in the United States and

Canada. Market integration affects growth, induces structural change, changes the location of economic activity, and depends on the viability of agriculture firms/farms (Vollrath and Hallahan, 2006).

The focus is researching market integration based on transmission shocks across the borders. The tested livestock markets are slaughter steers, hogs, whole chicken, two cuts of beef, and two pork products. The transmission shocks would be policies created by the United States and Canada. Most policies have a tendency to create barriers between markets. These barriers cause the markets to be inefficient or cause structural breaks between markets that were highly integrated. This research examines a time when the Canadian-U.S. Free Trade Agreement (CUSTA) and, later, the North American Free Trade Agreement (NAFTA).

The empirical model used in this research adopts a multi-faceted approach that is closely related to the theoretical underpinnings of LOP. In the empirical model, researchers control or assume delivery lags, transfer costs, seasonal cycles, and government policies. A detailed model is represented below:

$$\mathrm{pt}{=}\beta 0 + \beta 1_{pt}{}^{*} + \beta 2_{et} + \beta 3_{At} + \beta 4_{Atpt}{}^{*} + \beta 5_{Atet} + \beta 6_{i}\ (\text{specific commodity policy i}) + \mathrm{nt} \tag{1}$$

Here, researchers control for own-currency price and use dummy variables to control for government policies. The pt variable represents the domestic price, and β0 represents transfer costs. Variables β1 and (β1+β4) represent own-currency price elasticity before and after the CUSTA and NAFTA policies. The dummy variable, At, is 0 if the time frame is before CUSTA and NAFTA, and the dummy variables takes the value of 1 after the policy change. The nt variable represents the error term which is due to seasonality and cycles. It is best to remove the exchange rate from the equation because of the exchange rate's non-linearity (Goldberg and

Knetter, 1997). Then, (Vollrath and Hallahan, 2006) account for seasonality and cycles with the n_t term. This model cannot show the impacts of the exchange rate on commodity prices because of the price-adjustment lag. This model is linear, which is why it is best to remove variables that are non-linear. However, the variables that are controlled for may be statistically significant to the price changes between markets.

These parametric models have their flaws, such as assumptions about price behavior, and are too restrictive or unrealistic about the distributions (Serra, et al., 2006). Non-parametric techniques should have fewer, less-restrictive assumptions. Parametric-threshold models require stationary thresholds, but if the markets tend to have changing transfer costs, non-parametric techniques should be used (Serra, et al., 2006). In the past, most empirical models made assumptions about transfer costs, however, current studies have recognized the importance of including transfer costs (Serra, et al., 2006).

The Vietnamese rice market was studied heavily by (Lutz, et al., 2006) to see how integrated it was. The Vietnamese try and untangle the ramifications of policies enacted in 1975 that introduced collectivized agriculture. Originally, privatized trade was prohibited, and marketing organizations controlled the rice market, creating market barriers and leading to noncompetitive markets. In the last 20 years, much has been done to liberalize domestic rice markets. The liberalization is due to policy changes. The integration of the rice market is tested after the policy changes. Small millers have accumulated enough capital to deal with large-scale transfers (Luu and Hai, 2003). "This indicates that the liberalization policy has been successful and facilitated the private market" (Lutz, et al., 2006). A research paper by Minot and Goletti (2000) found that the market integration between spot markets is weak, and their research lead to (Lutz, et al., 2006) research topic. This weak relationship is an indicator that these markets are not behaving efficiently and that an arbitrage opportunity may exist. Markets that are not perfectly integrated can lead to inaccurate price information as well as produce being moved to surplus markets (Tomek and Robinson, 2003).

(Lutz, et al., 2006) empirical model is created to focus on the spatial price difference between rice markets. Monthly average prices were used by (Minot and Goletti, 2000), and they found that there was market deficiency between the northern and southern markets. Lutz concluded that Minot and Goletti's work was unjust because monthly averages do not represent day-to-day prices. Daily, or even weekly, price data would be much better for this type of analysis. Lutz et al. used weekly data because most traders use phones and because transportation can take up to weeks for moving the commodities. "Consequently, average month prices do not reflect the short-run adaptation process we are interested in" (Lutz, et al., 2006)

An econometric model called johansen maximum likelihood estimation was used by (Lutz, et al., 2006). They started with a simple mathematical model to test market integration based on multiple, co-integrating vectors. The model has a vector of market prices at time t, for the n markets under consideration, and assumes that the present market prices are related to their own and past values. In the equation, p is an endogenous variable, and if prices are stationary, the model can be estimated by OLS. However, if the prices are non-stationary, the value of p can be misleading. A Box-Jenkins method was used to deal with non-stationary prices. The problem with non-stationary prices co-movements cannot be realized. Lutz et al. combined both methods; however, the parameters enter the model in a non-linear way. Hence, they have to use maximum likelihood estimation. Maximum likelihood estimation can be used with linear or non-linear data. All markets are integrated in the long run, and the Ho Chi Minh City and the Mekong River Delta markets are strongly correlated in the short run (Lutz, et al., 2006).

To more accurately analyze market integration due to the effects of transmission shocks, a multivariate vector autoregresssion (VAR) model is used in (Vollrath and Hallahan, 2006) study. (Vollrath and Hallahan, 2006) tested McNew's (1996)'s and McNew and Fackler's (1997) notion of market connectedness using the VAR model. (Vollrath and Hallahan, 2006) combined the VAR and LOP models to generate this equation:

$$Pi\,,t \;=\sum_{j=1}^{m} \varphi ij1P1,t-j \;+\sum_{j=1}^{m} \varphi i\,j2P2,t-j\,+ \\ \sum_{j=1}^{12} \varphi i\,j4SDj+\varphi i15At \;+\; \varphi i1x(G) \;+\; \varepsilon i\,,t \tag{2}$$

There are three subscripts for each right-hand-side coefficient: the first one refers to the equation in the system; the second one is for season or lag-length; and the last one is for endogenous variables. The variables in the model are described as P1 (U.S. price), P2 (partner-country price), SDj (monthly seasonally dummies), A (policy dummy), and G (other government policies potentially affecting price) (Vollrath and Hallahan, 2006).

Akaike and Schwartz-Bayesian information criteria are (Lutz, et al., 2006) used to choose the number of lags for each endogenous variables (Vollrath and Hallahan, 2006). They also used the Wald test to ensure that the lags were long enough to model estimation-generated white-noise residuals. (Vollrath and Hallahan, 2006) also used (Pesaran and Shin, 1998) generalized impulse-response method because it does not impose mathematical transformation on the variables in the VAR part of the model.

Next, the Granger causality, impulse functions, and impact multipliers are used to generate insight about the nature of adjustment between the U.S. and Canadian livestock markets. These tests show how quickly the country responds to shocks in other countries. The vector autoregressive (VAR) model is useful because it is not necessary to transform non-stationary data to stationary data. (Plosser and Schwert, 1978) found that transforming data from non-stationary to stationary manipulated the data, leaving inaccurate results. The VAR model works much better because all significant variables are included. The VAR model is able to provide feedback about the effects on all endogenous variables. Only two things need to be distinguished: the variables that interact with each other and the largest number of lags needed. This model is supposed to be free of restrictions and assumptions, but one must decide how many lags should be included. In some cases, a large number of lags are needed to capture the dynamics of the data being modeled. Adding more lags to the model decreases the degrees of freedom, which can lead to overestimating the model.

Similar to (Vollrath and Hallahan, 2006) study (Serra, et al., 2006) used an autoregression model to test market integration. Serra et al. used locally weighted regression techniques to modify the parametric threshold autoregressive (TAR) model into a non-parametric model. Serra et al. hypothesized that it will create a smoother price behavior than the original TAR model. Local polynomial-fitting techniques require the adoption of several decisions, such as the local polynomial. Bandwidth needs to be selected for an appropriate local polynomial. A value close to 1 would be more biased with less white noise. A smaller value would be less biased and have more white noise.

A frequently used method to determine bandwidth is cross-validation (Serra, et al., 2006). The bandwidth is chosen based on minimizing the squared prediction error in the cross-validation method (Serra, et al., 2006).

Once the bandwidth is selected, a weighted, least-squares regression is estimated, and observations farther from x_k are weighted less (Serra, et al., 2006). Local Linear regression

(LLR) generates parameters that cannot be tested with a normal statistical test, so a graphical inspection of the plotted results and confidence interval are relied used to test results.

These auto-regression techniques work better with non-stationary data compared to parametric techniques. These non-parametric auto-regression models are not only better because they can model non-stationary data, but these models also tend to have fewer assumptions. Although auto-regression models have fewer assumptions than other parametric models, there is another empirical model with even fewer assumptions.

Copula is used to test market integration for an oriented strand board (Goodwin, et al., 2011). The use of copula helps imply a transfer-cost band which has often been assumed in other literature about market integration. Six different copula models were considered in (Goodwin, et al., 2011) research. The Gaussian, Student t, Clayton, rotated Clayton, Gumbel, and rotated Gumbel methods all have varying degrees of tail and state dependence as the degrees-of-freedom parameter changes. The choice of the copula depends on the degrees-of-freedom parameter. As the degrees-of-freedom parameter changes, the tail dependence also changes, and the type of copula that fits that tail dependence also changes. The choice of the copula function determines the nature of the correlation. More literature needs to address how to choose the correct copula model (Goodwin, et al., 2011). A familiar equation from autoregressive model is as follows:

$$\Delta\left(p_t^i - p_t^j\right) = a + b(p_{t-1}^i - p_{t-1}^j), \tag{3}$$

where p^i and p^j are logarithmic prices in regions i and j; a and b are parameters that reflect the degree of market integration; and b represents the LOP error, which is the difference in $p_{t-1}^i - p_{t-1}^j$. In some cases, a represents a proportion of the price difference as transfer costs.

(Goodwin, et al., 2011) used the widely recognized correspondence between Equation 3 and the linear Pearson correlation coefficient:

$$\hat{b} = \hat{p}\frac{\sigma_y}{\sigma_x}, \tag{4}$$

where y and x correspond to random variables, $\Delta\left(p_t^i - p_t^j\right)$ and $(p_{t-1}^i - p_{t-1}^j)$; p is the Pearson correlation coefficient; and $\sigma_y(\sigma_x)$ represents the standard deviation of random variable y (x). The linkage between markets i and j is represented by p. Both p and b have similar regime switching. This regime switching is dependent on market conditions. Copula comes into the model by considering the joint distribution function of $\Delta\left(p_t^i - p_t^j\right)$ and $(p_{t-1}^i - p_{t-1}^j)$. Sklar's Theorem, implies that any joint probability function can be represented in terms of a marginal densities function known as a "copula" (Sklar, 1959).

Copula models allow researchers to capture the extreme event or shock to a market that causes disequilibrium. These extreme events are found at the tails of a distribution, and different copula models allow researchers to analyze these price movements. By using copula, researchers are able to tell if there is a large or small price differential and to measure the speed of price adjustments back to equilibrium.

There are two methods for representing the multivariate distribution in terms of dependent marginal distributions (Goodwin, et al., 2011). Joint maximum likelihood estimation or two-stage statistical procedure are alternatives to estimating the copula parameter. (Goodwin, et al., 2011) uses the two-stage approach, Canonical Maximum Likelihood method.

The data consist of four regions: Eastern Canada, North Central United States, and Southeast United States. The Southwest U.S. research had a positive correlation for each market pair, which is required for spatial market integration. (Goodwin, et al., 2011) applied Ordinary

Least Squares Estimation and found a strong degree of integration between the markets. Next, six Maximum Likelihood Estimation models were utilized to fit the six different copula models. Different fit statistics were used to try to discover which of the six copula models worked best. The Cramer von Mises statistic is the preferred model-selection criteria (Goodwin, et al., 2011).

Interpretation of the tail dependence allows researchers to discover if one market tends to export to another consistently, and the price difference tends to be either positive or negative. Within the wood market, there was a definite basis pattern where one market price tended to be above all other markets (Goodwin, et al., 2011).

Researchers interpreted the copula estimates in two ways. First, they evaluate the probability distribution function (p.d.f) implied by the copula for the sample data. Next, they evaluate the copula estimates using standard marginal distributions (Goodwin, et al., 2011).

Goodwin et al. (2011) found that their research was similar to autoregressive models because market adjustments are generally quicker in response to large price differences. It was also discovered that copula models provide even stronger evidence of non-linearities in market linkage. They also found that it is difficult to select a specific parametric copula or copula family.

Portfolio Theory

Portfolio theory is used to help manage a diverse set of stocks. Later in the 1980s, it was used to find the risk-minimizing hedge ratio between two markets. The model is a simple mean-variance model, where hedgers are able to maximize their return subject for the amount of risk they were willing to take. Other methods of determining a proper hedge ratio would be the use of parametric modeling.

The original assumption is that most hedgers with a cash position, farmers, merchandisers, and end-users want to achieve the minimum amount of risk as possible. A traditional hedge assumes a hedge ratio of one. If the goal of the hedger is to completely offset the risk, he/she would choose a traditional hedge ratio, however, if the futures price and the cash price are not 100% correlated, the hedger could be over hedging or under hedging. A hedger would obtain the best hedge ratio by using the mean-variance model or some other non-parametric multivariate model. Also, by utilizing the mean-variance model, a hedger is able to adjust the hedge ratio to a risk level that he/she is willing to take based on the portfolio's higher return.

(Haigh, 1999) studied hedging strategies, and research found that portfolio theory works better for more risk-loving traders. The assumption made about commodity traders is that they only have a price risk associated with the commodity they are trading. However, a commodity trader also has to deal with the price risk associated with transportation and the basis risk. If the trader is an importer of the commodity, he/she also has to deal with the freight price risk and changes in the exchange rate. Multiple models were used when testing for an optimal hedge ratio. (Haigh, 1999) used an Ordinary Least Squares (OLS) model, a seemingly unrelated regression (SUR) model, and a multivariate GARCH (MGARCH) model to determine the optimal hedge ratio for a traders cash position. An assumption for this research is that hedgers are trying to minimize risk by using this non-parametric model (Haigh, 1999). The MGARCH model gave the highest percentage of risk reduction by hedging transportation and the exchange rate. Next, the SUR model gave the second-best risk-reduction percentage, followed by the OLS model.

If a hedger were to simply hedge grain, freight, and the exchange rate individually, with a hedge ratio of one, then the hedger would have overestimated the number of contracts needed to minimize the risk. The reason for this phenomenon is that assets in the portfolio could already partially hedge each other, hence the trader would need fewer contracts than if each asset were hedged alone. "Surprising, is the lack of importance of the CBOT contract for the grain importer" (Haigh, 1999 p.14). Hedging the exchange and freight rates acts like a natural hedge for the grain assets in the portfolio.

The results show how important it is for a hedger to analyze a portfolio with multiple assets together, rather than hedging them individually. However, a portfolio might present profitable return for the extra risk involved, and the regression model would not allow a trader to adjust his/her hedge ratio in a manner to measure the mean-variance.

Trading Strategies

Highly integrated markets that do not have a one-to-one price relationship will present a spatial-arbitrage opportunity. (Flores, 2011) researched a low-investment strategy used by a fresh produce farmer. The method Flores created could be similar to firms/farms that were interested in capitalizing on markets with highly variable price movements. There has been much literature about market integration, however, "there has been little attention given to assess the effect of the level of market integration on the opportunity of arbitrage within commodity markets" (Flores, 2011 p. 20).

(Flores, 2011) uses portfolio theory, which was trying to maximize returns while minimizing risk (VAR). The methods are about developing a strategy so that a trader can make decisions based on a two-market structure. The assumptions are high transfer costs, liquidity, market accessibility, price characteristics similar to financial instruments, infinite product availability at the base market, and always having a demand at the target market to cover the full shipment.

The decision-making policy has to do with the price differential or a threshold point. Another main objective of (Flores, 2011) research is to determine the optimal value of the threshold point. The assumption are made about the price distribution and the market behave randomly. The main objective is to develop methods for profitable arbitrage opportunities in this thesis, not necessarily selecting the correct distribution for transportation costs and prices.

A certain threshold value or price differential will result, on average, in a long-term profit (Flores, 2011). Pragmatic and theoretical approaches are used to locate this optimal threshold point. The pragmatic approach fixes a price differential between the two markets and applies different threshold values that maximize the expected rate of return. This process has many iterations; then, the data are collected to be analyzed. Once the data are collected, they are put into a histogram to determine the observations' frequency distribution.

(Flores, 2011) next step is to determine the expected profit per threshold and the standard deviations. (Flores, 2011) uses a statistical distribution that adequately fits the histograms created earlier. The components of operation and the number of times that arbitrage opportunities arise need to be considered before the optimal threshold value (K) is selected. The second approach to determine the optimal value of K would be to use the theoretical approach. This approach also optimizes expected profit; however, it uses the distribution of the price differentials for two market structures. The key parameters for the model are the product price per pound at market i and time t, transfer costs between locations i and j, and transfer time from market i to j. The transfer cost is assumed to be fixed throughout the operational period. The transfer time is determined by variables. All these variables form the expected profit model.

The expected profit model is two equations; one is the difference in price at time t. The other equation is the difference in lagged price at location i and the current price at location j.

(Flores, 2011) expected profit is then maximized, depending on the decision factor, K. Next, the differentiated equation is set equal to zero. Setting the equation equal to 0 makes it possible to find the global maximum which, in turn, finds the optimal threshold value, K.

Next, methods are developed for a firm/farm interested in a strategy for short-term profits based on current market conditions. The methods for this short-term spatial-arbitrage opportunity are developed similar to the previous long-term methods. A pragmatic approach uses a binomial lattice structure to determine the threshold that generates the highest probabilistic projections of profit and losses (Flores, 2011).

(Flores, 2011) developed a strategy to minimize the risk of a loss due to disappearance of the arbitrage opportunity for any given product. Markowitz's portfolio theory is the method used to reduce the trader’s risk. He uses a portfolio of commodities and determines the weights for each product and ships to a given origin that minimizes the risk while maximizing returns.

Return is calculated by the amount received due to the spatial arbitrage from the investment. Next, the rate of return is calculated by the difference between the amount received and the amount invested; and then divided by the amount invested. Then, the average rate of return is calculated along with the standard deviation. A lognormal distribution for the rate of return is used and tested with the Chi-Square Goodness-of-Fit Test. These parameters of the best fit are used to calculate the average rate of return and the standard deviation.

Summary

The literature review regarding Arbitrage, the Law of One Price, Market Integration, Portfolio Theory, and Trading Strategies has laid the foundation for this thesis’ research. The law of one price holds in the long term, but there are risky arbitrage opportunities in the short run. Different parametric and non-parametric models developed to study the law of one price have lead to the study of relationships between markets for different goods. The models have lead to studying markets between countries as well as how market barriers, markets shocks, etc. affect intermarket relationships.

Using portfolio theory to manage assets in a way that determines the amount of risk associated with a given return is important for risk-loving traders. Literature in this field is related to a hedger importing grain commodities and has multiple price-risky assets. This literature has found that combining the assets and then determining the hedge ratio gives a more accurate result than individually hedging each asset.

The research reviewed in this chapter deals with creating a trading strategy based on inter-market relationships diverging from the law of one price in the short run to realize some return. There is very little literature in the field of trading strategy, but there is a vast amount of literature in the law-of-one-price and inter-market relationship fields. The research reviewed in this chapter helps lay the foundation for research about trading strategies and arbitrage, the fundamental objectives of this thesis.

This study tries to incorporate some of the most recent methods from previous literature that were reviewed in this chapter to create a trading strategy that can locate markets with a large price spread. Next, portfolio theory allows us to combine our risky assets to establish a portfolio that minimize the risks of transportation, along with destination and origin basis, so that we can capitalize on the soybean market's disequilibrium.

The contribution of this research is to the literature about trading strategies and arbitrage, and uses the most current methods for market integration which allow for non-stationary, non-liner market-price data. Using copula allows the data to be simulated and to continue their dependency between assets. Fewer assumptions are made in these methods compared to the techniques used in previous research about trading strategies.

CHAPTER 3. THEORETICAL RELATIONS

Introduction

Previous research (Borenstein and Kellogg, 2012; Protopapadakis and Stoll, 2012; Goodwin et al., 2011) and the rest of the literature reviewed in Chapter 2 created a theoretical models that was somehow linked to the theory of competitive intermarket prices. Competitive intermarket prices are the major theoretical concept analyzed in this chapter. A trading strategy is developed based on the boundary fluctuation between trading regions. Soybean market boundaries are in continuous fluctuation, and the theory of competitive inter-market prices can help explain this fluctuation. (Wilson and Dahl, 2011) discovered that the PNW versus USG spread has increased. These spreads could be increasing due to changes in supply and demand and/or increased ocean-shipping costs. These spreads are quite volatile, so the market boundaries are always changing. (Borenstein and Kellogg, 2012), in a study about the oil industry, discovered barriers that prevent a location from shifting its excess supply to alternative markets offering a higher price. The Panama Canal has reached its capacity, much like the oil export pipeline in Cushing, Oklahoma. The capacity constraint indicates that, as the market boundaries are unable to shift, there are locations that cannot sell their commodities to a market with excess demand because of supply-chain barriers.

Theoretical concepts, such as arbitrage, the law of one price, and market integration, are all related to the theory of competitive inter-market prices. Because of arbitrage and the law of one price, there are competitive intermarket prices. Because of competitive intermarket prices, there is market integration. All other theoretical concepts considered in this chapter lay the foundation to help understand the theory of competitive intermarket prices. The next section in this chapter discusses Price Discovery. Then, Basis Theory is explained in detail. Next, the

Theory of Competitive Intermarket Prices is explained. Finally, the law of one price is explained in relation to this thesis topic.

Price Discovery

The direct functions of a market are transportation, storage, and transfer of ownership and are all extremely important for a functioning market. These direct functions are discussed in greater detail in the Theory of Competitive Intermarket Prices section. An important function is the movement of commodities across markets, and the most important function is price discovery. Supply and demand are the fundamentals of price discovery, and related topics found in microeconomic theory are discussed in this chapter.

Price discovery is sometimes less than perfect. If price discovery were to work perfectly, all buyers and sellers would have perfect information at the same, or zero, cost (Tomek and Robinson, 2003). If everyone truly had perfect information, then the market price would be in equilibrium. In practice, perfect market information is rarely available, so we have mechanisms where buyers and sellers can discover the true market-price equilibrium. Negotiation, administrative decisions, and auctions are the three categories of price mechanisms where price discovery takes place (Tomek and Robinson, 2003). Negotiations are mostly performed privately between a buyer and a seller. An example of a private negotiation would be a country elevator and the railroad negotiating transportation costs. Administrative decisions would be the price set by firm managers, such as the prices set at most retail stores. An auction is similar to the futures market at the Minneapolis Grain Exchange, which is a double auction (Schrimper, 2001). Buyers bid while sellers ask for any given price until an agreement between the players is reached. However, a price agreement is almost never reached on the first bid and asked prices because decisions are made with less-than-perfect market information.

Commodities, such as soybeans, have price discovery at multiple levels. Price discovery takes place globally, nationally, regionally, and locally. Price discovery is a searching process, and any given information set used to obtain a market equilibrium condition can contain a certain amount of noise (Tomek and Robinson, 2003). The complexity of price discovery increases as the market becomes more global. The larger the information set used, the more complex the price discovery process is. A larger information set carries more noise in the price-discovery process. Nationally, price discovery is more complex than regionally or at the country elevator because there are non-commercial buyers/sellers involved at the national level. Non-commercial buyers/sellers are using the futures market to seek profit and, in some cases, significantly alter the market. Price discovery at the national level or futures markets can significantly alter the cash price at country elevators. Commercial players in the futures market can also bring a fair amount of noise to the price-discovery process. The research conducted for this thesis completely avoids the complexity of the price-discovery process in the futures market because, for soybeans, every country elevator and port are subject to the futures market. Every port and country elevator are not subject to the same cash price, which is why Basis Theory is reviewed in a later section. The price discovery of the basis is conceived in a similar fashion.

Supply and demand are the local factors discussed in this section. Adam Smith was one of the first economists who had the idea of the "invisible hand" directing the flow of resources to locations with the greatest value (Nicholson and Snyder, 2007). The basics of the demand curve start with an individual desire to purchase a basket of goods and services with a limited amount of income. Each consumer is trying to purchase the right combination and quantity of goods and services to maximize his/her utility subject to his/her income constraint. “Utility” is a term used to describe someone's measurement of satisfaction from a set of goods purchased (Tomek and

Robinson, 2003). An assumption made about each individual is that he/she always prefers getting more than less of the goods and services. Each consumer has his/her own utility function for a set of goods, and the person's tastes and preferences change throughout his/her lifetime, altering the utility function. Figure 1 represents the difference in an individual's utility by purchasing alternative combinations of good X and good Y. U1, U2, and U3 represent the individual's indifference curves. Anywhere along the indifference curve represents the same utility for that individual. An individual is reaching a higher utility on the indifference curves located upwards and to the right. If the price of good X decreased, the individual would buy more of good X and possibly more of good Y. Price and quantity are inversely related based on the logical behavior of a consumer, which is why the demand curve is downward sloping. The inverse relationships between price and quantity are defined as the "law of demand" and can be explained by the substitution and income effect of a price change in Figure 1 (Tomek and Robinson, 2003).

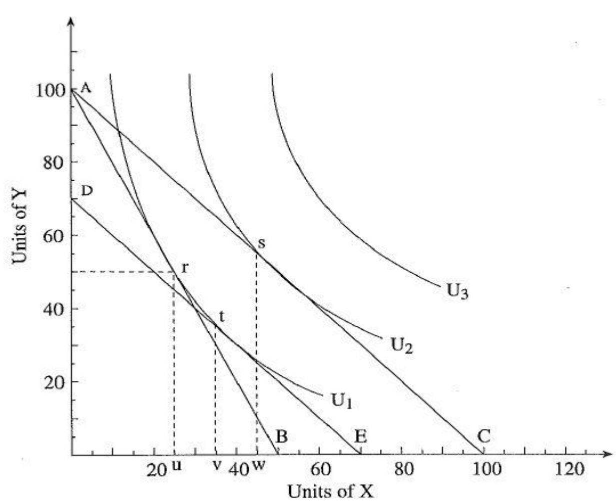


Figure 1. Individual Consumer Preferences
(Tomek and Robinson, 2003).

However, there are demand curves that are upward sloping, and this curve is called Giffen's paradox. A demand curve can be upward sloping if the good or service is an inferior good and if there are no close substitutes (Nicholson and Snyder, 2008). Giffen's paradox is explained in greater detail in Nicholson and Snyder (2007, 2008). Goods and service can be categorized into two broad categories, normal and inferior good. A normal good can either be a necessary good or a luxury good. The classification of a good is important because it determines if a good decreases/increases with a change in a consumer's real income.

Individual consumer demands produce a market demand. There are two different movements with the market demand. A change in quantity demand is a shift along the demand curve. A change in quantity demand is due to a change in price. A shift in demand is due to changes in population, income, prices of substitutes and complements, and consumers' tastes and preferences. As the population increases, more goods and services are needed, shifting the demand curve upwards and to the right. An increase in real income allows individuals to have a smaller budget constraint, allowing them to buy more goods and services, which shifts the demand curve upwards and to the right. However, if the good is an inferior good, consumers may prefer a more desirable good, and would shift the demand curve for the inferior good to the left. The demand curve for a normal good would shift to the right. A shift in demand is related to the prices for substitutes and complements because each individual is trying to maximize his/her utility. For example, if the price of corn increases relative to wheat, then chicken farmers buy less corn and more wheat to feed their chickens. Corn contains more energy than wheat, but the increased corn price decreases the chicken farmers' utility more than buying wheat with less energy.

Complements have a different impact on the related good because both goods are needed to satisfy the consumer. If the price of corn increases, then the demand for chickens decreases because corn and chickens are complements. Changes in consumers' tastes and preferences alter their utility function which causes the consumers' demand curve to shift. All prices, in theory, are linked in an interdependent system (Tomek and Robinson, 2003). These concepts are important to understand market demand. Agricultural products such soybeans produce multiple products, and each product has its own market demand. Another demand factor comes from global consumers' demand and the exchange rate between countries.

Another concept to better understand market demand is elasticity, which is the slope of the demand curve at its different points. Own-price elasticity shows the responsiveness of consumers' change in quantity relative to the price change and can be seen in Equation 5. Elasticity is calculated by the percentage change in quantity (Qi) over the percentage change in price (Pi).

$$Eii = \frac{\frac{\partial Qi}{Qi}}{\frac{\partial Pi}{Pi}} \tag{5}$$

Percentages are used to calculate elasticity to remove the conflict of different measuring units, which allows researchers to compare elasticity between products. There are three descriptions of price elasticity. An elastic demand curve has price elasticity greater than 1. An inelastic demand curve has price elasticity less than 1. A unitary elasticity demand curve has price elasticity equal to 1. Demand elasticity is an important factor to understand when trying to figure out how much the quantity demand is going to change due to the price change.

Cross-price elasticity and income elasticity are other important functions used to help understand the relationships between commodities and changes in real income. Cross-price elasticity is used to determine if a good is a complement or a substitute, and it also determines how changes in these goods affect one another. These types of elasticity are important to understand the demand relationship between different commodities because the substitutes and complements can greatly alter market demand, but does not need as much attention regarding the research conducted in this thesis. The concepts of elasticity are provided in great detail by Tomek and Robinson (2003) and Nicholson and Snyder (2007, 2008).

The market's supply curve is somewhat similar to the market's demand curve. Instead of individual consumers trying to maximize their utility to make the demand curve, the supply curve has individual firms that are trying to maximize their profits. Figure 2 shows a graph of an individual firm's marginal cost, average total cost, and the average variable cost. The mathematics behind a firm trying to maximize its profits is shown in great detail in (Nicholson and Snyder, 2008). For simplicity, a firms production is where marginal costs equal marginal revenue. Marginal cost is the price of producing one more unit, and marginal revenue is the return from producing an additional unit. Agriculture is assumed to be a perfectly competitive marketplace; they are price takers, so the marginal revenue of producing one more unit is equal to the market price. The marginal cost curve is upward sloping; as the market price increases, there is an increase in the profit-maximizing output (Tomek and Robinson, 2003).

A firm's average variable cost and average total cost are important when deciding whether to continue to produce goods. If the market price is below the average variable cost, then the firm is unprofitable and has reached its shutdown point. If the market price is below the average total cost, then production is still profitable, but the firm is unable to cover all of its fixed costs. However, the cost of shutting the firm down is greater than the loss on its fixed costs.

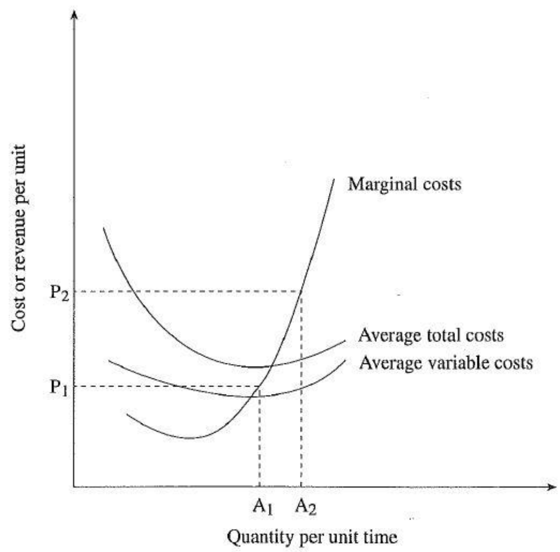


Figure 2. Cost Curves and Optimum Output at Alternative Prices (Tomek and Robinson, 2003).

Opportunity costs are also important when choosing whether to remain in production or to adjust the flow of the firm's resources to produce an alternate commodity. A farm can produce multiple products with the same long-term assets. A producer switches to an alternate commodity if the opportunity costs are too great. These decision variables are different across firms or farms. However, firms all make decisions based on the same influential variables.

Figure 3 represents the supply curve at alternate time periods. In the short run, there are uncontrollable variables, such as weather, disease, and pests. Through time, the supply curve is different in agriculture compared to other industries because the quantity supplied to the market cannot be increased during the growing season. Other industry supply curves could be altered instantly if the market price falls below the firm's average variable cost. In the short run, the supply curve is vertical because farms cannot alter the quantity supply because there is not enough time to produce more, but those uncontrollable factors can cause the supplied quantity to increase or decrease. However, in the short run, production may be augmented due to inventories or imports (Tomek and Robinson, 2003).

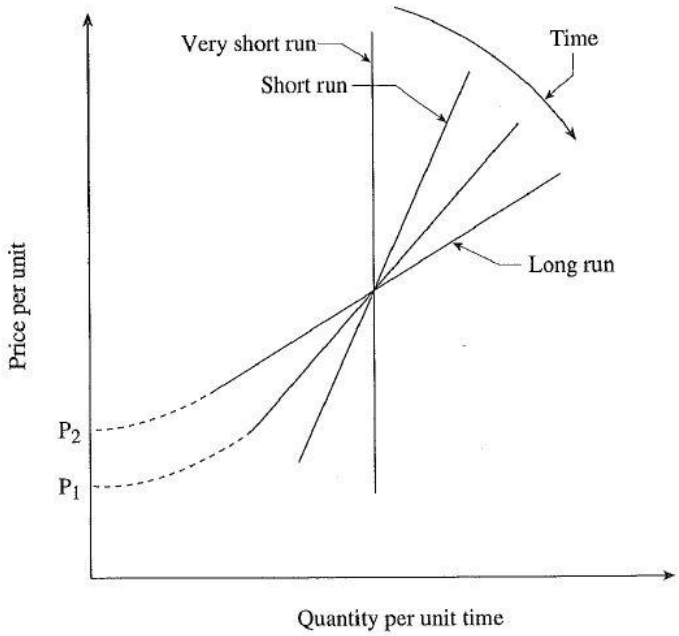


Figure 3. Changing Supply-Price Relationships Through Time (Tomek and Robinson, 2003).

In the short run, resources can still be altered to increase/decrease a supply. The supply curve could be viewed as a summation of individual farms' marginal cost curves. Through time, the supply curve becomes flatter because there is more time for farmers to adjust their production.

The long-run factors would be changes in technology, such as genetically modified crops or a new hybrid seed. These variables cause a shift in the supply curve. Movements along the curve are due to factors such as input prices, the prices of related goods, the prices of joint products, technology changes, or government policies. Combining these firms or farms together creates the market supply curve which is represented in Figure 3.

The elasticity of the supply curve depends greatly on time, in some cases, as noted in the previous section. The calculation of elasticity of supply is listed in Equation 6 where Q refers to quantity and P refers to price.

$$Eii = \frac{\frac{\partial Q}{Q}}{\frac{\partial Pa}{Pa}} \tag{6}$$

However, in the long run, the supply curve can depend greatly on the farm's geographical location. Some farms' locations restrict their ability to produce certain commodities due to climate or soil. A more restricted farm would be more inelastic than a less-restricted farm. Less-restrictive farms are more elastic and would be more willing to alternate crops depending on the market price. The supply curve's elasticity may vary along the curve in the long run due to sunk or switching costs.

The previous section reviewed the basics of the supply and demand theory. Now, the supply and demand can be combined to produce an equilibrium price. Marshall showed that demand and supply work simultaneously; therefore, in some situations, it is difficult to determine which one is causing the new equilibrium price (Nicholson and Snyder, 2007). The equilibrium price is where the supply and demand curves intersect. The simplicity of the Marshall's supply and demand is found in Figure 4 can be misleading because there have been many theories created to explain why supply and demand take this shape.

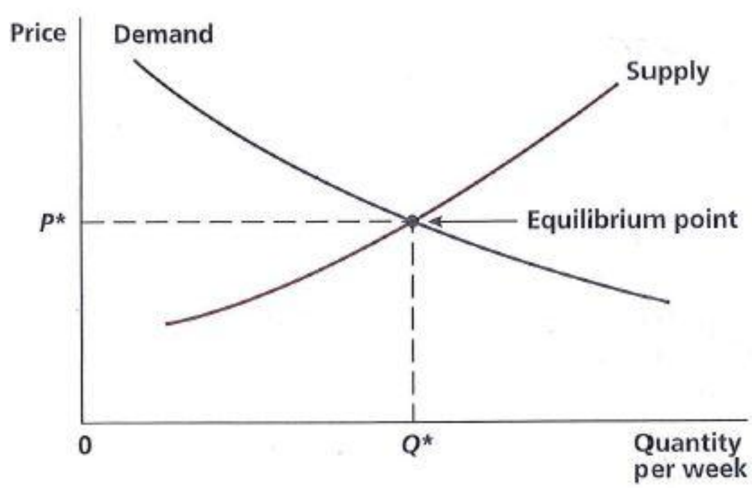


Figure 4. The Marshall Supply-Demand Cross (Nicholson and Snyder, 2007).

However, the supply-and-demand curve is not always linear. Supply and demand do not always replicate what is found in Figure 4. The complexity of supply and demand can be studied further through the mathematics in Nicholson and Snyder (2007, 2008), but the basic fundamentals were already reviewed in this section.

A perfectly competitive market assumes that all buyer and sellers have perfect market knowledge, that each buyer and seller act economically, and that there are zero barriers of entry in all directions. In theory, the price-discovery process would locate the true market-equilibrium price on the first bid and asking price. Perfectly competitive markets always shift commodities to the trade-deficit market, but these kinds of markets are rare. Most markets operate less than perfectly because they lack one of the assumptions for a perfectly competing market. When a market operates in a less-than-perfect fashion, there are trade deficits, and that market may never satisfy the consumers' demand until arbitragers discover the mispriced basis bids. The trade deficits that occur between markets are discussed in detail in the following section.

Basis Theory

The research conducted for this thesis is highly dependent on the basis. The basis is what sets regions apart from one another in price. The basis is used to determine market efficiency and market integration for this thesis. Understanding the integration and efficiency of a market helps determine where arbitrage opportunities are available, which helps to identify intermarket trading strategies. Understanding the basis helps explain one of the main concepts for the theory of competitive inter-market prices. The grain-flow shifts are due to changes in the basis or the supply and demand. There are many factors that differentiate the basis among regions.

Traditionally, it has been thought that the basis is cash minus futures price (Wilson and Dahl, 2011). The futures price is the expected future-delivery spot price at the end of the futures contract (Tomek and Robinson, 2003). The cash price is the current spot price. Futures and cash prices are known to be highly correlated, which is why futures contracts work well as a hedge. Both the futures and cash prices are determined by the current and expected supply and demand.

Changes in the basis are more predictable than changes in the futures price because the factors that affect the basis are more consistent. The futures market and spot prices signal the trader or producer long physical grain whether to store or sell. Inventory is a factor that can alter the grain supply within a growing season. There is a cost for storing inventory, and it is partially reflected in the basis. Through time, the change in the basis is equal to changes in storage costs, changes in transportation, and changes in quality by premium and discounts. If a merchandiser was to hedge his/her positions, he/she would have zero price risk but would still be subject to basis risk. Through time, the merchandiser would expect to gain a return on the basis equal to the storage costs (Tomek and Robinson, 2003). To determine the storage price, we need a supply and demand curve, which is represented in Figure 5.

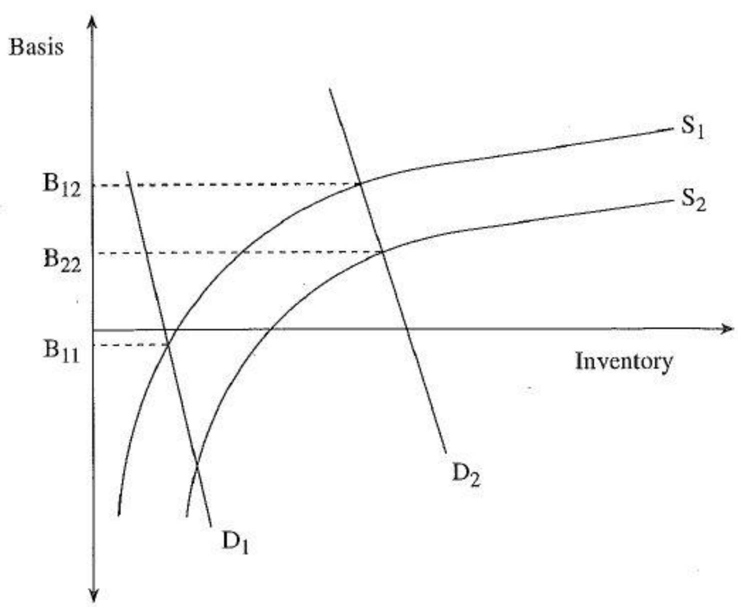


Figure 5. Supply and Demand Curve of Storage (Tomek and Robinson, 2003).

The supply curve for storage takes a non-linear shape due to the fixed storage interval and the variable costs, such as labor, energy, interest rate, and the value of the commodity being stored. The storage cost can be negative or positive. There can be times when grain is stored even though the economics are telling the grain handler to sell; this unprofitable storage occurs when processors need to store the commodity as an input to continue their processing operation, and is called a convenience yield (Tomek and Robinson, 2003). An alternative motive for processors to store grain unprofitably is because of transaction costs (Chavas, et al., 2000). Processors continue to store grain until the storage cost is greater than the transaction costs of delivering grain at a later date. The costs of storing grain become flat at a given amount of inventory because of economies of scale. The storage costs begin to increase again after inventory surpasses the maximum amount of storage available. Then, grain has to be stored outside and is subject to spoilage; is the upward slope of the storage supply. Supply shifts upwards and to the left, or downwards to the right, depending on the variable costs of storage. An increased interest rate shifts the supply curve upwards and to the left (Tomek and Robinson, 2003).

The demand function is similar to the concepts covered in the Theory of Supply and Demand section. The demand curve is downward sloping and shifts along the supply curve. The main shifter in demand is the difference in grain production from year to year. During periods of high production, the storage demand is greater. The demand for storage could be lower or higher during periods of low production. Long physical grain traders base their decision on the next year’s expected production. The predictability of the basis is due to the storage cost. A producer's demand for storage will be large at harvest time, and as a new growing season approaches, the demand will fall, decreasing the storage price.

Theoretically, the basis would partially equal the storage costs if the commodity was produced, stored, and consumed in the same region. In reality, regions trade grain with each other because some locations are more specialized for producing certain commodities than others or because some have a surplus supply or excess demand. Table 1 lists some major variables that affect the basis.

The variables given in Figure 6 are similar to the variables that affect trade in the theory of competitive intermarket prices. The basis is derived from the region offering the largest net price, and all other regions or locations offer the same basis minus transfer costs. Regions trade with each other, so there has to be a difference in basis that is less than or equal to transfer costs. If regions differ by a basis greater than the transfer costs, inefficiencies would be quickly arbitraged. If region cost differences are less than the transfer costs, then no trade will occur; refer to Table 1. Transportation is included in the transfer costs, and within transportation costs, there are many variables. Transportation by railroad includes variables such as rail tariff rates between regions, fuel service charges between regions, and rail car value from the primary or secondary market. Some country elevators are offered efficiency payments from the railroad for loading or unloading a shuttle train in a timely manner. The rebates should also be included as part of the transfer costs, where these rebates would reduce the transfer costs for products compared to regions that do not have the capability to load and unload shuttle trains. The last variable listed is margin, which is also known as the handling margin. The handling margin represents interest rates, the value of grain, labor, energy, and the cost of storage.

Table 1. Alternative Formulations for Grain Pricing or Basis Values (Wilson and Dahl, 2011).

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

Variable definitions:

C_o : cash price at origin
F : futures price
B_o : basis value at origin o
B_d : basis value at destination d
B_{dj} : basis value at destination dj
T : transportation costs
T_{oj} : transporation costs from o to j
R_{oj} : rail tariff rates from o to j
FSC_{oj}: fuel service charge from o to J
CAR : rail car values from either primary or secondary market
EP : efficency payments {OEP, DEP}
M : margins

The basis is an important factor in determining different cash prices between trading regions. Regions that trade with each other should have their basis intertwined. Regions that trade between each other should differ in basis by the transfer costs (Bressler and King, 1970). However, transfer costs are becoming more complicated due to each feature listed in Table 1 because of the amount of volatitiliy in the shipping industry (Wilson and Dahl, 2011). Volatily in the shipping industry is making market relaitonships more complex and difficult to predict. The theoretical concept behind the basis is that, through time, changes in the basis should be equal to storage costs. The current cash price is expected to converge to some futures contract, and when that happens, the difference in the cash and the futures contract price should differ by the transaction costs (Tomek and Robinson, 2003).

The price-discovery process happens in a similar fashion at each country elevator. All locations handling grain are subject to the same futures price, which is discovered by information regarding the supply and demand expectations. The Price Discovery section provides great detail about the theory of supply and demand. The spreads between futures markets is a determinate of supply and demand at country elevators because producers make decisions about current and future spot prices which affect the basis. Theoretically, the basis is known to be partially derived from the storage costs, and producers who decide to store more grain in their inventory will increase their storage cost. Another factor influencing the basis relates to the theory of competitive intermarket prices section. Country elevators or regions trade between each other because of local economic factors. The competition between regions intertwines the regions' basis, and now, transfer costs are a factor influencing the basis. If the trading region's basis disregards transfer costs, then arbitragers take advantage of the profitable opportunity.

Theory of Competitive Spatial-Market Prices

Chapter 2 reviewed the literature that discusses multiple theoretical models used to test for market integration and other theoretical models to test for market efficiency, which is related to how intermarkets compete between regions. Through the literature about market integration and testing the laws of one price, researchers have agreed on the non-linear behavior between markets. The rest of this section highlights the theory behind competitive intermarket prices and how the relationship between markets can be non-linear.

Spatial price relationships are determined by two main factors. Supply and demand help determine the equilibrium basis. As the basis at each region changes, it can alter the flow of commodities between regions. Similar to the changes in basis, changes in transfer costs between regions can also alter the flow of commodities.

For example, a heavily populated area would have excess demand, and a production area would have a supply surplus, both of which are represented in Figure 6. Region A would have a supply surplus, and region B would have excess demand. Each location would have a different equilibrium basis due to the laws of supply and demand discussed in the previous section. Suppose that there were 0 transfer costs between regions A and B and that there was a difference in basis similar to Figure 6. Traders would arbitrage the profitable opportunity until both markets shared the same basis (Bressler and King, 1970). Once these two markets were at the same basis, they would be following the law of one price, which was determined to be flawed in the short run according to research (Isard, 1977; Protopapadakis and Stoll, 2012; Thursby et al., 1986; Ardeni, 1989). Latest literature has discovered the law of one price was flawed in the short run because the methods discussed in Chapter 2 lead one to believe that regions trading with each other differed in price more than the transfer costs.

In this example, the excess supply and demand equals 15 units. Fifteen units would be traded, assuming zero transfer costs, but in reality, these costs are greater than zero. The number of units traded between markets would decline as transfer costs increase. Which can also be seen in Figure 6:(the lower graph by the x and y line). Transfer costs of 20 dollars would entail 0 units being traded. If the transfer costs equaled 10, there would be 7.5 units transferred. The basis at A and B would differ by the transfer costs after traders profit from the arbitrage opportunity.

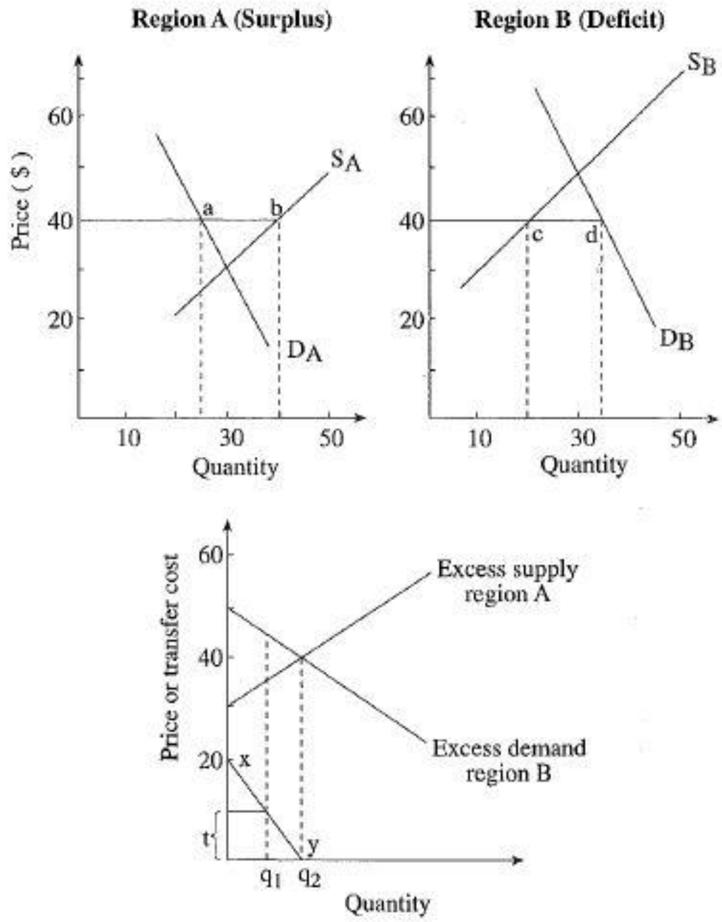


Figure 6. Two-Region Spatial Equilibrium Model
(Tomek and Robinson, 2003).

Figure 6 is similar to Figure 7 and has multiple locations; each location has its own basis. In this example, locations X and Y are mainly production regions, so they have a supply surplus and the cheapest basis. Markets A and B are mainly consuming regions, so these regions have excess demand. In this example, Market A would buy only from location X. Market B would buy from locations X and Y. In some instances, there are supply constraints similar to the oil-pipeline constraint discovered in (Borenstein and Kellogg, 2012). The same kind of constraints can happen with rail, barge, and ocean shipping. The other important decision factor is the transfer costs between regions.

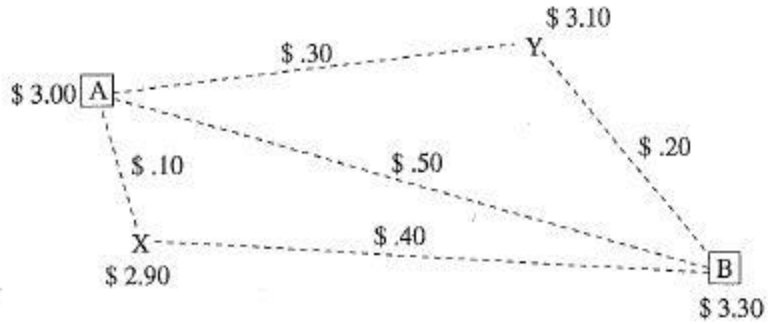


Figure 7. Hypothetical Markets
(Tomek and Robinson, 2003).

There are many variables besides transportation costs that are included in the transfer costs. The average transportation cost does not represent transfer costs or the arbitrage costs between two locations (Tomek and Robinson, 2003). Transfer costs include other variables, such as loading and unloading; entrepreneurial expertise and time; contracting; insurance; financing; and fees associated with testing, grading and meeting phytosanitary standards (Tomek and Robinson, 2003). Some other non-observable costs are the risks associated with moving a commodity over space (Tomek and Robinson, 2003). Some risks are time lapses in shipment, which would result in demurrage charges. There is the risk of contract failure, and most commodity prices are extremely volatile; therefore, contract failure could be costly. These costs are difficult to obtain because a majority of the transfer costs are private information.

Shipping different commodities can contain different relationships with transfer costs and haul lengths. Figure 8 shows four different transfer costs in relation to the length of haul: linear, horizontal, conventional, or exponential. Line A is a horizontal line, which means that transfer costs are the same regardless of the haul length. Line B is a conventional zone rate system because transfer costs increase with the length of haul and increase with a series of differentiated steps (Bressler and King, 1970). Transfer costs in line C takes on an initial charge, but then they increase linearly with the length of haul. Line D is exponential, which means that it is increasing at a decreasing rate through the haul length. The non-linear behavior of spatial-price relationships is due to changes in transfer costs through time.

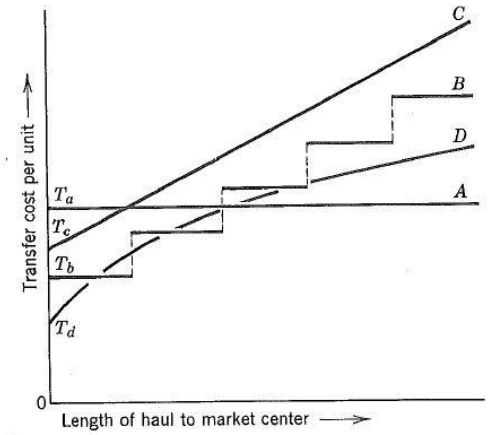


Figure 8. Alternative Transfer Costs-Distance Relationships (Bressler and King, 1970).

The non-linear behavior of transfer costs cause the market boundaries to constantly fluctuate with the changes in transfer costs. Transfer costs are random and this causes the non-linear relationship between markets. Figure 9 shows the mean and standard deviation of a line similar to line C in Figure 8. Even though line C increases with the length of haul, through time, it can also move somewhere between +1 and -1standard deviation.

Market boundaries can also fluctuate with changes in the local supply and demand for each marketing region. There are instances where the market boundary cannot adjust to the market's needs due to barriers. There are different kinds of barriers, such as geography, politics, and supply-chain constraints. For simplicity, Figure 10 only uses two markets to highlight the shift in market boundaries due to changes in basis and/or transfer costs.

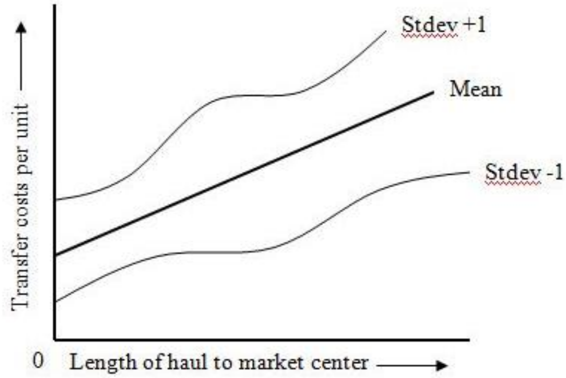


Figure 9. Mean Transfer Costs-Distance Relationship.

As the basis for market A decreases and the basis for market B increases, the boundary line shifts closer to market A. Producers located more than 275 miles from market A will ship their goods to market B. Producers located less than 275 miles from market A will ship their goods there.

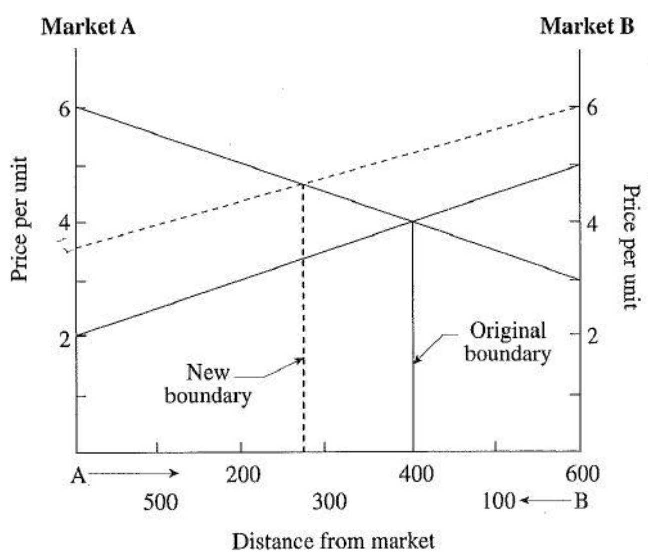


Figure 10. Effect of Changes in Market Prices and Transfer Costs (Tomek and Robinson, 2003).

Figure 10 is an example with only two markets and assumes that the boundary line is linear, which means transfer costs would resemble line C in Figure 8. The net basis price will vary along the boundary line, depending on distances to the destination market. Figure 11Figure 11 gives a representation of two market regions with multiple suppliers. This graph illustrates the variability along the boundary line, depending on distance. Each supplier can sell to either market, but the market offering the largest net price will receive the supplier's produce.

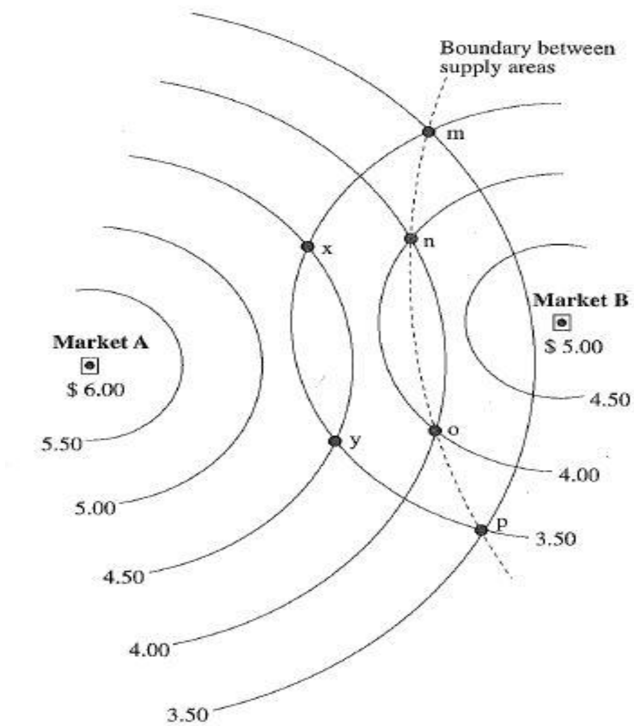


Figure 11. Boundary Between Area Supplying Alternative Markets (Tomek and Robinson, 2003).

Figure 11 also assumes transfer costs similar to line C in Figure 8, because the isocost contour lines are spaced equally apart. Transportation costs increase with the length of haul in a linear fashion, with transfer costs equal to T1-T0=T2-T1 (Bressler and King, 1970). Figure 11 is a simplistic example, but there can be multiple regions, and suppliers may have many regions to sell their produce. In reality, these isocost contour lines would not always be separated equally because of geography, alternate modes of transportation, and using multiple modes of transportation (Bressler and King, 1970). These topographical influences can greatly reduce the amount of resources flowing into and out of a location. Locations with topographical influences would contain boundary lines that are less likely to fluctuate enough to alter the flow of resources. There are alternative modes of transportation, and each mode depends on the haul length. Simple modes of transportation, such as trucks, usually have a higher transport rate. More complex modes or modes that include higher fixed costs, such as barges or ocean shipping, tend to have a lower cost per length of haul (Bressler and King, 1970). This concept is important to remember for this thesis because three modes of transporation are analyzed.

Spatial Arbitrage Theory

Arbitrage is the mechanism that aids in determining prices and production and consumption allocations (Bressler and King, 1970). The theory of spatial arbitrage is highly related to the law-of-one-price theory and theory of competitive spatial-market prices because it is the mechanism that allows spatial market to compete which forces the market to try and abide by the LOP. Spatial arbitrage is not a riskless arbitrage opportunity because a shipment cannot be delivered instantaneously, so the arbitrager is unaware if other shipments have been made to the destination market (Bressler and King, 1970). Even though shipments cannot be made instantly forward contracts can be used in some instance to lock in the destination market price and deliver at own leisure, which eliminates some risk.

(Baulch, 1997) explains the theoretical spatial arbitrage equations as follows:

$$P_t^i + K_t^{ij} = P_t^j, \tag{7}$$

P_t^i is the export market price or destination market; K_t^{ij} is the transfer costs from export market to the import market; P_t^j is the importing market price. If the market represents Equation 7 than trade occurs but there is not any arbitrage profits existing. Equation 8 represents a time when no trade occurs from export market to import market, however an arbitrage trade could occur from import to export market. If spatial markets do not represent the equilibrium condition in Equation 8 than there is some arbitrage opportunity existing.

$$P_t^i + K_t^{ij} < P_t^j, \tag{8}$$

Equation 9 represents an arbitrage opportunity from shipping from the export market to the import market because the export market plus transfer cost is cheaper than the import market.

$$P_t^i + K_t^{ij} > P_t^j, \tag{9}$$

Spatial arbitrage opportunities exist until an arbitrager recognizes the profitable opportunity and the profits match the risk involved in the trade. In some instances there can be barriers that prevents arbitragers from capitalizing on the arbitrage opportunity. If arbitrage opportunities exist than the markets place is not efficient and the LOP fails in the short run. The arbitrage mechanisms is what allows the LOP to succeed in the long-run.

Theory About the Law of One Price

Competitive intermarket prices are due to the theory for the law of one price. This theory states that markets should function efficiently so that any potential riskless profits through arbitrage trade are eliminated (Goodwin, et al., 2011). There has been much controversy about the law of one price, and the theory was reviewed in Chapter 2. The logic behind the law of one price is that markets, such as Figure 11, that trade with each other should only have one price. Past research has proven that LOP is true in the long run, however, in the short run, market boundaries are continuously fluctuating. The difference in basis between regions should vary only by transfer costs, and LOP may be true in the long run. Transfer costs are what cause the controversy among researchers who have studied the law of one price.

Early researchers assumed that a transfer cost is a constant variable through time. More recent research, such as (Goodwin, et al., 2011) has discovered that transfer costs are a random variable. (Goodwin, et al., 2011) used a copula to test the law of one price because a copula is a dependency measure that allows variables to fluctuate within their own distribution. An assumption made for this thesis is that the transfer cost fluctuates through time, but a majority of that fluctuation is due to transportation costs. The remaining transfer costs still fluctuate through time, but all locations should differ in transfer costs close to zero. The transportation-cost data are a random variable in the model due to the influential variables discussed in the section about the Theory of Competitive Spatial-Market Prices.

In the short run, there can be times when the basis between the two markets in Figure 10 should differ due to an excess demand or supply surplus. The difference in basis helps direct the flow of resources to a region that places more value on them. Because of the different basis between regions and the arbitrage trading, there is a mechanism to direct resources to an area that maximizes the value of that resource. The boundary fluctuation creates spatial arbitrage opportunities in the short run. Short-run arbitrage trading allows the law of one price to hold in the long run.

Summary

Price Discovery, the Theory of Competitive Spatial-Market Prices, and the Theory About the Law of One Price were summarized in great detail in this chapter. The section on Price Discovery was very basic, but there were some important concepts to consider. It is important to understand what factors influence supply and demand as well as the repercussions those variables have on the basis. This Chapter highlighted why regions trade with each other as well as the law of supply and demand to show how trading with each other adjusts the basis.

The section on the Theory of Competitive Spatial-Market Prices helped explain how transfer costs shift the boundary lines for whether regions trade with each other. This section highlighted the point that transportation costs are random, which can causes the boundary lines to constantly fluctuate with changes in those costs. Most variables that are included in the transfer costs are recognized because it is important to understand that there is more than just transportation costs when trading between regions. An important concept to take to the next chapter is that transportation costs are the only transfer considered in this model. Three modes of transportation analyzed in the model, rail, barge, and ocean shipping, and they rank from most expensive to least expensive for the length of haul. An assumption is made that all other transfer costs differ between regions close to zero.

The section on the Theory About the Law of One Price was discussed because it highlights an important concept for the next chapter. The law of one price stated that all markets should work efficiently enough to remove all profits from riskless arbitrage trading. However, in the short run, there are times when the basis can differ between regions more than the transfer costs, which is why methods are discussed to create a trading strategy.

CHAPTER 4. EMPIRICAL METHODS

Introduction

The merchandising industry has seen major shifts in recent years. The increased use of bio-fuels and China's demand for agriculture products have altered intermarket relationships between commodities. The changes in the agriculture industry has led to the importance of understanding intermarket relationships. The literature discussed in Chapter 2 indicates that there is great variation between intermarket relationships in the short run, and sparks interest in spatial-arbitrage opportunities.

There are two major objectives for this thesis. The first objective is to discover spatial-arbitrage opportunities in the soybean market. The next objective is to discover the locations that offer a spatial-arbitrage profit most often as well as the origins with the largest profit. Determining where the greatest spatial-arbitrage profit occurs and how often spatial-arbitrage opportunities exists provides information for a company interested in merchandising soybeans. The merchandising company would be able to determine where to place country elevators. The most important theory is dependence measures because the inputs in our simulation's optimization model need to hold the correct relationships between variables.

There are asymmetric and symmetric dependency measures used in research. An asymmetric dependency measure allows for a greater relationship to place more weight on one tail of the marginal distribution. A symmetric dependency measure places equal weight on both tails of the marginal distribution. There are many fallacies about the Pearson linear-correlation dependency method. Linear-correlation measures have their place with multivariate, normal distributions or elliptical distributions which entail symmetric dependences. However, linear correlation does not have a place in all multivariate distributions(Schmidt, 2006). Copula is a better dependence measure when dealing with asymmetric dependences or symmetrical dependencies because no assumptions are placed on the marginal distributions. The discussion about competitive intermarket prices and market boundaries in Chapter 3 highlights the importance of using copula as the dependence measure because of the fluctuating boundaries.

The next section describes Model Specification. The following section discusses data, distributions, and dependency measures. Dependence measures, such as Pearson linear correlation and tail dependence, are discussed. Within the tail-dependence measures section, the background of copula, copula families, copula parameter estimation, and best fit criteria are discussed. The last section describes the Simulation and Optimization Procedures, such as Monte Carlo Simulation.

Model Specification

Market integration, the law of one price, and spatial arbitrage are interrelated. Below, this relationship is explained mathematically The law of one price, or the law of market areas, can be explained with algebraic terms from (Bressler and King, 1970):

$$B_a - t_a = B_c - t_c, \tag{10}$$

where B is equal to the destination basis and t is equal to the transportation price from the origin to destination. Equation 10 represents a market equilibrium condition, and if Equation 10 fails to equal each other Equation 11 follows:

$$B_a - t_a \neq B_c - t_c, \tag{11}$$

then the boundary line between these location switches, and for a short period of time, any origin located on the boundary line would realize a spatial-arbitrage opportunity:

$$B_a > B_c + t_{ac}, \tag{12}$$

Where B_a is the basis at destination, B_c is the basis at the origin, and t_{ac} is transportation costs from the origin to destination. The following equation represents the profit function from the spatial arbitrage opportunity.

$$\pi = B_a - (B_c + t_{ac}), \tag{13}$$

this is simply the differential of these values and if the there is a increase in transportation costs or B_c there is no spatial arbitrage as follows:

$$B_a = B_c - t_c \tag{14}$$

The mathematical definition of spatial arbitrage is similar to the theoretical profit function as follows:

$$\pi = B_a * Q - c(B_c + t_a) * Q, \tag{15}$$

where $B_c = (B_{1,nt}, B_{2,nt}, \dots, B_{l,nt}) \epsilon \Re_+^L$ and $t_a = (t_{1,nt}, t_{2,nt}, \dots, t_{l,nt}) \epsilon \Re_+^L$ include input (origins basis and transportation costs) prices and $B_a = (B_{1,nt}, B_{2,nt}, \dots, B_{m,nt}) \epsilon \Re_+^M$ includes output (destination basis) prices. Variable c distinguishes the costs in the spatial-arbitrage profit. Variable Q represents the quantity of soybean bushels bought/sold in equal amounts and is determined by the risk constrained optimization model.

Because we have a theoretical profit function, which is ultimately similar to profit from the theory of spatial arbitrage, we can create an optimization model that is dependent on a simple mean-variance portfolio:

$$\begin{aligned} & Maximize\ \pi = (B_a * Q - c(B_c + t_a) * Q) \\ \text{st.}\quad & \sigma(B_{ac} t_a) \leq w, \end{aligned} \tag{16}$$

where w is the upper bound of risk and π is the profit from the spatial arbitrage in Equation 16 Variable σ is the portfolio risk, and B_{ac} and t_a are the risk associated with each random variable in the model.

Notation

The following notations describe the parameters in the risk constrained optimization. The decision variables are decided by the risk constrained optimization model and represent the Q in Equation 15 and 16.. The Price Coefficients represent the basis values at the origin and destination, and transportation costs. The remainder notations represents each of the 37 origins, 2 destinations, 46 railroad and barge transportations, 2 ocean freight, and 2 time periods. Time period 1 is the beginning of the week and time period 2. The destinations are PNW and USG, and cost, insurance, and freight (CIF), and free on board (FOB) are signifying the price at the destination.

<u>Decision Variables</u>

α = number of bushels sold to PNW or USG port track

β = number of bushels purchased from the origin

γ = number of transportation bushels

τ = number of ocean freight bushels

δ= number of bushels sold CIF

ρ = number of bushels sold FOB

<u>Price Coefficients</u>

$Track_j$ = price from selling at PNW or USG port track

CIF_k = price from selling at PNW or USG plus ocean freight from port to Japan

FOB_b= price from selling at PNW or USG FOB

$Origin_i$ = Cost of buying at the origin

$Tran_r$ = Cost of shipping by railroad or barge

$Freight_o$ = Cost of shipping from PNW or USG port to Japan

Subscripts

j = 1,2,3, . . . J = port destination

i = 1,2,3, . . . I = origins

r = 1,2,3, . . . R = mode of transportation

k = 1,2,3, . . . K = CIF destination

b = 1,2,3, . . . B = FOB destination

o = 1,2,3, . . . O = ocean freight

t = 1,2,3, . . . T = number of time periods

The merchandiser's goal for all sensitivities is to repetitively select the decision variables that have parameter coefficients that will maximize the portfolio's profit. Each of the following models is slightly different for what this research is trying to analyze.

Base Case

The base case specifies conditions that are most likely to persist as the most common commodity trading firms. Later sensitivities are compared with the base case to analyze the difference between sensitivities. The base case is meant to represent a firm that is not working as a vertically integrated company. A vertically integrated firm and a non-vertically integrated firm are very different. A vertically integrated firm owns more stages in the supply chain. Hence, Equation 17 is a non-integrated firm because the firm does not own any grain prior to the spatial-arbitrage opportunity. The non-integrated firm would just buy and sell soybeans simultaneously during period 1 as indicated in Equation 17. This firm is not exposed to basis risk or price risk because the commodity is simultaneously bought and sold. If the firm sells some quantity of track, then a constraint forces the firm to buy the same quantities at the origin and transportation mode. Track is the PNW basis price loaded on a rail car. The following profit function adds the revenue and costs, but the decision variables are restricted to having a negative sign that transforms the model to follow the generic Equation 15

$$
\begin{aligned}
&\mathrm{MAX}\ \pi = \sum_{j=1}^{J} \alpha_{j}\mathrm{Track}_{j} + \sum_{i=1}^{I} -\beta_{i}\mathrm{Origin}_{i} + \sum_{r=1}^{R} -\gamma_{r}\mathrm{Tran}_{r} \\
\text{st.}\quad & 0 \le \alpha_{j} \le 8{,}740{,}032 \\
& 0 \le \beta_{i} \le 832{,}384 \\
& 0 \le \gamma_{r} \le 832{,}384 \\
& \pi > 0 \\
& \textstyle\sum_{j=1}^{J} \alpha_{j} + \sum_{i=1}^{I} \beta_{i} = 0 \\
& \textstyle\sum_{j=1}^{J} \alpha_{j} + \sum_{r=1}^{R} \gamma_{r} = 0
\end{aligned}
\tag{17}
$$

The boundaries, or restrictions, are comprised of the number of bushels that can be selected, and they have a dual purpose. As indicated earlier, the profit function is similar to the theoretical profit function, however, due to the optimization procedure, the signs had to be adjusted.[1] Constraints, or boundaries, were added to compensate for the sign changes in the profit function. The boundaries for α constrain the number of bushels to be sold at the port between 0 and 8,740,032 bu/week. The assumption is that the maximum that a port facility can unload is 8,740,032 bu/week. Similarly, the decision variable, β, is the number of bushels to be sold and is constrained between 0 and 832,384. An assumption is that a majority, or all, origins in the model can unload or load maximum of two shuttle trains per week (832,384 bushels). The remaining constraints force the arbitrager to sell the same amount as he/she purchases. These constraints allow the model to capture the arbitrage profit between markets.

Sensitivities

Multiple sensitivities are conducted for this thesis and are used in comparisons with the base case: Adaptive to Changes in Risk, Risk Loving, Increase in Shuttle-Train Loading

[1] Because there are so many variables in the risk constrained optimization model, the profit function uses a sum product command in Microsoft Excel. The constraints force β and γ to be negative, transforming the empirical model back to the theoretical profit function.

Efficiency, Buy Track or CIF NOLA/Sell FOB, Vertical Integration Without Ocean Shipping, and Vertical Integration with Ocean Shipping. Each sensitivity is designed to capture spatial arbitrage, but the constraints and objective function change slightly and can be reviewed in the following sections.

Adaptive to Changes in Risk

This sensitivity is similar to the base case's empirical model. Becoming adaptive to changes in risk sensitivity is discovering the profitability of adapting to the changes in basis and transportation volatility over time. Over time, the volatility is constantly changing with market conditions, and this sensitivity is able to capture these risk changes. This sensitivity is able to detect if a certain location has become closer to/further from the market boundaries.

The difference between this sensitivity and the base case is that the firm is vertically integrated because soybeans can be purchased a week early; then, the firm stores the grain until the end of the week and everything gets sold at the end of the week. Hence, the firm in this sensitivity is subject to basis risk and transportation risk every week. The exponential weighted moving average is used to measure dynamic changes in volatility. However, the combined purchase from the beginning of the week and the end of the week should not surpass the total number of trains that can be loaded at any origin because that is the maximum any facility is expected to load in one week. At the end of the week, the merchandiser can still instantaneously buy soybeans from origins and sell the beans at either the PNW or USG. Because the firm is storing soybeans for a week, it is subject to basis risk. Along with changes in profits and risk, there is also a change with which origins looks more attractive. To achieve the sensitivity objective, multiple simulations are run, adjusting λ from .8 to .9 to 1. By using the exponentially weighted moving average, λ is adjusted in Equation 18. The adjustment of λ alters the calculation of σ, which is described in the following equation:[2]

$$\hat{\sigma} = \sqrt{(1-\lambda)\sum_{i=1}^{N}\lambda^{i-1}(x_i-\mu)^2} \tag{18}$$

Adjusting λ in Equation 18 affects the weighting scheme for historical data. When λ is close to 0, there is more weight on recent observations, and λ at 1 is weighting observations equally.

Variable σ in Equation 19 is the portfolio's standard deviation. Changes in λ adjust the weighting scheme when deriving variance, standard deviation, or volatility. Depending on the data set, the standard deviation could become larger or smaller. The time lag in Equation 19 forces the model to behave as a vertically integrated, company-owned interior, country elevator and port facilities.

$$\begin{aligned}
&\text{MAX } \pi = \sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt}\text{Track}_{jt} + \sum_{t=1}^{T=2}\sum_{i=1}^{I}-\beta_{it}\text{Origin}_{it} + \sum_{t=1}^{T=2}\sum_{r=1}^{R}-\gamma_{rt}\text{Tran}_{rt} \\
\text{st.}\quad &0 \le \alpha_{jt} \le 8{,}740{,}032 \\
&0 \le \beta_{it} \le 832{,}384 \\
&0 \le \gamma_{rt} \le 832{,}384 \\
&\pi > 0 \\
&\sigma < 30\% \\
&\textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt} + \sum_{t=1}^{T=2}\sum_{i=1}^{I}\beta_{it} = 0 \\
&\textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt} + \sum_{t=1}^{T=2}\sum_{r=1}^{R}\gamma_{rt} = 0 \\
&\textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt} \le 8{,}740{,}032 \\
&\textstyle\sum_{t=1}^{T=2}\sum_{i=1}^{I}\beta_{it} \ge -832{,}384
\end{aligned} \tag{19}$$

Risk Loving

The risk-loving sensitivity is similar to the base case, however, a merchandiser is, again, able to purchases soybeans at the beginning of the week and to defer selling the soybeans until

[2] From Equation 18, σ enters the constraints in Equation 19 as the left-hand side risk constraint.

the end of the week; the merchandiser is also able to simultaneously buy and sell at the end of the week. Allowing the firm to purchase soybeans at the beginning of the week is similar to operating vertically integrated because the model represents a firm already owns soybeans prior to the spatial-arbitrage opportunities. Because the firm is vertically integrated and storing soybeans from one week to the next, there is basis risk. The only difference is that, instead of being more risk averse and weary of risk changes, the firm is risk loving. If a firm accepts more risk than the portfolio, profits should increase to some extent. This sensitivity is able to determine the origins that are most likely to contribute to the portfolio's spatial arbitrage. The origins that contribute the greatest amount of spatial arbitrage for the risk are singling out the other origins and vice versa.

Multiple simulations are run, adjusting the risk measure σ from 10% to 20% and 30%. The portfolio variance is combined and transformed to the portfolio standard deviation, σ, which is the risk measure's coefficient.

$$\begin{aligned}
&\pi = \sum_{t=1}^{T=2}\sum_{j=1}^{J} \alpha_{\mathrm{jt}}\mathrm{Track}_{\mathrm{jt}} + \sum_{t=1}^{T=2}\sum_{i=1}^{I} -\beta_{\mathrm{it}}\mathrm{Origin}_{\mathrm{it}} + \sum_{t=1}^{T=2}\sum_{r=1}^{R} -\gamma_{\mathrm{rt}}\mathrm{Tran}_{\mathrm{rt}} \\
\text{st.}\quad & 0 \le \alpha_{\mathrm{jt}} \le 8{,}740{,}032 \\
& 0 \le \beta_{\mathrm{it}} \le 832{,}384 \\
& 0 \le \gamma_{\mathrm{rt}} \le 832{,}384 \\
& \pi > 0 \\
& \sigma < 30\% \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J} \alpha_{\mathrm{jt}} + \sum_{t=1}^{T=2}\sum_{i=1}^{I} \beta_{\mathrm{it}} = 0 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J} \alpha_{\mathrm{jt}} + \sum_{t=1}^{T=2}\sum_{r=1}^{R} \gamma_{\mathrm{rt}} = 0 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J} \alpha_{\mathrm{jt}} \le 8{,}740{,}032 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{i=1}^{I} \beta_{\mathrm{it}} \ge -832{,}384
\end{aligned} \tag{20}$$

<u>Increase in Shuttle-Loading Efficiency</u>

This sensitivity seeks to determine how an origin is better able to capitalize on spatial-arbitrage opportunities compared to less-efficient country elevators. Under this sensitivity, the shuttle-train loading capacity is increased from one to five trains per week. For this sensitivity, we selected Ayr, ND, as the origin for the illustration because it had average arbitrage profits from the base case. It is interesting to see how an origin that has average arbitrage opportunities can earn more than a less efficiency elevator that does not upgrade their loading technology. This sensitivity was achieved by adjusting the loading constraints at Ayr, ND, loading shuttle trains capacity from one to five in a week. PNW and USG are still constrained to only unload 8,740,032 bushels, hence some locations that are less profitable should be selected less.

$$\pi = \sum_{\mathrm{t=1}}^{\mathrm{T=2}} \sum_{\mathrm{j=1}}^{\mathrm{J}} \alpha_{\mathrm{jt}} \mathrm{Track}_{\mathrm{jt}} + \sum_{\mathrm{t=1}}^{\mathrm{T=2}} \sum_{\mathrm{i=1}}^{\mathrm{I}} -\beta_{\mathrm{it}} \mathrm{Origin}_{\mathrm{it}} + \sum_{\mathrm{t=1}}^{\mathrm{T=2}} \sum_{\mathrm{r=1}}^{\mathrm{R}} -\gamma_{\mathrm{rt}} \mathrm{Tran}_{\mathrm{rt}}$$

$$\begin{aligned}
\text{st.}\quad & 0 \le \alpha_{\mathrm{jt}} \le 8{,}740{,}032 \\
& 0 \ge \beta_{\mathrm{it}} \ge 832{,}384 \\
& 0 \ge \gamma_{\mathrm{rt}} \ge 832{,}384 \\
& \pi > 0 \\
& \sigma < 30\% \\
& \textstyle\sum_{t=1}^{T=2} \sum_{j=1}^{J} \alpha_{\mathrm{jt}} + \sum_{t=1}^{T=2} \sum_{i=1}^{I} \beta_{\mathrm{it}} = 0 \\
& \textstyle\sum_{t=1}^{T=2} \sum_{j=1}^{J} \alpha_{\mathrm{jt}} + \sum_{t=1}^{T=2} \sum_{r=1}^{R} \gamma_{\mathrm{rt}} = 0 \\
& \textstyle\sum_{\mathrm{t=1}}^{\mathrm{T=2}} \sum_{\mathrm{j=1}}^{\mathrm{J}} \alpha_{\mathrm{jt}} \le 8{,}740{,}032 \\
& \textstyle\sum_{t=1}^{T=2} \sum_{i=1}^{I} \beta_{\mathrm{it}} \ge -832{,}384
\end{aligned} \tag{21}$$

Buying Track or CIF NOLA/Sell FOB

This sensitivity evaluates the spatial arbitrage from the trading FOB margin. The revenue in this sensitivity is FOB, which stands for the basis price loaded on a ship at the port. Buying track is the price for soybeans delivered to the port and loaded on railcars. Buying CIF NOLA is purchased soybeans delivered to port and loaded on barges. A merchandiser will trade through the port with the greatest FOB price because there is a greatest arbitrage opportunity. There is also risk in this sensitivity because a merchandiser is able to purchase track at the beginning of the week and to hold it until the end of the week or period 2. At the end of the week, the merchandiser is still able to simultaneously buy/sell soybeans and rail to achieve spatial arbitrage. If the PNW and USG ports are in a one-to-one relationship, the merchandiser will just be trading ocean-shipping differential. This sensitivity determines which destination has the greatest FOB margin and, therefore, which port is earning the greatest profits. The port that has the greatest spread could be due to the oil and protein quality differences between soybeans grown in northern or southern states.

The price coefficients are randomly drawn for FOB destinations and track origins. The ports can only unload 8,740,032 bushels in a week. The quantities sold at the port have to be purchased in the same amount from each origin.

$$\pi = \sum_{t=1}^{T=2}\sum_{b=1}^{B}\rho_{\mathrm{bt}}\mathrm{FOB}_{\mathrm{bt}} + \sum_{t=1}^{T=2}\sum_{j=1}^{J} -\alpha_{\mathrm{jt}}\mathrm{Track}_{\mathrm{jt}}$$

$$\begin{aligned}
\text{st.}\quad & 0 \le \alpha_{\mathrm{jt}} \le 8{,}740{,}032 \\
& 0 \le \rho_{\mathrm{bt}} \le 8{,}740{,}032 \\
& \pi > 0 \\
& \sigma < 30\% \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{\mathrm{jt}} + \sum_{t=1}^{T=2}\sum_{b=1}^{B}\rho_{\mathrm{bt}} = 0
\end{aligned} \tag{22}$$

Vertical Integration Without Ocean Shipping

This sensitivity is about a merchandising company that is vertically integrated from origin to port, but does not trade ocean freight. A merchandiser in this scenario is similar to the last sensitivity. The merchandiser gains this margin from purchasing soybeans from the local farmers and then storing and shipping them to the PNW, USG, or some domestic demand. The merchandiser is already taking on basis risk, but this model is able to determine which locations have a large spatial arbitrage. The merchandisers can still spatial arbitrage soybeans at the end of the week like the other sensitivities. The origins are still limited to the amount of grain they can load during the week. The combined purchase from the beginning of the week and the end of the week cannot be greater than two shuttle trains a week. The amount of grain purchased at the origin has to match the amount of grain sold at the ports. The amount of ocean freight to be purchased has to match the sum of all of the grain purchased at the origin. The port facility is only able to unload a limited number of bushels in a week.

$$\pi = \sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt}\mathrm{Track}_{jt} + \sum_{t=1}^{T=2}\sum_{i=1}^{I}-\beta_{it}\mathrm{Origin}_{it} + \sum_{t=1}^{T=2}\sum_{r=1}^{R}-\gamma_{rt}\mathrm{Tran}_{rt}$$

$$\begin{aligned}
\text{st.}\quad & 0 \le \alpha_{jt} \le 8{,}740{,}032 \\
& 0 \le \beta_{it} \le 832{,}384 \\
& 0 \le \gamma_{rt} \le 832{,}384 \\
& \pi > 0 \\
& \sigma < 30\% \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt} + \sum_{t=1}^{T=2}\sum_{i=1}^{I}\beta_{it} = 0 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt} + \sum_{t=1}^{T=2}\sum_{r=1}^{R}\gamma_{rt} = 0 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\alpha_{jt} \le 8{,}740{,}032 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{i=1}^{I}\beta_{it} \ge -832{,}384
\end{aligned} \tag{23}$$

Vertical Integration with Ocean Shipping

This sensitivity is about a merchandiser's company that is vertically integrated. A firm that is vertically integrated has ownership of alternative stages in the supply chain. In this case, the vertically integrated firm owns country elevators and export facilities. This sensitivity shows that, if a grain-handling company owns the most profitable locations, its profits will increase. The merchandiser gains this margin from purchasing soybeans from the local farmers, and then storing and shipping them to some destination. The merchandiser is already taking on basis risk, but this model will determine which locations would have a large spatial arbitrage.

The merchandisers can still spatial arbitrage soybeans at the end of the week like the other sensitivities. The origins are still limited to the amount of grain they are able to load during the week. The combined purchase for the beginning and the end of the week cannot be greater than two shuttle trains a week. To better represent a vertically integrated merchandising firm, the amount of grain purchased at the origin has to match the amount of grain sold at the ports. This constraint forces the model to behave as a vertically integrated firm. The amount of ocean freight to be purchased has to match the sum of all grain purchased at the origin.

$$\pi = \sum_{t=1}^{T=2}\sum_{k=1}^{K}\delta_{kt}CIF_{kt} + \sum_{t=1}^{T=2}\sum_{i=1}^{I} -\beta_{it}Origin_{it} + \sum_{t=1}^{T=2}\sum_{r=1}^{R} -\gamma_{rt}Tran_{rt} + \sum_{t=1}^{T=2}\sum_{o=1}^{O} -\tau_{ot}Freight_{Ot}$$

$$\begin{aligned}
\text{st.}\quad & 0 \le \delta_{kt} \le 8{,}740{,}032 \\
& 0 \le \beta_{\mathrm{it}} \le 832{,}384 \\
& 0 \le \gamma_{\mathrm{rt}} \le 832{,}384 \\
& 0 \le \tau_{ot} \le 16{,}800{,}000 \\
& \pi > 0 \\
& \sigma < 30\% \\
& \textstyle\sum_{t=1}^{T=2}\sum_{k=1}^{K}\delta_{kt} + \sum_{t=1}^{T=2}\sum_{i=1}^{I}\beta_{\mathrm{it}} = 0 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{k=1}^{K}\delta_{kt} + \sum_{t=1}^{T=2}\sum_{r=1}^{R}\gamma_{\mathrm{rt}} = 0 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{j=1}^{J}\delta_{kt} + \sum_{t=1}^{T=2}\sum_{o=1}^{O}\tau_{ot} = 0 \\
& \textstyle\sum_{\mathrm{t}=1}^{\mathrm{T}=2}\sum_{\mathrm{k}=1}^{K}\delta_{kt} \le 8{,}740{,}032 \\
& \textstyle\sum_{t=1}^{T=2}\sum_{i=1}^{I}\beta_{\mathrm{it}} \ge -832{,}384
\end{aligned} \tag{24}$$

Data Sources, Distribution, and Dependence Measures

Data Sources

The extensive data set used for this research was collected and used in Wilson and Dahl (2011). These soybean data are weekly numbers from 2004-2009. The data used by Wilson and Dahl (2011) were collected in O'Neil (2010). The data collected by (O'Neil, 2010) were from the following sources: barge freight rates (USDA-AMS Transportation Service Division), Rail Freight Rates (BNSF tariffs), CIF NOLA Barge Soybean Basis (Advanced Trading LLC; Bloomington, IL), Secondary Rail Car Value (Trade West Brokerage), PNW Rail Soybean Basis (Advanced Trading LLC, Blooming IL), rail fuel surcharge rates (Trade West Brokerage Co. and BNSF website), and origin basis price level (DTN prophet market information system). Wilson and Dahl (2011) collected 10 more origin base price levels. Also, ocean shipping rates from USG and PNW to Japan were collected by Wilson and Dahl (2011).

All the origins collected by O'Neil (2010) and Wilson and Dahl (2011) are not used in this research. The rail freight rates, daily car value, and rail fuel surcharge rates are used to calculate the transportation costs per bushel. The rail rates, barge rates, and ocean shipping rates need to be transformed to have the same units as the origin and port basis, in dollars per bushel.

Distributions

Input data distributions are very important to understand before making assumptions about which dependence measure is most appropriate for estimating the empirical models described in the Base Case and Sensitivity section. Table 2 highlights the importance of considering the use of copula as the dependence measure for Monte Carlo simulation because the sample variables described below indicate that these variables are non-normal. The variables in Table 2 are extremely skewed to the right, which means long right tails and short left tails[3].

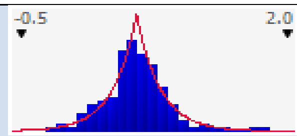
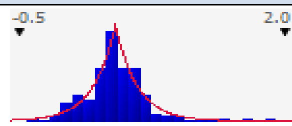
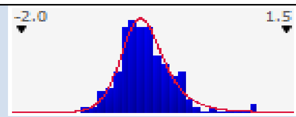
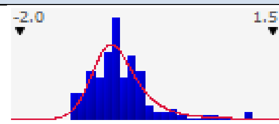
Table 2. Descriptive Statistics for a Sample of Input Data.

Variables	PNW Basis	NOLA Basis	Albany Basis	Alden Basis
Mean	0.61	0.45	-0.34	-0.59
STDEV	0.29	0.28	0.33	0.38
Skewness	0.61	1.42	0.99	1.56
Kurtosis	2.56	5.96	3.09	4.91

Table 3 contains graphs of the best fit distribution and the parameters that fully indicate that the input variables are not normally distributed. Below, the alternative dependence measures used and their assumptions are explained in greater detail to aid in selecting the most appropriate dependence measure for the research goals.

[3] The following tables and graphs on represent a few selected variables because there are so many variables used in this thesis it is too difficult to present them in this document. Upon viewers request full tables are available from the author.

Table 3. Graphs and Distribution Parameters for the Best Fit Distribution.

Variables	Graphs	Distribution Parameters
PNW Basis		Laplace(0.60000,0.29505)
NOLA Basis		Laplace(0.43000,0.27257)
Albany Basis		LogLogistic(-1.9601,1.5932,9.1456)
Alden Basis		LogLogistic(-1.7742,1.1368,5.9862)

Pearson Linear Correlation

Linear correlation and copula are alternate methods used for the simulation optimization models. Linear correlation is a dependence measure that is used in many calculations to measure risk, to reduce risk through a portfolio of assets, and to develop a cross-hedge. Linear correlation is calculated by the covariance divided by the product of standard devotions for X and Y. The liner correlation coefficient is defined as follows:

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} \tag{25}$$

The covariance causes a problem because the integral is taken over the domain of the variables and depends on the joint and marginal distributions (Nelsen, 2006). From the covariance measure, we have found that the linear correlation measurement is not good for measuring dependency structures that are not linear, or if X and Y have different probability distribution functions (Cherubini, et al., 2012).

Researchers need to be careful when using linear correlation because the upper and lower bounds are unknown or biased (Cherubini, et al., 2012). The linear correlation methodology was used in early market-integration research, which led to uncertainty about the law of one price. The movements from liner-correlation to liner-regression models are based on the same normality assumptions. Liner regression has the same assumptions as linear correlation:

$$\rho = \beta\sqrt{Var(X)/Var(Y)} \tag{26}$$

Choosing a linear dependence measure when the data set is not normally distributed and has thick tails gives biased results. Table 4 represents a sample linear-correlation matrix for a few variables that was used in the Normal Risk Constrained Optimization models.[4]

Table 4. Pearson Linear Correlation Matrix.

Variables	PNW Basis	NOLA Basis	Albany Basis	Alden Basis	Alton Basis	Aurora Basis	Ayr Basis	Bayard Basis	Beatrice Basis
PNW Basis	1.00	0.66	0.51	0.56	0.71	0.42	0.65	0.54	0.55
NOLA Basis	0.66	1.00	0.59	0.42	0.45	0.46	0.35	0.41	0.40
Albany Basis	0.51	0.59	1.00	0.78	0.67	0.83	0.66	0.78	0.77
Alden Basis	0.56	0.42	0.78	1.00	0.76	0.84	0.83	0.96	0.92
Alton Basis	0.71	0.45	0.67	0.76	1.00	0.63	0.91	0.81	0.83
Aurora Basis	0.42	0.46	0.83	0.84	0.63	1.00	0.72	0.85	0.80
Ayr Basis	0.65	0.35	0.66	0.83	0.91	0.72	1.00	0.86	0.86
Bayard Basis	0.54	0.41	0.78	0.96	0.81	0.85	0.86	1.00	0.94
Beatrice Basis	0.55	0.40	0.77	0.92	0.83	0.80	0.86	0.94	1.00

[4] Because there are 87 variables in the linear-correlation matrix, it is too large to include in the text or in the appendix, but the correlation matrix is available upon request.

Copula

Copula is a more complex dependency measure and allows for greater flexibility. Copula parameters are unlike the Pearson linear correlation because the marginal distribution can be separated from the joint distribution and takes the shape of an empirical distribution. It would be appropriate to use a normal distribution if the underling goal of the methodology was to analyze the data set for long-run outcomes, but the scope of this research is interested in short-run outcomes.

Selecting the correct copula for the problem at hand is the most crucial step. Based on the assumption defined in the following section and the distributions of the input data discussed previously, copula is found to be superior to using Pearson's linear correlation.

Copula was introduced by A. Sklar in 1959 when he was answering a question about the multi-dimensional probability function and its lower dimensional margins from M. Frechet and G. Dall' Aglio (Ubeda and Molina, 2003). M. Frechet and G. Dall' Aglio asked Sklar a question related to their work on bivariate and trivariate distribution functions with given univariate margins.

Nonparametric measures are used to test dependencies between random variables. Then, copula found its way to managing risk in finance and the insurance industry because of the copula's non-linear capabilities (Goodwin, et al., 2011). Recently, copula has found its way into studying integrated market relationships (Goodwin, et al., 2011), which is related to this study. This section lists the basic concepts of copula. The next section discusses the most common copula families and the makeup of the copulas within those families that were tested for use in the research questions at hand.

Transforming Marginal Distribution Functions

For some random variables (rvs), $X_{i,}$ with continuous distribution functions, F_i, $i=1,2, U_1=F_1(X_1)$, $U_2= F_2(X_2)$, both are uniformly distributed random variables on [0,1]. For some joint distribution function (dfs) with marginal dfs, F_1,F_2:

$$\begin{aligned} &F(x_1,x_2) = P(X_1 \le x_1, X_2 \le x_2) \\ &= P(F_1(X_1) \le F_1(x_1), (F_2(X_2) \le F_2(x_2)) \\ &= P(U_1 \le F_1(x_1), U_2 \le F_2(x_2)) \\ &= C(F_1(x_1), F_2(x_2)) \end{aligned} \tag{27}$$

The C stands for some copula, a distribution function $[0,1]^2$ with standard uniform margins; C is the distribution function of the random vector $(U_{1,}U_2)^T$. Transforming the marginal distribution function to a uniform one allows for many other transformations.

Skalar's Theorem

We have some random variables, $X_1,...,X_d$, with continues distribution functions $F_{1,}...,F_d$, and joint distribution function, F. Then, there exists a unique copula, C a distribution function on $[0,1]^d$ with uniform margins such that all $x=(x_1,...,x_d)^T \in \Re^d$:

$$F(x1, \dots, xd) = C(F1(x1), \dots, Fd(xd)) \tag{28}$$

If one is interested in a particular copula because of concentration on the dependence towards a tail, but the interest is in the dependence of the other tail, one could write the inverse, F_i^{-1}, of the copula to obtain $u= (u_1,...,u_d)^T \in [0,1]^d$ as follows:

$$C\ (u1, \dots, ud)\ =\ F(F1-1(u1), \dots, Fd-1(ud)) \tag{29}$$

By using generic Equation 28, we can construct a two-stage joint distribution function. A marginal distribution function, $F_{1,}...,F_d$, and add a copula of your choice for tail dependence. However, the pervious straightforward method of selecting a copula based on the distribution function would bias the results.

Generic Equation 28 fixes the marginal distribution function, $F_{1,}...,F_{d}$, and Equation 29 allows for the coupling of the marginal dfs with a interdependence through some copula. Generic Equation 29 is the formulation of copulas. Some of the most common copula families are Archimedean and Elliptical.

There are several copula families: Elliptical and Archimedean, which are Gaussian, Student t, Gumbel, Clayton, and Frank. The following copula families are tested for the best-fitted copula for any given portfolio in this research, which is why copula is briefly explained in the next sections.

Elliptical Copula

Gaussian and Student t copulas are part of the Elliptical copula family. Gaussian and Student t copulas are symmetric because they do not place additional probability on the tails, but Student's t copula has some tail dependence.

<u>Gaussian Copula</u>

The Gaussian copula is defined as follows:

$$C^{Ga}(v,z) = \theta_{\rho XY}\left(\theta^{-1}(v), \theta^{-1}(z)\right) \tag{30}$$

From this equation, we can see that $\theta_{\rho XY}$ is the joint distribution function, with ρXY as the linear correlation coefficient and θ is the normal distribution function. From the defined equation above, we have

$$\theta_{\rho XY}\left(\theta^{-1}(u), \theta^{-1}(v)\right) = \int_{-\infty}^{\theta^{-1}(u)} \int_{-\infty}^{\theta^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left(-\frac{x^2 - 2\rho xy + y^2}{2(1-\rho)^2}\right) dxdy \tag{31}$$

Because the Gaussian copula is parameterized by the linear coefficient, which follows concordance order, the Gaussian copula is positively ordered with respect to the parameter which lies between -1 and 1:

$$C^{Ga}_{\rho=-1} \prec C^{Ga}_{\rho<0} \prec C^{Ga}_{\rho=0} \prec C^{Ga}_{\rho>0} \prec C^{Ga}_{\rho=1} \tag{32}$$

We can see that the copula can reach its upper and lower bound:

$$C^{Ga}_{\rho=-1} = C^{-} \tag{33}$$
$$C^{Ga}_{\rho=1} = C^{+} \tag{34}$$
$$C^{Ga}_{\rho=0} = C^{\perp} \tag{35}$$

As for dependence measures, one can show that Gaussian copulas have neither upper nor lower tail dependence unless ρ=1:

$$\lambda_U = \lambda_L = \begin{cases} 0\ iff\ \rho < 1 \\ 1\ iff\ \rho = 1 \end{cases} \tag{36}$$

Student t Copula

The other elliptical, symmetric copula is described below. As we can see, the Student t copula starts with a similar equation as the Gaussian copula. However, the two equations are different because of the added v parameter for the degrees of freedom:

$$T_{p,v}(v,z) = t_{p,v}(t_v^{-1}(v), t_v^{-1}(z)) \tag{37}$$

The Student t copula is different from the Gaussian copula because it has tail dependence and is defined as followed:

$$C_{p,v} = (u,v) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \left\{1 + \frac{x^2 - 2\rho xy + y^2}{\nu(1-p^2)}\right\}^{-(\nu+2)/2} \tag{38}$$

The Student t copula converges to the Gaussian copula as the number of degrees of freedom increases (Vose, 2008). The smaller the degrees of freedom, the greater the difference between the two elliptical copulas. When the degrees of freedom are small, the Student t copula is star shaped with the greatest concentration on the main diagonal, but as the degrees of freedom increase, it looks more like the Gaussian copula. The easiest way to differentiate the Elliptical copulas is the number of observations found in the tails of the Student t copula compared to the Gaussian copula. Like the Gaussian copula, the Student t is bounded by the linear correlation coefficient from -1 to 1 and is positively ordered with respect to ρ for the degrees of freedom. However, these elliptical copulas are better than the Pearson linear correlation when the researcher is interested in extreme dependence because copulas can reach the upper and lower bounds because of the following equations.

$$C^{s}_{v,-1} = C^{-} \tag{39}$$
$$C^{s}_{v,1} = C^{+} \tag{40}$$
$$C^{s}_{v,0} \neq C^{\perp} \tag{41}$$

As for tail dependence, for finite v or degrees of freedom

$$\lambda_U = \lambda_L = \begin{cases} > 0 \; iff \; \rho > -1 \\ 0 \; iff \; \rho = 1 \end{cases} \tag{42}$$

Archimedean Copula

The Archimedean copula families are asymmetric because they place more probability on the distribution tails compared to Elliptical copula families. Copula will be much more attractive for data sets to emphasize asymmetric tail dependence. The Archimedean copula is generated as follows:

$$C^{A}(\mathrm{v}, \mathrm{z}) = \theta^{-1}(\theta(\mathrm{v}) + \theta(\mathrm{z})) \tag{43}$$

The generator is strict Archimedean copula iif $\theta(0) = +\infty$. Each copula within the Archimedean copula family has its own, unique generating parameter, and Table 5 has them derived.[5]

Table 5. Archimedean Copula Family.

Gumbel	
Copula	$C(v,z;\alpha) = \exp(-[(-\ln v)^\wedge\alpha + (-\ln z)^\wedge\alpha]^\wedge(1/\alpha)$
PDF	$C(v,z;\alpha) = \frac{C(v,z;\alpha)(\log z \cdot \log v)^{\alpha-1}}{uv((-\log z)^{\alpha}+(-\log v)^{\alpha})^{2-\frac{1}{\alpha}}}\left(((-\log z)^{\alpha} + (-\log v)^{\alpha})^{\frac{1}{\alpha}} + \alpha - 1\right)$
Parameter Range	$\alpha \in [1, \infty)$
Kendall's Tau	$\tau_\alpha = 1 - \frac{1}{\alpha}$
Tail Dependency	$\lambda_L = 0, \lambda_U = 2 - 2^{1/\alpha}$
Clayton	
Copula	$C(v,z;\theta) = \left(z^{-\theta} + v^{-\theta} - 1\right)^{-\frac{1}{\theta}}$
PDF	$C(v,z;\theta) = (1+\theta)(zv)^{-\theta-1}\left(z^{-\theta} + v^{-\theta} - 1\right)^{-2-\frac{1}{\theta}}$
Parameter Range	$\theta \in [-1, \infty)\backslash\{0\}$
Kendall's Tau	$\tau_\theta = \frac{\theta}{\theta+2}$
Tail Dependency	$\lambda_L = 2^{-\frac{1}{\theta}}, \lambda_U = 0$
Frank	
Copula	$C(v,z;\beta) = -\frac{1}{\beta} ln\left(1 + \frac{\left(e^{-\beta z} - 1\right)\left(e^{-\beta v} - 1\right)}{\left(e^{-\beta z} - 1\right)}\right)$
PDF	$c(v,z;\beta) = c(1-z, 1-v; \beta)$
Parameter Range	$\beta \in [-\infty, \infty)\backslash\{0\}$
Kendall's Tau	$\frac{[D_1(\beta) - 1]}{\beta} = \frac{1-\tau}{4}$
Tail Dependency	$\lambda_L = \lambda_U = 0$

[5] Detailed definitions and proofs are explained in great detail in Nelsen, R.B. 2006. *An introduction to copulas*. 2nd ed. New York: Springer.

Copula Parameter Estimation

Copula is superior to alternative dependence measures when focusing on the short term because it allows separation of the marginal distribution from the joint distribution. The marginal distribution is the distribution that represents each variable in the data set. The copula estimation is used to combine the marginal distribution for each variable into a multivariate distribution.

Maximum likelihood estimation is used to estimate the multivariate copula. It is estimated by the following equation:

$$\hat{\delta}_2 = argmax_{\hat{\delta}_2} \sum_{t=1}^{T} \ln c\left(\hat{G}_x(x_t), \hat{H}_y(y_t), \delta_2\right), \tag{44}$$

where $\hat{\delta}_2$ is the estimated copula parameter, or Kendall's tau; argmax is the mathematical function that provides the argument to maximize; ln is the natural logarithm; and $\left(\hat{G}_x(x_t), \hat{H}_y(y_t), \delta_2\right)$ are the estimated marginal distributions for x and y. The copula parameters for all the copulas in this section are estimated by SAS. Table 6 lists the estimated copula parameters from SAS.

The data set contained highly correlated variables, especially for the transportation variables. The strong correlation between these variables created great difficulty in estimating the copula parameters for Archimedean and Elliptical copulas, and the Akaike information criterion (AIC). The best-fit copula for this research was selected with less-than-perfect information. The AIC best-fit criteria were not available from the SAS experimental copula procedure. The scatter plots of the original data set supported using the Gaussian copula, but this information was less than perfect. This research had too many variables to estimate a copula parameter, which caused the Kendall's tau correlation matrix to not be positive semi-definite.

In order to estimate the copula parameters for Archimedean and Elliptical copulas, all the transportation data had to be removed from estimation, except for three variables. Equation 45 calculated the margins between ρ_{gpb}, which stands for rail PNW, rail USG, and barge transportation costs, and x_{gpb}, which is the remaining transportation variables. Removing the margins forced some highly correlated variables to be excluded when estimating the copula parameter. The removed variables had to be placed back into the data set after the copula-parameter estimation.

$$Margin = \rho_{gpb} - x_{gpb} \tag{45}$$

New price level data were estimated from the sample copula parameters listed in Table 6. With these new price-level data, the margins removed from Equation 46 can be added back with Equation 46.

$$Margin - \hat{\rho}_{gpb} = \hat{x}_{gpb} \tag{46}$$

Equation 46 allows for $\hat{x}_{gpb}$ (new price level data created the margins) minus $\hat{\rho}_{gpb}$ the (new price level data calculated by the copula parameters). Removing the margins allows the copula parameters in Table 6 to become positive semi-definite.

Table 6. Sample of Gaussian Copula Parameters.

Variables	PNW Basis	NOLA Basis	Albany Basis	Alden Basis	Alton Basis	Aurora Basis	Ayr Basis	Bayard Basis	Beatrice Basis
PNW Basis	1.0	.71	.57	.62	.73	.49	.68	.58	.57
NOLA Basis	.71	1.0	.63	.49	.49	.48	.40	.44	.42
Albany Basis	.57	.63	1.0	.78	.68	.84	.67	.79	.77
Alden Basis	.62	.49	.78	1.0	.80	.82	.84	.95	.92
Alton Basis	.73	.49	.68	.80	1.0	.65	.92	.83	.83
Aurora Basis	.47	.48	.84	.82	.65	1.0	.72	.85	.81
Ayr Basis	.68	.41	.67	.84	.92	.72	1.0	.86	.86
Bayard Basis	.58	.44	.79	.95	.83	.85	.86	1.0	.94
Beatrice Basis	.57	.42	.77	.92	.83	.81	.86	.94	1.0

Table 5 represents a sample of the Gaussian copula parameters estimated in SAS with maximum likelihood estimation.[6] The values in Table 5 illustrate Kendall's tau estimates, but Kendall's tau and linear correlation cannot be compared. Kendall's tau and linear correlations are not comparable because both types of dependence measure different types of relationships. Kendall's tau measures the probability of x and y moving in the same direction. For instance, the PNW and NOLA basis have a relationship of .713, which means that, if the PNW basis increases, the NOLA basis has a 71% chance of increasing. Table 4 represents a linear-correlation matrix, and the relationship between the PNW and NOLA basis has a 66% positive liner relationship. The PNW and NOLA basis always increase with a 66% positive relationship.

[6] Because there are 87 variables in Kendall's tau matrix, the size of the table is too large to be illustrated in the text or in the appendix. Kendall's tau matrix is available upon request.

Because the AIC criteria were not estimated for all of the copula families, they were not used in the selection process. There were a large number of variables used to estimate the copula parameters, so AIC was not available. Since there are so many variables or degrees of freedom, the copula would converge to a Gaussian copula (Vose, 2008). Instead, scatter plots of the original data and the transformed data are utilized to help select the best-fit copula.

Figure 12 and 13 are scatter plots of the original data. Also, the underlying assumption for each copula family is used to select the best-fit copula. The research conducted in this thesis is not only interested in capturing the tail dependency, but also capturing the dependency in-between the tails, hence the elliptical family is chosen. There are 87 variables in the data set, which forces a Student t copula to converge into a Gaussian copula (Vose, 2008). The underlying assumption forces the Gaussian copula to be the best fit, and Figure 14 is a sample scatter-plot matrix of the Gaussian copula.

The Gaussian copula is then used to estimate 10,000 new random variables that are used with the sensitivity models. Before the new random variables are used in the empirical models, the transportation data that were removed have to be added to the new data set. The margins between the three transportation variables and the remaining variables are calculated before estimating the copula parameter. These margins are then added back to the newly estimated data to complete the data set with Equation 46.

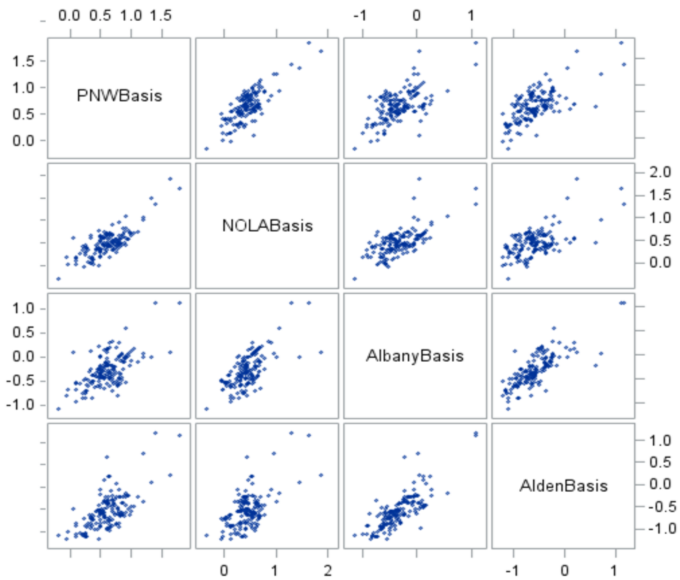


Figure 12. Original Scatter Plot Matrix.

From the original scatter plot in Figure 12, the data seem to have greater tail dependence when the values are small compared to when they are large. Transforming the data set in Figure 13 better reveals the relationship between variables, which allows for a simplistic way of choosing the best-fit copula. From Figure 13, the data represent a Student t copula shape, but the Alden and Albany relationship is shaped like a Gaussian copula. Because of the parameters in the Student t copula and the large number of variables estimated in this research, a Gaussian copula is the best fit. The scatter plot matrix of the estimated copula data in Figure 14 represents the original data scatter-plot matrix in Figure 12. Both figures show high-tail dependence when values are low compared to when the values are high.

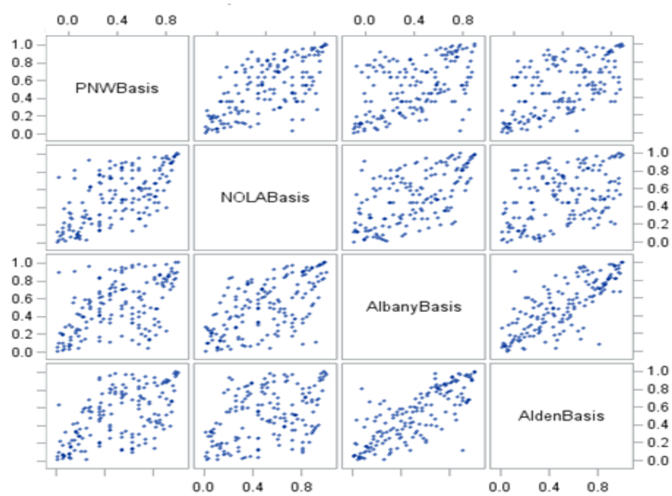


Figure 13. Transformed Scatter-Plot Matrix.

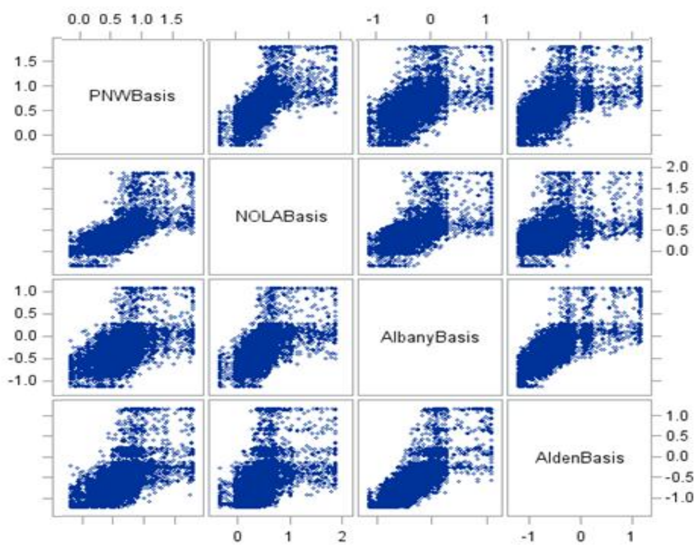


Figure 14. Empirical Margins, Gaussian Copula Scatter Plot Matrix.

Simulation and Optimization Procedures

A portfolio is repetitively estimated to maximize spatial-arbitrage profit and to minimize risk. Spatial-arbitrage opportunities are quantified as the percentage of time the optimization model finds each origin profitable enough to include in the portfolio. Constraints are included in the optimization model to restrict the amount of risk that the portfolio can have. Constraints also force the model to behave as a non-integrated firm to a fully vertically integrated. Origins and destinations are restricted by the amount of soybeans that can be loaded and unloaded in a week.

Monte Carlo simulation is used and allows for repetitive optimization. Monte Carlo simulation uses the marginal distribution from variables in the data set and randomly draws values from that distribution. The simulation is repetitively optimized in some models from 100 to 1,000 iterations. The two different dependency methods are the only variation between the Normal Risk Constrained Optimization and Copula Risk Constrained Optimization. Monte Carlo simulation pulls from a normal marginal distribution in the Normal Risk Constrained Optimization. All of the variables are linearly correlated. However, with the Copula Risk Constrained Optimization method, Monte Carlo simulation is pulling draws from an empirical marginal distribution, and the data set is related by a Gaussian copula.[7]

The linear programming(Solver, 2013) quadratic is the optimization procedure used to maximize portfolio profits for these empirical models. The algorithm used in the optimization procedure is called a standard linear problem/quadratic. The software used for estimating the empirical models is Premium Solver (2013). Premium Solver uses a primal simplex method with two-sided bounds on the variables. Premium Solver is able to handle up to 2,000 decision variables. Microsoft Excel uses a primal simplex method, but it is limited to 200 decision variables. When setting up the empirical model, the number of variables approximately doubles from the original 87. The number of constraints allowed with both software programs is also significantly different, forcing this researcher to use Premium Solver.

[7] The second major difference between these two methods is that @Risk has Monte Carlo simulation that uses a distribution function that can be correlated linearly for Normal risk constrained optimization model while the Copula risk constrained optimization model uses a looped macro code to pull the data estimated in SAS into the Copula Risk Constrained Optimization Model so that the macro acts like Monte Carlo simulation in @Risk.

Summary

Chapter 4 explained in great detail for the base case and the five sensitivities this research explored. The empirical model specification was explained in detail. This chapter also explained the Data Sources, Distribution, and Dependence Measures used with the Normal Risk Constrained Optimization and Copula Risk Constrained Optimization methods. The statistical measures and distribution graphs support the use of copula as the main statistical method for the research. Chapter 5 explains the Results from the empirical models and the methods described here in great detail.

CHAPTER 5. RESULTS

Introduction

Chapter 4 explained the model specifications and methods used to analyze the base case and sensitivities. Two alternate dependency measures are used in this research: copula and linear correlation. These alternate methods are described as Normal Risk Constrained Optimization and Copula Risk Constrained Optimization. Normal Risk Constrained Optimization utilizes assumptions that are widely used and accepted in academic research. Normal Risk Constrained Optimization is used to simplify the analysis at the beginning stages of research. Copula Risk Constrained Optimization is the base case for this research and is compared to Normal Risk Constrained Optimization to illustrate the results of the overall difference between the underlying assumptions explained in Chapter 4. Normal Risk Constrained Optimization and Copula Risk Constrained Optimization results are similar with respect to the difference between the dependency measures and distribution assumptions.

Copula Risk Constrained Optimization is the base-case assumption for this research, and each sensitivity's results are explained in great detail. The base case is compared to each sensitivity to discover the profitability of alternating a business structure. Results obtained for the base case represent a non-vertically integrated company that is merchandising soybeans. Spatial arbitrage is obtained in the base case by simultaneously buying/selling the soybeans when an arbitrage opportunity arises, so merchandisers inherit no price or basis risk. The merchandiser inherits no price or basis risk because the company is not storing any soybeans. The base case is non-integrated, and soybeans are simultaneously bought/sold, making the base case ideal to compare with each sensitivity.

The adaptive sensitivity results explain merchandisers' behavior in selecting certain origins for purchase changes as they become more sensitive to changes in market volatility. The risk-loving sensitivity allows for the discovery of market boundaries.

The risk-loving sensitivity is also able to prove that there are greater spatial-arbitrage profits if a firm is willing to allow more risk. Origins that have smaller spatial-arbitrage profits are located the furthest from the market boundaries and have little risk. Locations closer to the market boundaries have the greatest spatial-arbitrage profits and the greatest amount of risk.

The sensitivity analyzing the increase for an origin's train-loading efficiency is used to figure out how a more-efficient origin is able to capitalize on a larger amount of the spatial-arbitrage profit compared to its competitors. Ayr, ND, had average spatial-arbitrage profits in the base case and is selected as the origin to increase shuttle-loading efficiency. Shuttle-train loading efficiency is increased from loading one train a week to five trains.

The vertical-integration sensitivity results are the most interesting. These results are used to determine how profits and risk increase as a company becomes more vertically integrated from the base case to including ocean shipping. These sensitivities also show how the difference in the ocean shipping rate from PNW or USG effects the decision about what port to use when selling soybeans.

First, the results for the base case are explained using copula as the dependence measure. Next, the explanation of key points from the results for each sensitivity is illustrated, such as being adaptive to changes in risk, being risk loving, increased shuttle-train loading efficiency, buy track or CIF NOLA/sell CIF, vertical integration without ocean shipping, and vertical integration with ocean shipping. The chapter ends with a Summary.

Copula Base-Case Results

Copula places fewer restrictions on the marginal distributions, and an empirical distribution is used for this analysis. Empirical marginal distribution represents the actual data set used for this research exactly. Maximum likelihood estimation is used to estimate the copula parameter. All of the marginal distributions are combined to form a joint distribution, which is represented by the copula parameter. An appropriate copula needs to be selected, and the AIC fit statistic is most widely used to compare copulas. However, the AIC fit statistic is not always available, so scatter plots of the data are used for this thesis. Also, assumptions and details about parameters in the derived copula are used in this research. Gaussian, or normal, copula is selected to best represent the data set collected for this research. This research requires an empirical model that represents the original data to analyze short-run events, which is why copula is the tool used.

This chapter explains the results of the base case, which represents a soybean trading firm that is non-integrated and has no strategized plan for capturing spatial arbitrage. This sensitivity is created to best represent a firm as the simplest form. The frequency of spatial arbitrage is an empirical issue, but there are locations that have greater spatial-arbitrage opportunities; those locations are near the market boundaries. For the base case and each sensitivity, the percentage of time that spatial arbitrage was profitable and selected for the optimal portfolio is included in the results. The base case is a non-integrated firm, so there is no vertical strategy; hence, the firm does not store any soybeans, so the firm inherit no price or basis risk. Which allows the base case to be a good comparison for the risk and integration sensitivities.

Figure 15 illustrates the results. The size of each dot represents the average weekly spatial-arbitrage profit. Underlying the spatial-arbitrage profits in Figure 15, each county’s soybean production per bushel is represented. Darker colors indicate greater soybean production than lighter colors. It could be supply-and-demand issues or transportation rates causing the spatial arbitrage. The results in Figure 15 show the greatest spatial arbitrage occurring towards the edges of the greatest soybean production.

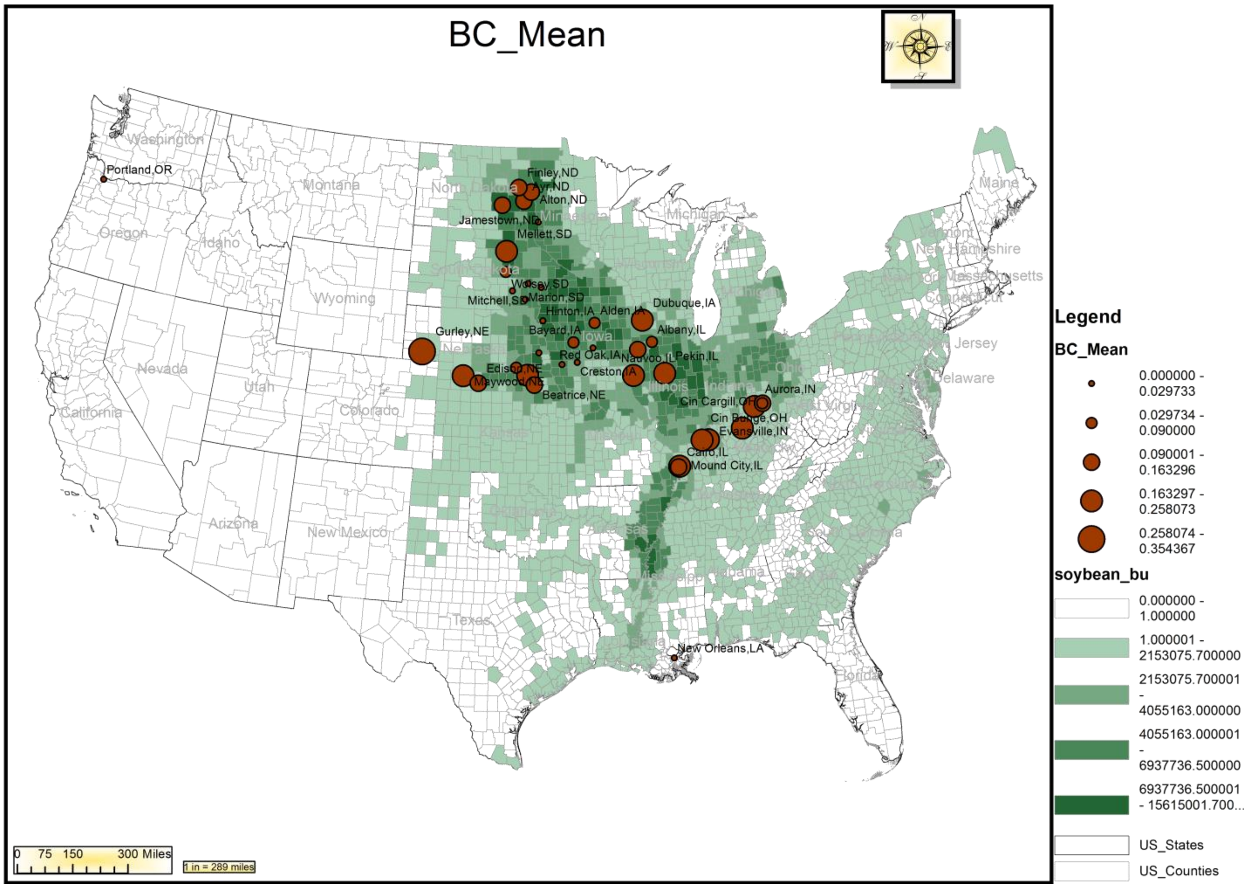


Figure 15. Copula Risk Constrained Optimization Base Case.

Figure 16 represents the probability of each origin being selected in the portfolio and the destination where each origin is most likely to ship soybeans. From this figure, it is easy to see that most locations along the Mississippi River ship south via barge to the USG. Origins located in Nebraska are indifferent about which destination to ship soybeans because those locations, such as Dorchester, NE, are located on the market boundaries. Dorchester, NE, has, on average, weekly arbitrage profits of $.20/bu. The spatial arbitrage for Bradshaw, NE, always occurs when shipping to the USG, with average weekly arbitrage profits of $.09/bu.

Two methods are used in this research, and there are some noticeable differences. Normal Risk Constrained Optimization results for Alton, ND, have an average profit of $178,439, or $.21/bu, and the empirical model chooses that location 57% of the time and the remainder 43% of the time there are no spatial arbitrage opportunities. Alton, ND, soybeans are shipped to PNW 50% of the time and to USG 7% of the time. Copula Risk Constrained Optimization estimated Alton, ND, with an average profit of $109,230, or $.13/bu, and the empirical model chooses that location 60% of the time and the remainder of the time there are not spatial arbitrage profits. Using Copula, Alton, ND, soybeans are shipped to PNW 56% of the time and go to USG 4% of the time. Normal Risk Constrained Optimization overestimates some origins' profits and underestimates the percentage of time, on average, that there is spatial arbitrage.[8] The difference between these methods could be selecting the right and wrong origin to build or buy an existing facility in hopes of capturing spatial-arbitrage profits. Table 7 and 8 show the results for all origins using Copula and Normal risk constrained optimization.

[8] The appendix displays full tables of both Normal Risk Constrained Optimization and Copula Risk Constrained Optimization average weekly arbitrage profits as well as the profits per bushel to compare all 37 origins. The appendix also shows both methods' average weekly portfolio profits, standard deviation, value at risk, and profit/risk ratio.

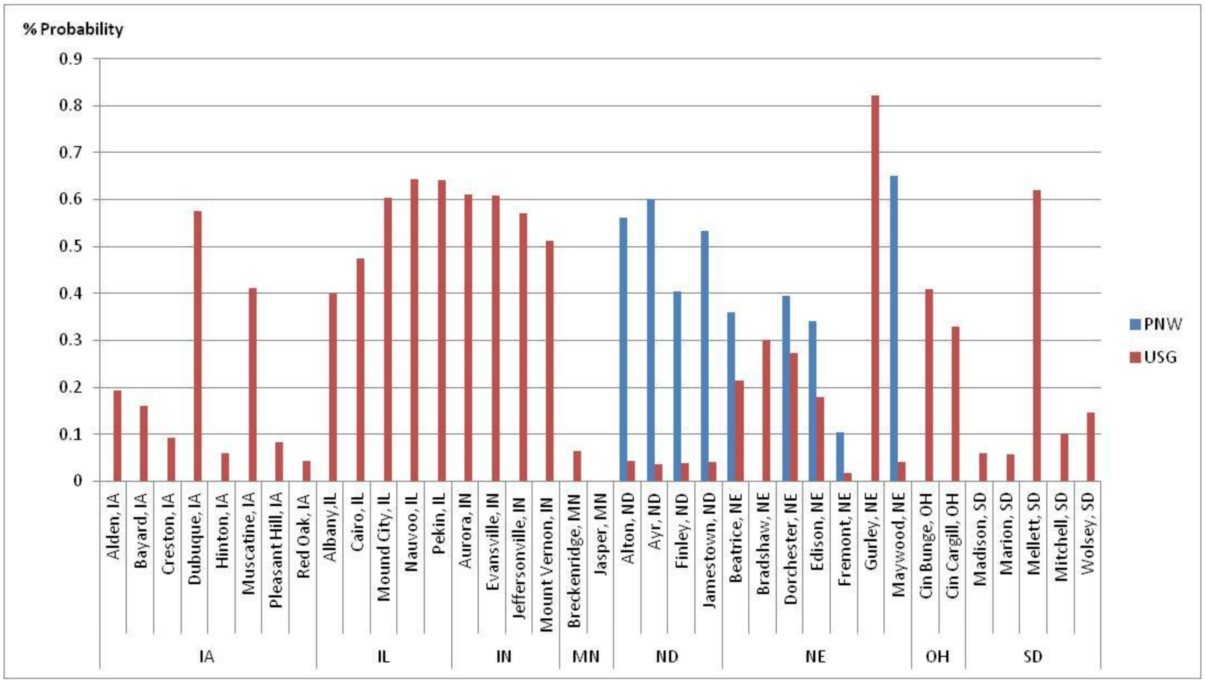


Figure 16. Copula Risk Constrained Optimization Probability of Profit/ Shipping Direction.

Profit is the product of profits per bushel and the number of bushels selected to be shipped by the simulation’s optimization model. Bushels are the decision variable for each origin and destination. The number of bushels shipped from each origin is constrained by their loading-capacity constraint. Each destination is constrained by its unloading capacity constraints. The simulation’s optimization model maximizes profit with a minimal amount of risk, and this constraint is why the model does not choose to ship all the available bushels from the most profitable location.

Table 7. Copula Risk Constrained Optimization Base Case.

Origins	$/Week	$/bu	Stdev	1/CV	PNW	USG
Albany, IL	71,807	0.09	111,127	0.65		40%
Alden, IA	40,126	0.05	112,374	0.36		19%
Alton, ND	109,230	0.13	145,193	0.75	56%	4%
Aurora, IN	179,530	0.22	203,673	0.88		61%
Ayr, ND	118,740	0.15	196,425	0.61	60%	3%
Bayard, IA	32,374	0.04	102,569	0.32		16%
Beatrice, NE	98,996	0.12	150,808	0.66	36%	21%
Bradshaw, NE	72,917	0.09	148,449	0.49		30%
Breckenridge, MN	15,244	0.02	68,851	0.22		6%
Cairo, IL	133,260	0.16	191,373	0.70		47%
Cin Bunge, OH	96,397	0.12	165,007	0.58		41%
Cin Cargill, OH	57,061	0.07	113,636	0.50		33%
Creston, IA	19,767	0.03	86,302	0.23		9%
Dorchester, NE	165,014	0.20	209,113	0.79	39%	27%
Dubuque, IA	186,078	0.23	232,074	0.80		57%
Edison, NE	99,102	0.12	160,207	0.62	34%	18%
Evansville, IN	211,696	0.26	246,336	0.86		61%
Finley, ND	96,279	0.12	171,304	0.56	40%	4%
Fremont, NE	16,663	0.02	67,942	0.25	10%	2%
Gurley, NE	292,758	0.35	242,373	1.21		82%
Hinton, IA	11,251	0.02	64,860	0.17		6%
Jamestown, ND	99,512	0.12	148,816	0.67	53%	4%
Jasper, MN	0	0.00	0	0.00		0%
Jeffersonville, IN	168,912	0.21	205,971	0.82		57%
Madison, SD	12,117	0.02	59,290	0.20		6%
Marion, SD	11,590	0.02	61,950	0.19		6%
Maywood, NE	165,037	0.20	189,551	0.87	65%	4%
Mellette, SD	181,553	0.22	205,064	0.89		62%
Mitchell, SD	24,686	0.03	94,228	0.26		10%
Mound City, IL	158,425	0.19	191,039	0.83		60%
Mount Vernon, IN	197,068	0.24	262,528	0.75		51%
Muscatine, IA	100,143	0.13	162,758	0.62		41%
Nauvoo, IL	191,177	0.23	214,441	0.89		64%
Pekin, IL	178,627	0.22	194,729	0.92		64%
Pleasant Hill, IA	12,629	0.02	57,159	0.22		8%
Red Oak, IA	6,100	0.01	33,533	0.18		4%
Wolsey, SD	53,682	0.07	154,293	0.35		15%

Normal Risk Constrained Optimization base case has average weekly portfolio profits of $5,291,855, which is significantly higher than the Copula Risk Constrained Optimization base average weekly portfolio profits of $3,685,545. These differences are solely due to the variation in the input distributions and the type of dependence used to correlate the input variables. In comparison, Normal Risk Constrained Optimization and Copula Risk Constrained Optimization output distributions are both lognormal, but they take different shapes from Figure 17 and 18. Normal Risk Constrained Optimization does not have a larger probability of zero profit, and Copula Risk Constrained Optimization shows a greater probability of zero profit.

Because the overall portfolio profits are much higher in the Normal Risk Constrained Optimization base case, some origins' arbitrage profits must also be greater than the Copula Risk Constrained Optimization base-case results. Alton, ND, for example, has $178,439/week profits, or $.21/bu, and is selected to have spatial-arbitrage opportunities 57% of the time for Normal Risk Constrained Optimization. Copula Risk Constrained Optimization results illustrate that Alton, ND, has $109,230/week profits, or $.13/bu, and is selected to have spatial-arbitrage opportunities 60% of the time. This one location can illustrate the difference in assumptions placed on distributions and dependency measures. Because of having fewer assumptions on distributions and the ability to have non-linear relationships, Copula Risk Constrained Optimization is superior to Normal Risk Constrained Optimization. Normal Risk Constrained Optimization overestimates the Alton, ND, arbitrage profits and underestimates the spatial-arbitrage opportunities.

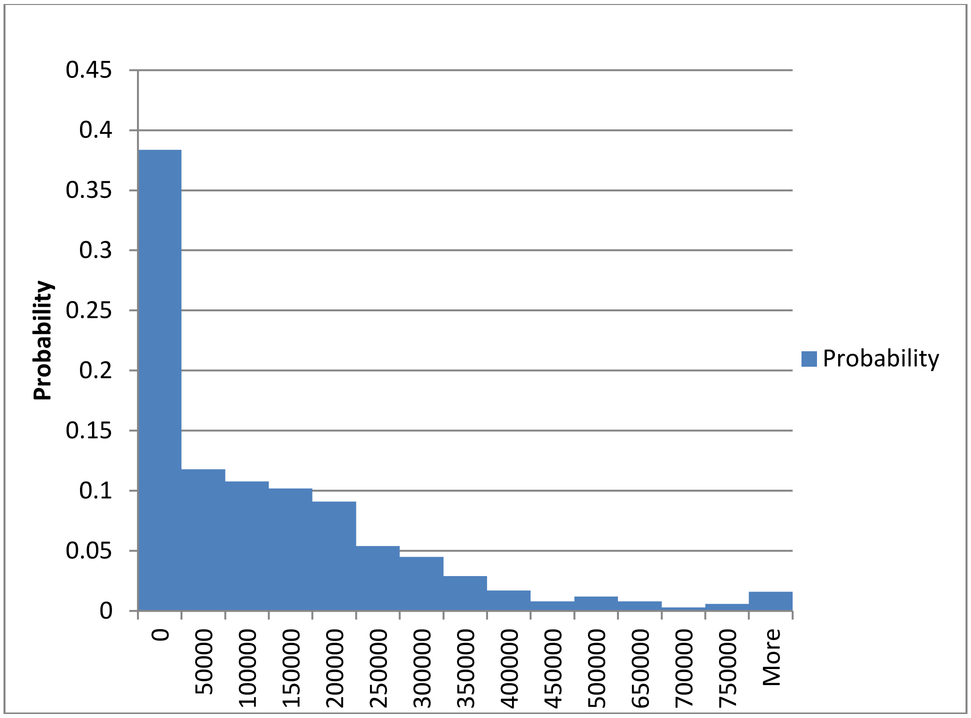


Figure 17. Copula Risk Constrained Optimization Ayr, ND, Profit/Week Distribution.

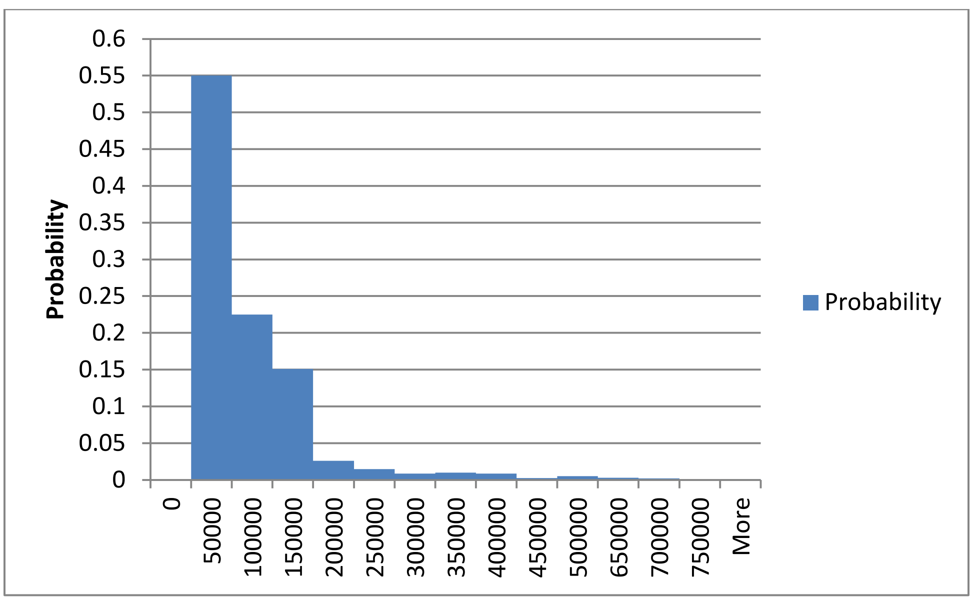


Figure 18. Normal Risk Constrained Optimization Ayr, ND, Profit/Week Distribution.

Table 8. Normal Risk Constrained Optimization Base Case.

Origins	$/Week	$/bu	Stdev	1/CV	PNW	USG
Albany,IL	139,935	0.17	256,634	0.55		40%
Alden, IA	109,975	0.13	226,864	0.49		29%
Alton, ND	178,439	0.21	258,001	0.69	50%	7%
Aurora, IN	207,871	0.26	321,367	0.65		48%
Ayr, ND	229,619	0.28	345,453	0.67	52%	7%
Bayard, IA	67,853	0.08	184,137	0.37		20%
Beatrice, NE	156,860	0.19	252,781	0.62	38%	13%
Bradshaw, NE	117,073	0.15	226,052	0.52		32%
Breckenridge, MN	71,184	0.09	198,839	0.36		18%
Cairo, IL	143,755	0.18	237,516	0.61		43%
Cin Bunge, OH	111,705	0.14	219,375	0.51		36%
Cin Cargill, OH	108,620	0.13	209,412	0.52		35%
Creston, IA	46,041	0.06	148,346	0.31		13%
Dorchester, NE	177,341	0.22	287,416	0.62	36%	14%
Dubuque, IA	213,652	0.26	339,756	0.63		45%
Edison, NE	209,687	0.25	311,457	0.67	37%	17%
Evansville, IN	150,120	0.19	291,741	0.52		39%
Finley, ND	162,928	0.20	286,813	0.57	41%	6%
Fremont, NE	226,906	0.27	418,450	0.54	30%	13%
Gurley, NE	305,550	0.37	347,546	0.88		64%
Hinton, IA	38,703	0.05	148,516	0.26		11%
Jamestown, ND	188,962	0.23	294,137	0.64	47%	6%
Jasper, MN	21,834	0.03	100,856	0.00		6%
Jeffersonville, IN	193,764	0.24	303,330	0.64		47%
Madison, SD	54,823	0.07	170,587	0.32		14%
Marion, SD	36,941	0.05	131,924	0.28		10%
Maywood, NE	375,517	0.45	484,348	0.78	46%	22%
Mellett, SD	91,928	0.12	225,462	0.41		20%
Mitchell, SD	55,177	0.07	176,446	0.31		15%
Mound City, IL	181,442	0.22	257,926	0.70		54%
Mount Vernon, IN	155,000	0.19	305,357	0.51		38%
Muscatine, IA	154,226	0.19	272,627	0.57		37%
Nauvoo, IL	176,346	0.22	286,463	0.62		43%
Pekin, IL	227,474	0.28	312,222	0.73		52%
Pleasant Hill, IA	31,231	0.04	114,716	0.27		11%
Red Oak, IA	121,659	0.15	303,870	0.40		21%
Wolsey, SD	97,615	0.12	236,110	0.41		21%

Sensitivities

Each of these sensitivities is designed to capture spatial arbitrage, and there is more explained from the results than just spatial arbitrage. Market boundaries are constantly fluctuating with changes in the basis between markets and transportation costs. Origins that have become more risky in recent years have shifted to the new market boundaries. Adaptive to changes in risk, risk loving, increase in shuttle-train loading efficiency, buy FOB/sell track or CIF NOLA, vertically integrated without ocean shipping, and vertically integrated with ocean shipping results are explained in detail in the following sections.

Adaptive to Changes in Risk

As explained in Chapter 4, this sensitivity uses model specifications similar to the vertical integration without ocean-shipping model. The difference between these two sensitivities is that the empirical model for adaptive to changes in risk sensitivity uses the exponential weight moving average (EWMA) to aid in calculating the portfolio variance. The EWMA is used to forecast volatility by weighting the historical data set differently through time by adjusting λ. The most common λ is set at .94 for forecasting volatility, but for this sensitivity, the objective is to determine how the empirical model selects alternative origins as λ is adjusted from .8, to .9 and 1.

The base case has equal weights across all time periods, and a comparison between the two sensitivities is represented in Figure 19. When λ is set to .8, there is more weight on the most recent observations. As λ is adjusted to .9 and 1, there is more of an equal weight across observations. Viewing Figure 19, the output from the empirical model shows that some origins have become more risky for the most recent variables while other variables are less risky. As we increase λ, some variables switch from being the most risky to being the least risky and vice versa.

Figure 19 shows that Alton, ND, has become more risky in recent years because the profits decrease when placing more weight on recent years. Placing an equal weight across observations, Alton was less risky in the past. The greater variability in Alton, ND, is due to the shifts in agriculture in recent years; these changes were explained in Chapter 1. Alton, ND, could now be hypothesized to be located closer to the market boundary in recent years. If located close to the market boundary, an origin basis would adjust constantly while outside influences shift the destination market where Alton, ND, will sell its soybeans.

Other locations, such as Alden, IA, have become less risky in recent years because, when more weight is placed on past observations, the profit decreases. The profit for a grain trading firm in Alden, IA, decreases because Alden contributes less profit for the amount of risk added to the portfolio. Alden, IA, is the opposite of Alton, ND, because Alton is farther from the market boundary, which is why the risk for this location has decreased.

Risk Loving

This sensitivity is also involved with understanding changes in the risk measures affect how the empirical model selects the optimal origins for the portfolio. A risk-loving individual is willing to have a greater risk for a small amount of profit. This sensitivity also uses the same empirical model as the vertically integrated without ocean shipping sensitivity. The portfolio variance is combined and transformed into the portfolio's standard deviation. This sensitivity adjusts σ from 10% to 20% and 30% standard deviation. The objective of this sensitivity is to see how a merchandising company's profits change and the market boundaries' locations. Origins located close to a market boundary should have greater spatial-arbitrage opportunities.

The risk-loving sensitivity illustrates locations that are selected less and some that are selected more. This sensitivity is important to understand when a merchandising company is searching for locations that can deliver spatial-arbitrage opportunities. The more risky origin basis has, on average, the greatest potential for producing the largest spatial-arbitrage opportunity. The locations that are closest to the market boundaries are the most risky because the basis at that origin is constantly changing from the impacts of supply and demand at the origin and destination bases. Transportation costs are also fluctuating, and the combination affects which destination market offers the greatest net price.

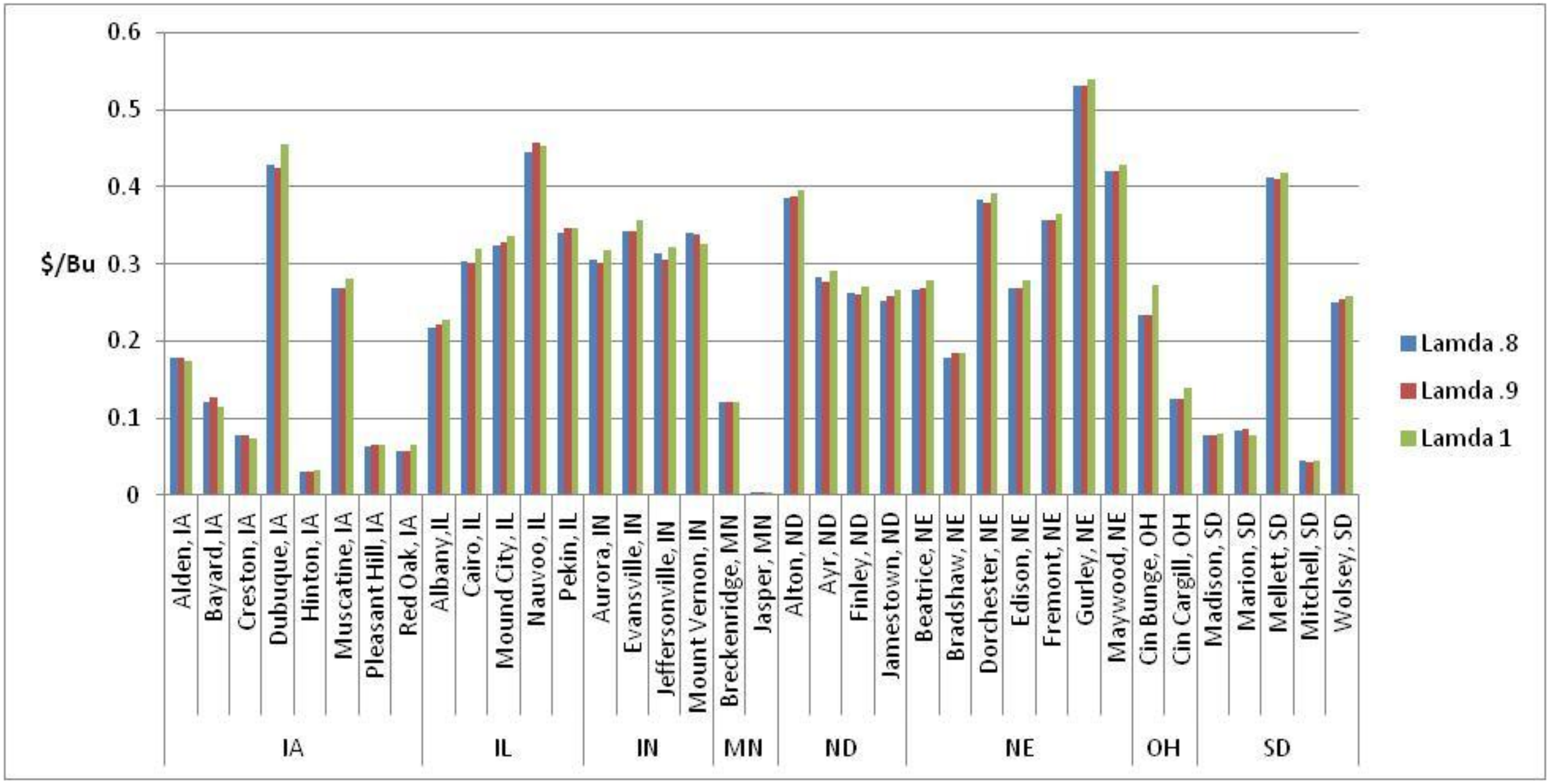


Figure 19. Adaptive to Changes in Risk.

Figure 20 shows that Albany, IL, is a location that was offering average-size arbitrage profits, but as σ increases to 20%, the profits for this origin increase. Then, as σ increases to 30% ,Albany's profits decrease. Alternate location's profits are greater, but the risk is also larger. Figure 20 proves that greater spatial-arbitrage profits are present, but capturing those profits depends on the amount of risk a firm is willing to allow.

As indicated in Chapter 3, an arbitrager only invests in a profitable arbitrage opportunity if the reward is worth the risk. If the arbitrage opportunity is not great enough for the amount of risk the firm would receive from the trade, then the market will remain non-integrated until those assets drift farther and increase the spatial-arbitrage profit. Once there is a greater spatial-arbitrage profit or the company allows more risk, the arbitrager will invest enough capital to trade those mispriced assets.

This sensitivity result clarifies that there are more spatial-arbitrage opportunities in the marketplace, but depends on the willingness to accept more risk. Some locations, such as Albany, IL, are a safer trade than locations such as Mellette, SD. This location might occasionally offer large spatial-arbitrage profits, but the majority of the time, the reward is not worth the risk. Most locations in Iowa, South Dakota, and Indiana have decreasing profits as σ is increased. Which indicates that these locations have a small amount of risk as well as spatial-arbitrage profits. North Dakota, Nebraska, and Illinois have greater spatial-arbitrage profits as σ increases, which means that these locations have more risk and are located closer to market boundaries.

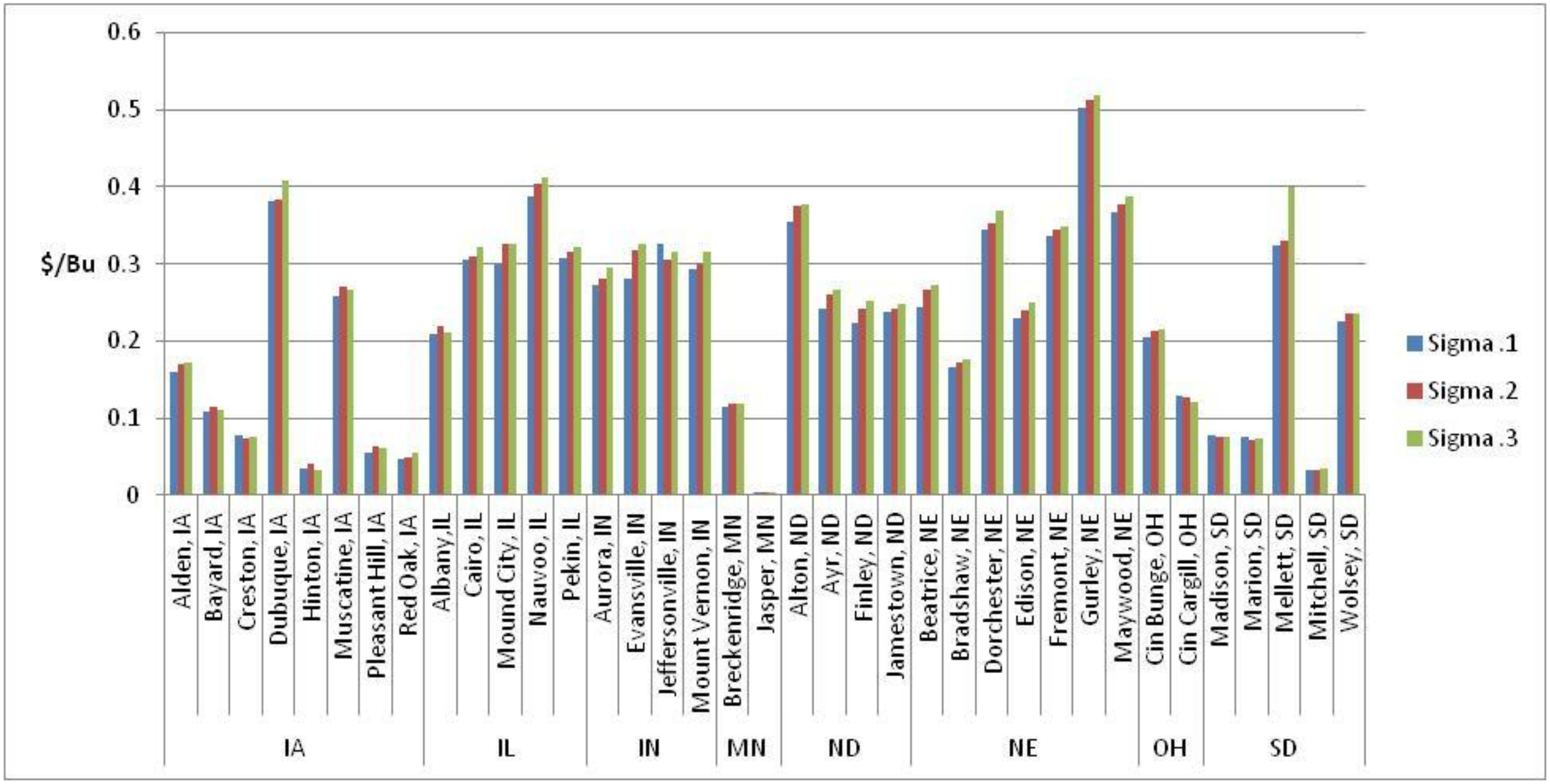


Figure 20. Risk Loving.

Increase in Shuttle-Train Loading Efficiency

This sensitivity addresses the increased loading capacity for a shuttle loader. The ability to increase an origin's loading capacity with average profits allows a greater amount of spatial arbitrage. The base-case restrictions imply that port facilities are only able to unload about 8,740,032 bushels in a week. This sensitivity allows for a firm to increase the loading capacity at Ayr, ND from one to five trains a week, and all the competitors are only able to load two trains in a week. By selecting only one location (Ayr, ND), this sensitivity determines the ability of one location to gain the maximum spatial-arbitrage opportunity available. The model specifications used for this sensitivity are the same as the vertical integration without ocean shipping sensitivity.

Figure 21 compares the profits for Ayr, ND, with Gurely, NE, when the maximum number of shuttle trains that they are able to load in a week goes from one to five.[9] Figure 21 identifies that investing in technology at an origin that returns average arbitrage profits can greatly increase the ability to gain arbitrage opportunity compared to a alternate location that has the greatest spatial-arbitrage profits in the base case. The spatial-arbitrage profits for Gurely, NE, remain the same as Ayr, ND, because a firm is more efficient at loading shuttle trains and their average arbitrage profits increase drastically. The increase in Ayr, ND, profits proves that there are greater spatial-arbitrage opportunities, but facilities are constrained to capture the full arbitrage potential.

Ayr, ND, increases its average arbitrage profit from $101,360 when loading 1 shuttle train to $596,726 for loading 5 shuttle trains. Increase a firms loading shuttle-train capacity from

[9] The appendix has a full table with all of the profits from increasing the trains from one to five.

one to five at Ayr, ND, only slightly affects other locations' ability to be selected by the empirical model.[10]

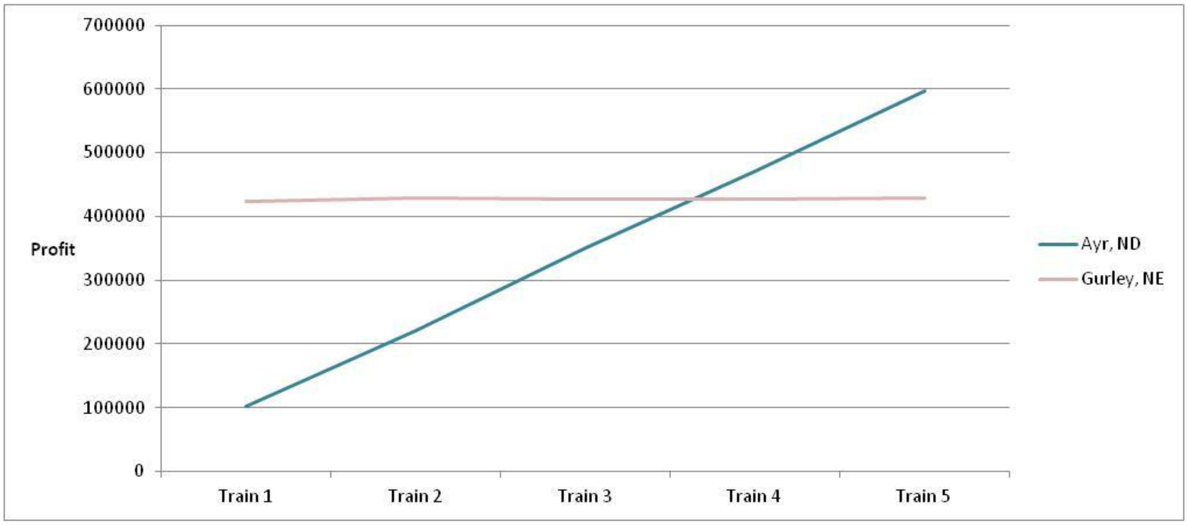


Figure 21. Increase in Shuttle-Train Loading Efficiency.

Buying Track or CIF NOLA/Sell FOB

This sensitivity is not vertically integrated and the firm is only trading soybeans at the port. In this case, the firm buys track and sells FOB. The difference is called the FOB margin, the difference in track basis and transferring soybeans from the railcar onto an ocean vessel. If the USG port is receiving soybeans via barge, it is called CIF NOLA basis. Again, the FOB margin, in this case, transfers the soybeans from the barge to an ocean vessel at the USG port. This sensitivity mainly determines when to sell FOB and when to buy Track or CIF NOLA. Both the PNW and USG ports have to constantly adjust their FOB basis bid as the ocean-shipping rates change. As indicated in Chapter 1, ocean shipping rates have become more volatile, so these locations have to constantly adjust their FOB basis bids to stay competitive

[10] The appendix contains tables with the probability of each origin being selected for each sensitivity, including the base case.

with each other. Similarly, the ports have to adjust their Track or CIF NOLA basis bids to maintain some FOB margin.

Buying Track or CIF NOLA basis and then selling FOB basis has similar profits to some origins in the basis case; is seen in Figure 22. Both the base case and this sensitivity are not vertically integrated, but they are still very different. Based on the results in Figure 22, the USG port offers greater arbitrage opportunities than PNW. The USG port, on average, has an arbitrage profit of $.09/bu, and the PNW port only offers an average arbitrage profit of $.05/bu. These profits are significantly smaller than if the company was vertically integrated from the origin to port to ocean vessels. The riskiness of the arbitrage opportunity increases as a firm becomes more vertically integrated, and is represented by Table 9. As indicated earlier, the profits from this strategy are not very high for the amount of risk involved. Of all of the integration steps, this strategy is, by far, the worst compared to other stages in the supply chain.

Vertical Integration Without Ocean Shipping

This sensitivity deals with a company that owns origin and port facilities. This firm would have the ability to purchase shuttle trains in advance compared to simultaneously buying/selling soybeans and buying transportation. This sensitivity is used to determine how becoming more vertically integrated allows a company to capitalize further on spatial arbitrage, but this company would also inherit more risk. This added risk is found in Table 9. Becoming more vertically integrated increases the profits and risks because there are more stages in the transfer of goods. A vertically integrated company is able to capitalize on the FOB margin discussed for the previous sensitivity for buying track or CIF NOLA/selling FOB by being more integrated, also from shipping between origin and destination. Figure 22 shows the results from the base case and sensitivity buying track or CIF NOLA/selling FOB to fully integrated owning ocean shipping. From the results in Figure 22 it is obvious to see that becoming more vertically integrated spreads the risk and increases profit compared to the previous sensitivity.

Gurley, NE, has the greatest arbitrage profits of $.47/bu. From these results, a couple key points are intriguing. First, the key locations around the market boundaries are able to be singled out in Figure 22, and becoming more vertically integrated increases the arbitrage profits.

By using these empirical models, it would be easy to determine where companies should be investing their capital for country elevators to gain spatial-arbitrage profits. As a company becomes more vertically integrated, the average probability that an origin is selected for the portfolio changes. The results show that some locations are selected more because they exhibit greater spatial-arbitrage profits due to the company being more vertically integrated. In Figure 22, comparing Aurora, IN, the arbitrage profits increase, on average, $.37/bu, and this location's probability of arbitrage opportunities increases from 55% to 81%. The reason the spatial-arbitrage opportunities increase with vertical integration is because the company already owns the assets it needs to profit from the spatial arbitrage, so it gains from the weekly basis change. The location is subject to basis risk. For risk-adverse arbitragers, this strategy is second best to become vertically integrated.

Vertical Integration with Ocean Shipping

Vertical integration with ocean shipping is only different from the previous sensitivity because it allows the company to own the right to ship soybean bushels in advance via ocean shipping. Going from non-vertically integrated to full vertical integration creates a $.25/bu increase in the average spatial-arbitrage profits. By including ocean shipping in this sensitivity, the spatial-arbitrage profits increase by $.11/bu compared to the previous sensitivity. The extra $.11/bu comes from becoming more vertically integrated with ocean shipping for the two ports analyzed in this thesis. The conclusion from this sensitivity, along with the other sensitivities, is that there is spatial arbitrage along the entire supply chain, which is why the profits increase as we continue to add assets. The risks also increase, which is explained in Table 9.

Origins such as Ayr, ND, have average spatial-arbitrage opportunities increase from 60% for the base case to 69% for the vertically integrated with ocean shipping sensitivity. Ayr, ND, consistently ships to the PNW as its firm becomes more vertically integrated. Iowa, South Dakota, and Minnesota are all poor locations to expand vertically integrated. North Dakota, Nebraska, and Illinois all have good origins to include in the expansion of vertical integration.

Again, the added profits are from the added assets to the companies. There is a lot more flexibility for a company that is vertically integrated. A company is more aware of the changes at each stage of the supply chain. Being more integrated allows the merchandiser to plan in advance in order to capture the spatial arbitrage to its fullest potential.

Table 9. Portfolio Profits.

Sensitivity	Profit	STDEV	1/CV	7 Day VAR	
				1%	5%
Base Case	$3,685,545	$2,380,735	1.55		
VI w/o Ocean	$6,573,203	$4,802,950	1.37	$(5,647,255)	$(4,867,808)
VI w/ Ocean	$9,727,407	$11,444,601	0.85	$(10,037,396)	$(9,521,198)
Sell FOB/Buy Track	$2,335,716	$3,255,609	0.72	$(2,325,481)	$(1,370,956)

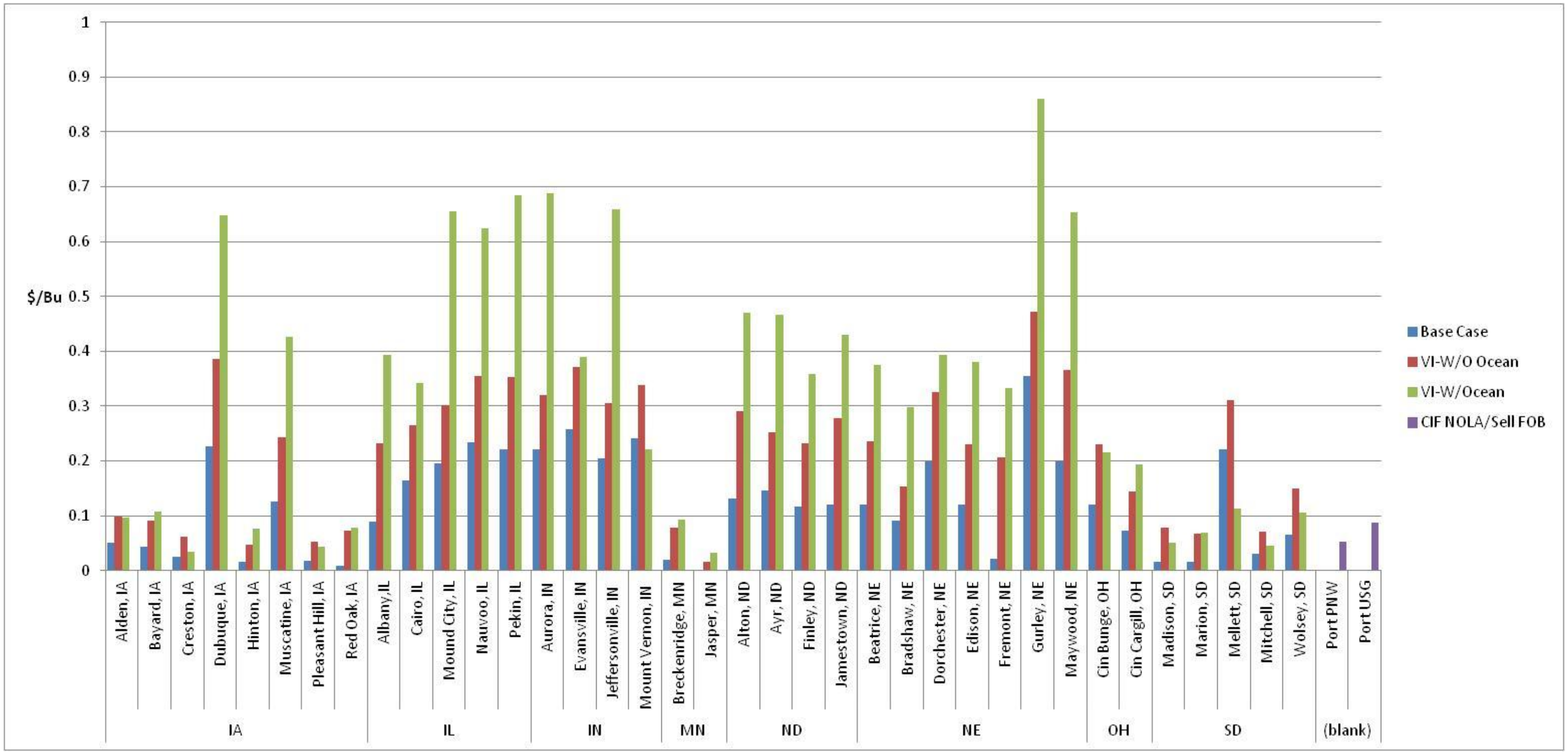


Figure 22. Non-Integrated to Vertically Integrated with Ocean Shipping.

From Table 9, it is easy to see that, when becoming more vertically integrated, the portfolio's profits increase significantly. The Selling FOB/Buying Track or CIF NOLA sensitivity has the smallest portfolio profits because it only capitalizes on the spatial arbitrage at the port. For every dollar increase in the Sell FOB/Buy Track, the standard deviation, or risk, increases by 72%. There is greater risk trying to arbitrage the FOB margin or the PNW track with the PNW FOB compared to the other sensitivities. The VAR is much smaller for this sensitivity because Selling FOB/Buy Track deals with smaller quantities and the potential profits are much smaller, hence the maximum at risk is $2,325,481, with 99% confidence under normal market conditions.

Table 9 shows that ocean shipping has become more risky (Wilson and Dahl, 2011). Both sensitivities that include ocean shipping have the worst 1/CV (coefficient of variation) ratio and VAR. The base case and vertically integrated without ocean shipping sensitivities have the greatest return for the risk. The portfolio theory suggests that an investor would prefer to participate in a portfolio of assets that earns higher profits with the least amount of risk. Table 9 shows results that are very important for a company trying to discover whether a firm would be willing to invest capital to become more vertically integrated and how vertically integrated the firm wants to be in the supply chain.

Comparing Figure 23, 24 and 25 illustrates that the probability of earning higher profits for a portfolio is much higher the more vertically integrated a firm. Each stage in the supply chain has a lognormal distribution. Because these sensitivities are a simulation optimization model, there is never a portfolio profit that is less than zero.

Becoming more vertically integrated increases the portfolio's profits as seen in Table 9, but the sensitivity that seems to have the most reward for the risk is the base case which is non-

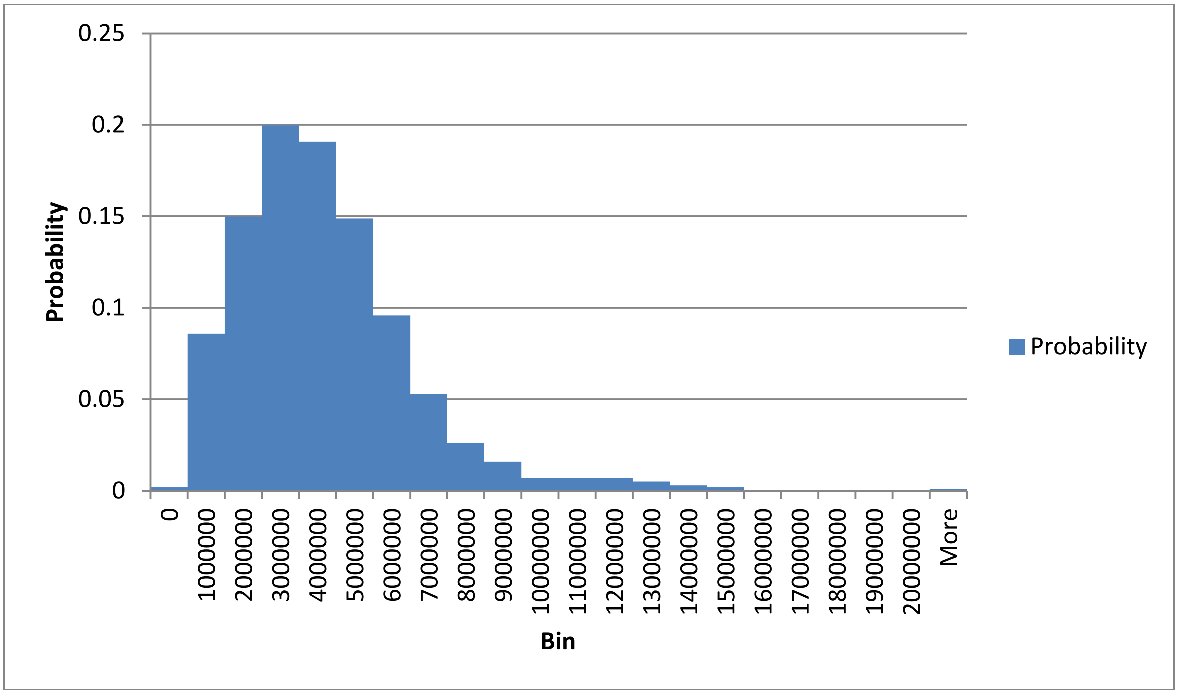


Figure 23. Copula Base-Case Portfolio’s Profit/Week Distribution.

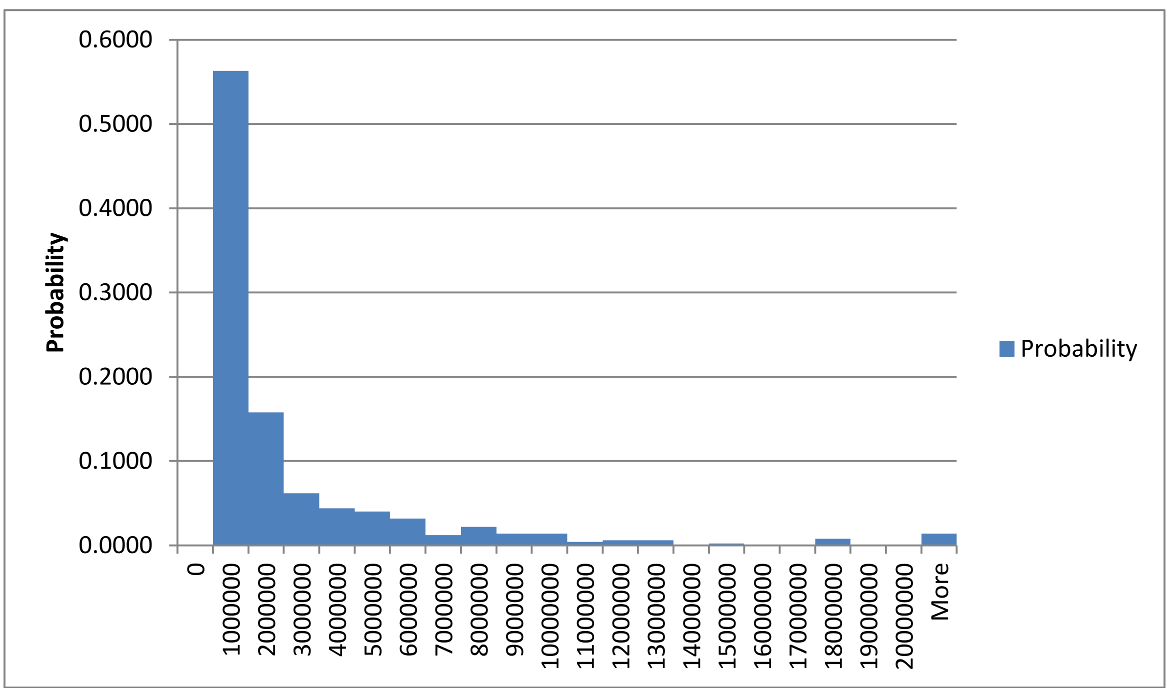


Figure 24. Copula Buy Track or CIF NOLA/Sell FOB Portfolio Profit/Week Distribution.

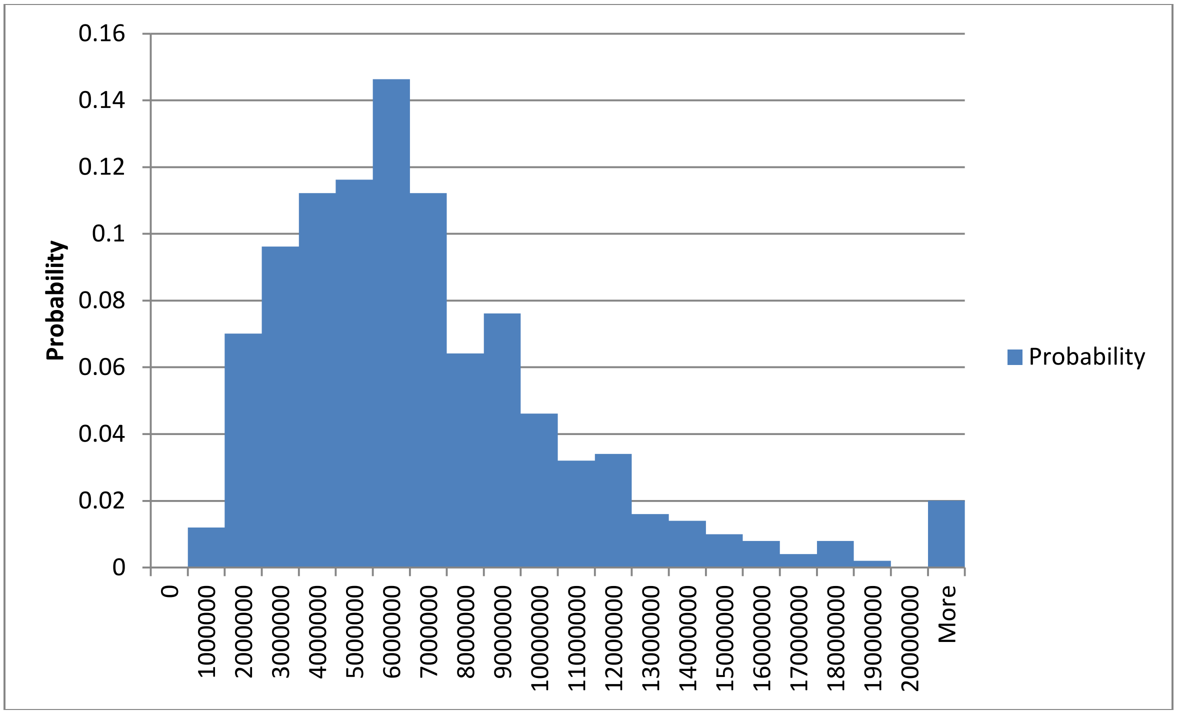


Figure 25. Copula Vertical Integration W/O Ocean Ship Port Profit/Week Distribution.

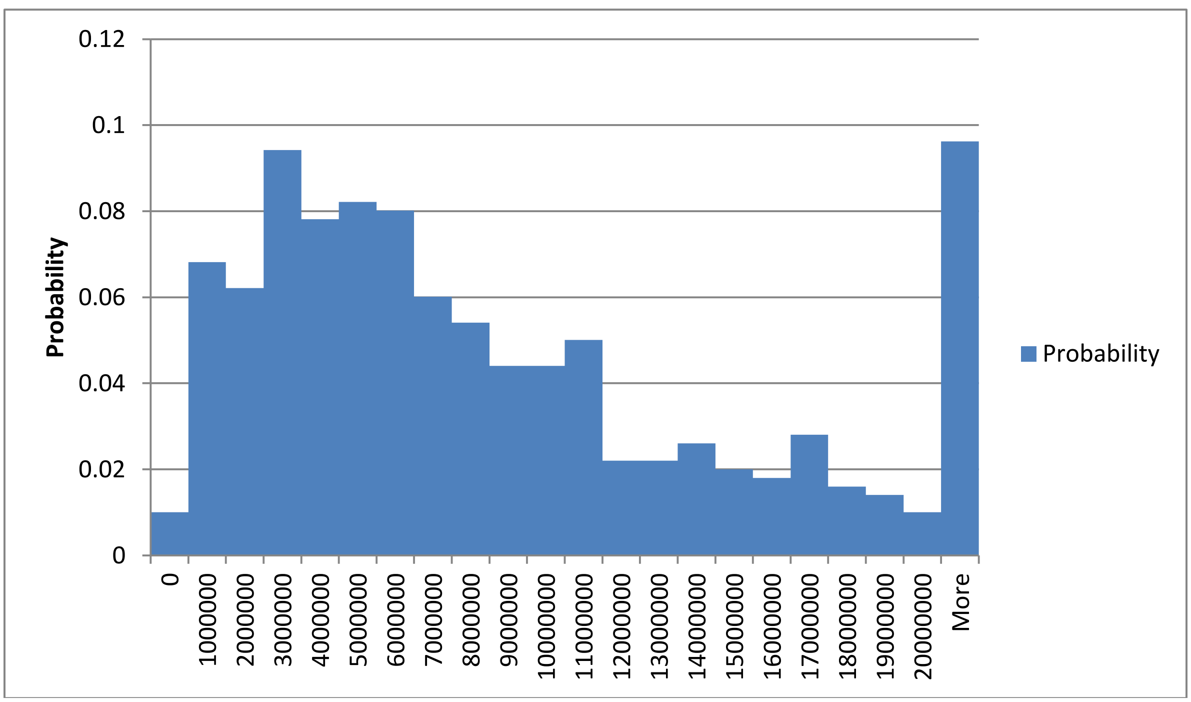


Figure 26. Copula Vertical Integration W/Ocean Ship. Port Profit/Week Distribution.

integrated. From the 1/CV ratio, the base case is the most rewarding for the amount of risk, but the base case is not vertically integrated and is only trading locations that deliver spatial arbitrage simultaneously.

Summary

This chapter presents results from the Copula Risk Constrained Optimization models that were developed for each sensitivity in Chapter 4. From the sensitivity results discussed in this chapter, there is a better understanding about the spatial-arbitrage profit opportunities and risks for each sensitivity. The base case, adaptive to changes in risk, risk loving, shuttle-loading efficiency, vertically integrated without ocean shipping, vertically integrated with ocean shipping, and sell FOB/buy track or CIF NOLA sensitivities are reviewed using copula as the dependence measure and an empirical distribution. Results for the Normal Risk Constrained Optimization models are quite similar and are located in the appendix.

The base case is the most normal sensitivity, and it proves to provide the greatest reward for the risk presented in Table 9. The base case represents a non-vertically integrated company. Vertically integrated without ocean shipping is deemed to be the second-best outcome for the average spatial-arbitrage profits for the risk. Once a company adds ocean shipping to its portfolio, the profits for the amount of risk decrease. The sensitivity involved with selling FOB and buying track or CIF NOLA is indicated as the worst portfolio of assets.

The sensitivities regarding changes in risk, along with whether a company is more risk adverse or risk loving, are presented in Chapter 5. These results indicate that, as a company becomes more risk loving, it purchases fewer soybeans from the least risky locations and more soybeans from the more risky, but more profitable, origins. The risk-loving sensitivity results allow this research to discover locations that are close to market boundaries.

Similar to the risk-loving sensitivity, the sensitivity concerned with becoming adaptive to changes in risk shows how the market boundaries have shifted to alternate locations. These sensitivities provide useful information for companies interested in spatial-arbitrage soybeans. Companies can decide from what origins they would benefit the greatest for the investment of their working capital. The result also provides information about whether a company wants to become more vertically integrated.

CHAPTER 6. CONCLUSION

Problem

Commodity-trading firms traditionally traded soybeans via barge to the USG, and there was little volatility in transportation and soybean basis. The agriculture industry has seen many changes, including increased volatility for the futures price, basis, and transportation costs. Commodity traders have to analyze many variables to develop a profitable trading strategies. Risk is important to assess the profitability of trading strategies. Where to buy, through what port to sell, and by what mode of transportation are decisions that reduce the portfolio's risk. Transportation, grain inventory, etc. should be planned in advance to effectively arbitrage. "Arbitrage" is a term that refers to the ability to profit from mispriced assets. The profitability that comes from the trading strategy is called spatial arbitrage.

Spatial arbitrage can arise from many of the changes seen in the agriculture industry, such as the increased volatility in ocean shipping, railroad, barge transportation, and soybean basis. This added risk makes it more difficult for the soybean market to be integrated, allowing short-term spatial arbitrage opportunities. There has been a greater demand for soybeans from China, which influences the market's boundary lines. Other factors influencing the boundary lines are the capacity limits at the Panama Canal, which is similar to the export pipeline that is at capacity at Cushing, Oklahoma. As a result, there are short-term spatial-arbitrage opportunities in the marketplace, and soybean trading firms could be interested in capitalizing on these profitable opportunities.

Traditionally, the companies involved with soybean trading relied on many different facts when discovering where to invest working capital for a country elevator. The ability to capture some of the spatial-arbitrage profits on the table is a new factor to consider when investing working capital in country elevators. Other alternatives are making improvements to existing facilities to make them more efficient by increasing the shuttle-train loading capacities. Becoming more vertically integrated may allow a country elevator to capture spatial arbitrage throughout the entire supply chain. Some stages in the supply chain may offer more spatial-arbitrage profits while other stages may offer a greater amount of risk.

The increased volatility in ocean shipping, railroad, barge transportation, and soybean basis causes market boundaries to shift more often. There has been much controversy about the law of one price, which was reviewed in Chapter 2. Competitive intermarket prices are due to the theory about the law of one price. This theory states that markets should efficiently function so that any potential profits through arbitrage trade are eliminated. The soybean-basis volatility has increased from $.10/bu to $.30 a bushel (Wilson and Dahl, 2011). Since 1980, China's soybean demand increased fourfold to 34.4 million metric tons (Tuan, et al., 2004). Ocean shipping, railroad, and barge rates have not only become more volatile, but they have also seen an increasing trend in price. However, the railroad industry has become more competitive with the barge industry. This transportation change has a huge influence on the market boundaries. Origins that, before, would always ship via barge have more choices. Because the railroad has a more competitive rate, some origins are more likely to be indifferent about the port to which they are going to sell.

Objectives

The boundaries have shifted for the soybean market, and there has been an increased flow towards the PNW. Spatial-arbitrage opportunities exist due to the market-boundary shifts. Key contributors were discussed in great detail in Chapter 1. The main objective is to capture spatial arbitrage so that a trading strategy can be developed with a limited amount of risk. The empirical model repetitively develops a portfolio that maximizes profits with a limited amount of risk. From the repetitive optimization, the results show which origins have the potential for the greatest spatial-arbitrage profits and how often, on average, that spatial-arbitrage opportunity arises.

From the empirical models developed in this thesis, the origins that offer the greatest spatial-arbitrage opportunities in the soybean markets are located. This time frame is when bio-fuels and ethanol became a major player in the domestic demand for soybeans. This added demand created an increase in production for soybeans. China's demand for soybeans overwhelmed the expected demand for 2004 to 2009. From the sensitivities' empirical models about being risk loving and adaptive to changes in risk, the research is able to discover shifts in the market boundaries. An empirical model is created to analyze the benefits from upgrading an origin's shuttle-train loading capacity by choosing an origin that gains average spatial-arbitrage profits from the base case.

The other empirical models hope to discover the profitability from spatial arbitrage as a non-vertically integrated grain-trading firm compared to a vertically integrated firm. From this empirical model, the research seeks to quantify if the added profits from becoming more vertically integrated are worth the added risk to which a company is exposed. The empirical models tests whether becoming more vertically integrated is worth the added arbitrage profit. The stages go from non-vertically integrated to integrated by owning origin facilities and port facilities. Next, the stage of just arbitraging the difference between FOB basis and tack basis or CIF NOLA basis is analyzed. The final vertically integrated stages test a firm that owns origin facilities, port facilities, and ocean freight.

Empirical Methodology

Price discovery is an important concept to understand intermarket relationships. A perfectly competitive market assumes that all buyer and sellers have perfect market knowledge, that each buyer and seller act economically, and that there are zero barriers of entry in all directions. In theory, the price-discovery process would locate the true market-equilibrium price. Perfectly competitive markets always shift commodities to the trade deficit market, but these markets are rare. Most markets operate less than perfectly because they are lacking one assumption of a perfectly competing market. When a market operates in a less-than-perfect manner, there are trade deficits, and that market may never satisfy the consumers' demand until arbitragers discover the mispriced basis bids. At some point in time, a demand surplus does occur in all markets. Price discoveries, the theory of competitive spatial market price, and the theory about the law of one price are all highly related concepts for market integration and spatial arbitrage.

Spatial price relationships are determined by two main factors. Supply and demand determine the equilibrium basis. As the basis at each region changes, it can alter the flow of commodities between regions. Similar to the changes in basis, changes for the transfer costs between regions can alter the flow of commodities between regions. Each supplier can sell to either market, but the market offering the largest basis will receive the supplier's produce, eliminating any trade deficit.

A model of spatial arbitrage is where profits from buying origin soybeans, shipping, and selling at export locations are positive. The random variables are the soybean basis at each origin, transportation costs, and destination basis. Basis data for 37 origins in the Upper Midwest and along the Mississippi River from 2004-2009 are used for this research. The Pacific

Northwest and United States Gulf are the two ports, or destinations, to which each origin is shipping when spatial-arbitrage opportunities arise.

The extensive data set used for this research was collected and used in Wilson and Dahl (2011). The soybean basis was weekly data from 2004-2009. Some of the data used in Wilson and Dahl (2011) were collected in O'Neil (2010).

A simulation optimization model was specified in Chapter 4 and was subject to constraints that limit the decision variables or bushels. The model also forced an equal number of bushels to be purchased from the origin, sold at the port, and with the appropriate amount of space by some mode of transportation. Monte Carlo simulation was used to capture the randomness for these variables. The random variables in the simulation optimization model were highly correlated, and that correlation needed to be captured.

Distributions for the underlying data were assessed to determine the appropriate marginal distribution and correlation that would suffice, overall, as the best dependency measure. In most cases, the resulting distributions were non-normal. Because the distributions were non-normal, copula was selected as the most appropriate way to replicate the relationship between the random variables in the simulated optimization model. Copula is a much more complex dependency measure, but the importance of measuring non-normal distributions in the data set with the appropriate dependence measure cannot be stressed enough. Copula was introduced by A. Sklar in 1959 when he was answering a question about the multidimensional probability function and its lower dimensional margins by M. Frechet and G. Dall' Aglio. M. Frechet and G. Dall' Aglio asked Sklar the question about their work on bivariate and trivariate distribution functions with given univariate margins.

Copula methods were used to determine the most appropriate copula. The Gaussian copula was selected as the most appropriate dependence relationship because there were 87 variables for this research. A Student t copula would probably be more significant, however, if the degrees of freedom are greater than 30 the Student t converges to a Gaussian copula. The scatter plots for the original data set are represented very well by the Gaussian copula, which is displayed in Chapter 5. Instead of using a normal distribution such as the Normal Risk Constrained Optimization models, the Copula Risk Constrained Optimization models use an empirical distribution which takes the exact form of the original data set.

The Copula Risk Constrained Optimization model was evaluated as the base case, and these results were compared to the Normal Risk Constrained Optimization model for illustration. Normal Risk Constrained Optimization was not an appropriate method to represent the base case because a majority of the variables had a non-normal distribution and had a non-linear relationship. Finally, a number of interesting sensitivities were evaluated, such as being adaptive to changes in risk, risk loving, buy track or CIF NOLA/sell FOB, vertically integrated without ocean shipping, vertically integrated with ocean shipping, and an increase in shuttle-train loading efficiency.

Summary of Results

The objective of this research was to develop a portfolio of origins that can maximize profit from spatial arbitraging to the PNW or USG. There were 37 origins located throughout the Upper Midwest and along the Mississippi River. The two destination locations were the Pacific Northwest and the U.S. Gulf ports. Railroad, barge, and ocean shipping were the modes of transportation used in this research. The repeated optimization was accomplished through Monte Carlo simulation, which allows the simulated optimization model to pull random draws from distributions created by the original observations. The new random variables were placed into the seven models specified to capture the thesis objectives. The seven empirical models were the base case, risk loving, adaptive to changes in risk, increase in shuttle-train loading efficiency, vertically integrated without ocean shipping, vertically integrated with ocean shipping, and sell FOB/buy track or CIF NOLA. These empirical models are all very similar and are very similar to a profit function. Revenue is the destination basis, and the costs are origin basis and transportation rates.

The base case is designed to represent the simplest scenario and is easily compared to the other sensitivities. From the base case, it is not possible to recognize past boundary lines, but existing boundary lines are easily seen by the origins representing the greatest weekly average spatial-arbitrage profits. The average spatial-arbitrage profit across all locations is about $.12/bu, with a standard deviation of about $.09/bu for the base case. Gurley, NE, has the greatest weekly average spatial-arbitrage profits, indicating that this origin is the closest to the market boundary line between the PNW and USG. Gurley, NE, has the greatest spatial-arbitrage profits of all locations at $.35/bu and is selected 82% of the time. Gurley, NE, shipped to the USG 82% of the time. Dorchester, NE, has average arbitrage profits of $.20/bu, shipping to the PNW 39% of the time and to the USG 27% of the time. The results have a lognormal distribution with large right-hand tails for each origin and as a portfolio. Comparing Normal Risk Constrained Optimization with Copula Risk Constrained Optimization, both models have lognormal distributions. Normal Risk Constrained Optimization output has a greater probability of $100,000 than Copula Risk Constrained Optimization, which has a greater probability of $0, for Ayr, ND.

The risk-loving sensitivity is used to compare the base case whether allowing a company to accommodate more risk for a greater spatial-arbitrage profits for the portfolio. Adjusting σ, which is the portfolio's variance transformed to the standard deviation, will allow the researcher to discover origins with greater amounts of risk. Locations with the greatest amount of risk also provide more spatial-arbitrage opportunities. Hence, the less risky location's basis does not change very often, creating fewer chances for spatial-arbitrage opportunities. These origins are much more risky because they are located on the market boundary between the PNW and USG. Origins in the Upper Midwest have the greatest increase in profits as the risk constraint, σ, is increased from .1 to .2 and .3 standard deviations. Gurley, NE is also a location that has increased profits as σ increased; however, its average weekly profits per bushel did not increase the most of the 37 origins. These results are an indicator that Gurley, NE, is already shipping at capacity. To allow the portfolio to accommodate more risk, the model selects the next locations that could maximize the portfolio's spatial-arbitrage profits. These locations are relatively close to the market boundaries.

As explained in Chapter 4, this sensitivity uses model specifications that are similar to the vertical integration without ocean shipping model. The difference between these two sensitivities is that the empirical model for being adaptive to changes in risk sensitivity uses the exponential weight moving average (EWMA) to aid in calculating the portfolio's variance. The EWMA is used to forecast volatility by weighting the historical data set differently through time by adjusting λ. Most commonly, λ is set at .94 for forecasting volatility, but for this sensitivity, the objective is to determine how the empirical model selects alternate origins as λ is adjusted from .8 to .9 and 1. If λ is .8, the firm is more adaptive to changes in volatility because it places more weight on the most recent observations. The results from this sensitivity reveal origins that used to be relatively close to market boundaries, but as changes in the agriculture industry continue, these boundary lines shift to new locations. Alton, ND, has become more risky in recent years, but placing more of an equal weight across observations, this origin was less risky in the past. The greater variability in Alton, ND, is because of agriculture changes in recent years that were explained in Chapter 1. Alton, ND, could be closer to the market boundary in recent years. Being located close to the market boundary, an origin basis would adjust constantly while outside influences shift the destination market and where Alton, ND, will sell its soybeans.

An increase in the shuttle-loading efficiency sensitivity is regarding the increase in the loading capacity for a shuttle loader. The ability to increase an origin's loading capacity with average profits greatly increases its chance for capturing a greater amount of spatial arbitrage. The port facilities are only able to unload about 8,740,032 bu a week. The loading capacity constraints for Ayr, ND increase from one to five trains and all of the competitors are only able to load two trains in a week. By only selecting one location (Ayr, ND), this sensitivity is able to determine the ability of this one location to capitalize on the maximum spatial-arbitrage opportunity available.

The vertical-integration sensitivities are the most interesting of the empirical models that were estimated. These results are used to determine how the profits and risk increase as a company becomes more vertically integrated from the base case to vertically integration that includes ocean shipping. These sensitivities also show how the difference in the ocean shipping rates from PNW or USG affects the decision about what port to use when selling soybeans. These sensitivity results allow a firm to see how vertically integrated the company should be to capture more spatial-arbitrage profits. A firm that owns a facility at Gurley, NE, is non-integrated, or base case, at $35/bu and is vertically integrated at $.86/bu. Hence, the greatest returns are from origins that are able to load as many trains in a week as possible because the ports can only unload 8,740,032 bu a week. If a firm is concerned with the earnings/risk ratio, nonintegrated is less risky for the amount of profit. As a portfolio, a non-integrated firm has the best profit for the amount of risk with a ratio of 1.58, meaning that the profit is 1.58 times the risk.

Contributions and Implications

This thesis' contribution is to the research about market integration, market efficiency, the law of one price, and spatial arbitrage. Researchers that use Parametric and nonparametric modeling have been debating the law of one price for many years.

The study done by (Borenstein and Kellogg, 2012) about the increasing spread between the West Texas Intermediate (WTI) oil price and Brent crude oil is highly related to the thesis objectives. Oil has different grades, but in reality, they should have similar prices through arbitrage. Before oil fracking in North Dakota and Canada, the WTI and Brent crude oil had similar prices (Borenstein and Kellogg, 2012). This study used a basic parametric model, such as an OLS model, to regress price changes for crude oil and Midwest fuel prices.

China has gone through a great economic transition since 1988. China is interested in how integrated its commodity marketplace is compared to historical market integration across a time period of great policy changes (Park, et al., 2002). China is interested in how well merchandisers are able to detect spatial arbitrage. In the research for this paper, researchers use a parametric model, such as a parity-bounds model, that follows Baulch (1997) and Sexton et al. (1991). Next, the conventional innovation-accounting procedures, such as the Granger causality, impulse functions, and impact multipliers are used to generate insights about the nature of adjustment between the U.S. and Canadian livestock markets. These tests are just to show how quickly the country responds to shocks in other countries. Researchers use a parametric model, such as the vector autoregressive (VAR) model, because it is not necessary to transform non-stationary data to stationary data. Copula is used to test market integration through time in oriented strand board in the United States (Goodwin, et al., 2011). Copula is just an input for a vector autoregressive model is combined, into a non-parametric model.

In this thesis, a model of spatial arbitrage is where profits from buying origin soybeans, shipping them, and selling them at export locations are positive. The random variables are soybean basis at each origin, transportation costs, and destination basis. Basis data for 37 origins in the Upper Midwest and along the Mississippi River from 2004-2009 are used in this research. The Pacific Northwest and United States Gulf are the two ports, or destinations, to which each origin is shipping when spatial-arbitrage opportunities arise. The model also forces an equal number of bushels to be bought from the origin, transported, and sold at port. Monte Carlo simulation is used to capture this randomness for these variables. The random variables in the simulated optimization model are highly correlated, and that correlation needs to be captured.

Distributions for the underlying data were assessed to determine the appropriate distribution and correlation that would suffice, overall, as the best dependency measure. In most cases, the resulting distributions were non-normal. Because the distribution was non-normal, copula was selected as the most appropriate way to replicate the relationship between the random variables in the simulated optimization model.

This thesis is different than previous literature because multiple origins and destinations are analyzed for potential spatial-arbitrage opportunities. The profits from spatial arbitrage at these origins are included in the results, and the literature reviewed in this thesis is only concerned with how well the market is related or integrated. The results in this research can be used to determine, on average, how often each origin has an arbitrage opportunity. The thesis research can be utilized to determine if the markets are integrated the same way as the literature review. A parametric model, such as a quadratic programming model, is used in this research. Because copula is used, it allows the quadratic programming model to become more of a non-parametric model. The empirical model in this thesis creates a portfolio and considers risk as a constraint on spatial-arbitrage profit.

This research used the soybean basis market to establish short-run arbitrage opportunities, which coincides with the most recent research on market integration and the law of one price. The nonparametric model used in this research also obtains the percentage of time that each origin has spatial-arbitrage profits. With this research, a firm is better able to select strategies for where it would like to make improvements to existing country elevators or where it would like to purchase and build new country elevators to capture spatial-arbitrage profits.

Research conducted for this thesis supports the changes in agriculture that were exemplified in previous research, such as (Wilson and Dahl, 2011). There has been a change in the agriculture industry since 2004; the boundary lines have noticeably shifted. The shift in the boundary lines is what caused the spatial-arbitrage opportunity.

The research from this thesis also suggests there are very high similarities between the U.S. soybean market and the WTI oil market in (Borenstein and Kellogg, 2012), because both have spatial-arbitrage opportunities and barriers aiding in the spatial arbitrage. The Panama Canal is at capacity, restricting any further flow of soybeans through the USG to China, and the WTI export pipeline has reached capacity, limiting the amount of oil shipped for export. It has been noted in (Wilson and Dahl, 2011) that there are soybean-quality differences from production in northern states to southern states. The southern states have a much higher protein and oil content than northern-producing states. China would much rather receive its soybeans from the USG than the PNW.

Some major implications from this research are the size of spatial-arbitrage opportunities, such as $.35/bu at Gurley, NE. These spatial-arbitrage opportunities very geographically, such as Iowa and Minnesota locations having very few spatial-arbitrage opportunities. North Dakota, South Dakota, and Nebraska all have average or above average spatial-arbitrage profits. The vertical-integration sensitivity suggests that the greatest return for the risk is a non-integrated firm. A fully integrated firm has the greatest spatial-arbitrage profits but has a larger amount of risk.

The transportation costs do not make up all the costs of transferring goods from point A to point B. An assumption is made that all locations should have very few differences between the remaining transfer costs. This assumption may bias the results upwards slightly, but origins with the greatest spatial arbitrage would still be considered the most profitable for spatial arbitraging soybeans.

Further Research

Future research could expand on the empirical models developed in this research to include a data set to analyze international spatial arbitrage, such as Brazil and Ukraine. The data set used in this research was only concerned with domestic spatial arbitrage but was expanded to see how market boundaries change when soybeans were shipped to Japan. Data could also be gathered to examine alternate commodity markets to see how those markets compare with the soybean market. It would be interesting to see how the quality difference in the soybean market compares to the wheat market. The wheat market considers quality differences, offering premiums and discounts to accommodate various quality characteristics.

The empirical model created for this thesis could also be expanded to specialty crops that are commonly imported from Canada or Mexico to see how they influence domestic price relationships. These results could aid in policy decisions and, potentially, barriers created by current policies.

The data used in this thesis are from 2004-2009, so the origin and destination basis, as well as the transportation costs, could be updated. Also, a greater number of origins within the United States could be added to the data set to better analyze market boundaries. To complicate the model, further quality characteristics could be included to determine how quality differential affects spatial arbitrage and the flow of soybeans from the central United States. As markets become more volatile, there is greater difficulty abiding by the law of one price. There will always be some short-run spatial arbitrage profits for commodities until technology is developed to streamline the supply chain.

REFRENCES

(2013) "Linear Programming and Quadratic Programming." In., pp. Premium Solver.

Ali, A., L.-S. Hwang, and M.A. Trombley. 2003. "Arbitrage Risk and the Book-to-Market Anomaly." *Journal of Financial Economics* 69:355-373.

Ardeni, P.G. 1989. "Does the Law of One Price Really Hold for Commodity Prices?" *American Journal of Agricultural Economics* 71:661.

Baulch, B. 1997. "Transfer costs, Spatial Arbitrage, and Testing for Food." *American Journal of Agricultural Economics* 79:477.

Borenstein, S., and R. Kellogg. 2012. "The Incidence of an Oil Glut: Who Benefits from Cheap Crude Oil in the Midwest?" National Bureau of Economic Research.

Bressler, R.G., and R.A. King. 1970. *Markets, prices, and interregional trade*: Wiley.

Buongiorno, J., and J. Uusivuori. 1992. "The Law of One Price in the Trade of Forest Products: Co-Integration Tests for U.S. Exports of Pulp and Paper." *Forest Science* 38:539-553.

Chavas, J.-P., P.M. Despins, and T.R. Fortenbery. 2000. "INVENTORY DYNAMICS UNDER TRANSACTION COSTS." *American Journal of Agricultural Economics* 82:261.

Cherubini, U., F. Gobbi, S. Mulinacci, and S. Romagnoli. 2012. *Dynamic Copula Methods in Finance*: John Wiley & Sons Ltd.

Clark, T.A. 1984. "Violations of the Gold Points, 1890-1908." *The Journal of Political Economy*:791-823.

Denicoff, M.R. 2007. "Ethanol transportation backgrounder: Expansion of US corn-based ethanol from the agricultural transportation perspective." USDA

Engle, R.F., and C.W.J. Granger. 1987. "CO-INTEGRATION AND ERROR CORRECTION: REPRESENTATION, ESTIMATION, AND TESTING." *Econometrica (1986-1998)* 55:251-251.

Flores, H.M. 2011. "Opportunistic Fresh Produce Commercialization under Two-Market Disintegration." ARIZONA STATE UNIVERSITY.

Goldberg, P.K., and M.M. Knetter. 1997. "Goods prices and exchange rates: What have we learned?" *Journal of Economic Literature* 35:1243-1272.

Goodwin, B.K., M.T. Holt, G. Onel, and J.P. Prestemon 2011 "Copula Based Nonlinear Models of Spatial Market Linkages." In. Pittsburgh, Pennsylvania, Agricultural and Applied Economics Association.

Haigh, M.S. 1999. *Volatility spillovers between foreign exchange, commodity and freight futures prices : Implications for hedging strategies*. College Station, TX: Dept. of Agricultural Economics, Texas A & M University.

Hummels, D. 2007. "Transportation costs and international trade in the second era of globalization." *The Journal of Economic Perspectives* 21:131-154.

Isard, P. 1977. "How Far can We Push the 'law of one price'?" *The American Economic Review* 67:942-942.

Lutz, C., C. Praagman, and H. Luu Thanh Duc. 2006. "Rice market integration in the Mekong River Delta." *Economics of Transition* 14:517-546.

Luu, T., and D. Hai. 2003. "The Organization of the Liberalized Rice Market in Vietnam." University of Groningen.

Markowitz, H. 1952. "Portfolio Selection." *The Journal of Finance* 7:77-91.

McNew, K. 1996. "Spatial market integration: Definition, theory, and evidence." *Agricultural and Resource Economics Review* 25:1-11.

McNew, K., and P.L. Fackler. 1997. "Testing market equilibrium: is cointegration informative?" *Journal of Agricultural and Resource Economics*:191-207.

Miljkovic, D., G.K. Price, R.J. Hauser, and K.A. Algozin. 2000. "The barge and rail freight market for export-bound grain movement from midwest to Mexican Gulf: an econometric analysis." *Transportation Research Part E: Logistics and Transportation Review* 36:127-137.

Minot, N., and F. Goletti. 2000. *Rice market liberalization and poverty in Viet Nam*: International Food Policy Research Inst.

Nelsen, R.B. 2006. *An introduction to copulas*. 2nd ed. New York: Springer.

Nicholson, W., and C.M. Snyder. 2007. *Intermediate Microeconomics and Its Application*: Thomson Learning EMEA, Limited.
---. 2008. *Microeconomic theory: basic principles and extensions*: Thomson/South-Western.

O'Neil 2010 "Transportation and The Farmers Bottom Line." In *Commodity Consulting.*

Park, A., H. Jin, S. Rozelle, and J. Huang. 2002. "Market emergence and transition: arbitrage, transaction costs, and autarky in China's grain markets." *American Journal of Agricultural Economics* 84:67-82.

Park, H., J.W. Mjelde, and D.A. Bessler. 2007. "Time-varying threshold cointegration and the law of one price." *Applied Economics* 39:1091-1105.

Pesaran, H.H., and Y. Shin. 1998. "Generalized Impulse response analysis in linear multivariate models." *Economics Letters* 58:17-29.

Plosser, C.I., and G.W. Schwert. 1978. "Money, income, and sunspots: measuring economic relationships and the effects of differencing." *Journal of Monetary Economics* 4:637-660.

Protopapadakis, A., and H.R. Stoll. 2012. "Spot and futures prices and the law of one price." *The Journal of Finance* 38:1431-1455.

Schmidt, T. 2006. "Coping with copulas." *Chapter forthcoming in Risk Books: Copulasfrom theory to applications in finance*.

Schrimper, R.A. 2001. *Economics of agricultural markets*: Prentice Hall.

Serra, T., B.K. Goodwin, J.M. Gil, and A. Mancuso. 2006. "Non-parametric Modelling of Spatial Price Relationships." *Journal of Agricultural Economics* 57:501-522.

Sexton, R.J., C.L. Kling, and H.F. Carman. 1991. "Market integration, efficiency of arbitrage, and imperfect competition: methodology and application to US celery." *American Journal of Agricultural Economics* 73:568-580.

Shleifer, A., and R.W. Vishny. 1997. "The Limits of Arbitrage." *The Journal of Finance* 52:35-55.

Sklar, A. 1959. "Fonctions de répartition à n dimensions et leurs marges." *Publ. Inst. Statist. Univ. Paris* 8:11.

Solver, P. (2013) "Linear Programming and Quadratic Programming." In.

Spiller, P.T., and C.J. Huang. 1986. "On the extent of the market: wholesale gasoline in the northeastern United States." *The Journal of Industrial Economics*:131-145.

Thursby, M.C., P.R. Johnson, and T.J. Grennes. 1986. "The law of one price and the modelling of disaggregated trade flows." *Economic Modelling* 3:293-302.

Tomek, W.G., and K.L. Robinson. 2003. *Agricultural product prices*: Cornell University Press.

Tuan, F.C., C. Fang, and Z. Cao. 2004. *China's soybean imports expected to grow despite short-term disruptions*: USDA, Economic Research Service.

Ubeda, M., and J.J.Q. Molina (2003) "What are copulas?" In *VII Jornadas Zaragoza-Pau de Matemática Aplicada y estadística: Jaca (Huesca), 17-18 de septiembre de 2001.* Prensas Universitarias de Zaragoza, pp. 499-506.

Vollrath, T., and C. Hallahan. 2006. "Testing the integration of US–Canadian meat and livestock markets." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 54:55-79.

Vose, D. 2008. *Risk analysis : a quantitative guide*. 3rd ed. Chichester, England ; Hoboken, NJ: Wiley.

Wilson, W. 2012. "Global Fundamentals:Changes in Agricultural Trade & Marketing."Unpublished, North Dakota State University|.

Wilson, W.W., and B. Dahl. 2011. "Grain pricing and transportation: dynamics and changes in markets." *Agribusiness* 27:420-434.

APPENDIX

Table A1.Copula Base Case and Vertical Integration Average Profit.

	Base Case			VI w/o Ocean			VI w/Ocean		
Origins	Mean	Stdev	1/CV	Mean	Stdev	1/CV	Mean	Stdev	1/CV
Albany,IL	$71,807	$111,127	0.646	$188,089	$285,969	0.658	$311,186	$599,442	0.519
Alden, IA	$40,126	$112,374	0.357	$78,112	$261,156	0.299	$69,884	$365,381	0.191
Alton, ND	$109,230	$145,193	0.752	$240,221	$315,532	0.761	$387,323	$617,556	0.627
Aurora, IN	$179,530	$203,673	0.881	$259,292	$369,195	0.702	$560,512	$767,597	0.730
Ayr, ND	$118,740	$196,425	0.605	$208,679	$264,352	0.789	$382,284	$613,936	0.623
Bayard, IA	$32,374	$102,569	0.316	$71,970	$233,216	0.309	$85,940	$354,128	0.243
Beatrice, NE	$98,996	$150,808	0.656	$194,275	$298,159	0.652	$308,520	$589,550	0.523
Bradshaw, NE	$72,917	$148,449	0.491	$123,347	$319,166	0.386	$226,711	$586,862	0.386
Breckenridge, MN	$15,244	$68,851	0.221	$61,561	$258,509	0.238	$74,636	$430,228	0.173
Cairo, IL	$133,260	$191,373	0.696	$214,388	$336,234	0.638	$268,211	$551,104	0.487
Cin Bunge, OH	$96,397	$165,007	0.584	$184,872	$337,471	0.548	$161,654	$333,917	0.484
Cin Cargill, OH	$57,061	$113,636	0.502	$113,961	$231,951	0.491	$148,841	$452,583	0.329
Creston, IA	$19,767	$86,302	0.229	$45,777	$208,118	0.220	$25,306	$155,016	0.163
Dorchester, NE	$165,014	$209,113	0.789	$268,495	$344,424	0.780	$325,350	$601,772	0.541
Dubuque, IA	$186,078	$232,074	0.802	$317,666	$398,226	0.798	$509,841	$689,076	0.740
Edison, NE	$99,102	$160,207	0.619	$190,838	$289,371	0.659	$315,806	$591,100	0.534
Evansville, IN	$211,696	$246,336	0.859	$303,856	$465,454	0.653	$286,851	$620,731	0.462
Finley, ND	$96,279	$171,304	0.562	$192,499	$322,714	0.596	$295,294	$588,293	0.502
Fremont, NE	$16,663	$67,942	0.245	$171,747	$819,964	0.209	$276,409	$700,764	0.394
Gurley, NE	$292,758	$242,373	1.208	$388,093	$405,615	0.957	$711,885	$764,968	0.931
Hinton, IA	$11,251	$64,860	0.173	$37,283	$157,902	0.236	$62,985	$368,224	0.171
Jamestown, ND	$99,512	$148,816	0.669	$230,529	$363,847	0.634	$356,000	$618,110	0.576
Jasper, MN	$0	$0	0.000	$13,341	$97,872	0.136	$27,152	$167,449	0.162

Table A1. Copula Base Case and Vertical Integration Average Profit (continued).

	Base Case			VI w/o Ocean			VI w/Ocean		
Origins	Mean	Stdev	1/CV	Mean	Stdev	1/CV	Mean	Stdev	1/CV
Jeffersonville, IN	$168,912	$205,971	0.820	$248,239	$311,587	0.797	$522,124	$730,936	0.714
Madison, SD	$12,117	$59,290	0.204	$64,497	$289,180	0.223	$42,578	$203,569	0.209
Marion, SD	$11,590	$61,950	0.187	$51,023	$188,193	0.271	$56,206	$231,011	0.243
Maywood, NE	$165,037	$189,551	0.871	$303,173	$408,623	0.742	$540,332	$659,831	0.819
Mellett, SD	$181,553	$205,064	0.885	$246,964	$333,719	0.740	$92,541	$296,491	0.312
Mitchell, SD	$24,686	$94,228	0.262	$58,161	$252,682	0.230	$36,551	$218,412	0.167
Mound City, IL	$158,425	$191,039	0.829	$243,100	$351,064	0.692	$534,753	$776,153	0.689
Mount Vernon, IN	$197,068	$262,528	0.751	$272,219	$428,368	0.635	$157,820	$452,090	0.349
Muscatine, IA	$100,143	$162,758	0.615	$196,046	$299,319	0.655	$341,288	$699,757	0.488
Nauvoo, IL	$191,177	$214,441	0.892	$287,980	$374,217	0.770	$503,898	$767,959	0.656
Pekin, IL	$178,627	$194,729	0.917	$285,123	$355,933	0.801	$550,022	$732,000	0.751
Pleasant Hill, IA	$12,629	$57,159	0.221	$41,432	$162,382	0.255	$35,198	$174,792	0.201
Red Oak, IA	$6,100	$33,533	0.182	$59,742	$247,474	0.241	$59,943	$336,069	0.178
Wolsey, SD	$53,682	$154,293	0.348	$122,279	$317,084	0.386	$87,412	$314,765	0.278

Table A2. Copula Buy Track/CIF NOLA/Sell FOB/Adaptive/Risk Average Profit.

	Buy Track & CIF/Sell FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Port PNW	$878,006	$1,322,699						
Port USG	$1,457,711	$2,441,300						
Albany,IL			$178,171	$253,306	$176,692	$252,972	$184,798	$252,592
Alden, IA			$142,773	$343,384	$142,434	$343,604	$140,902	$344,717
Alton, ND			$321,541	$388,541	$322,635	$388,701	$329,449	$386,719
Aurora, IN			$243,389	$331,269	$244,958	$335,110	$256,927	$340,494
Ayr, ND			$235,111	$294,444	$229,562	$293,581	$241,721	$291,746
Bayard, IA			$94,572	$294,008	$103,557	$300,970	$96,332	$295,664
Beatrice, NE			$217,990	$347,201	$218,306	$347,741	$227,711	$341,826
Bradshaw, NE			$144,224	$406,819	$148,366	$408,077	$149,999	$408,992
Breckenridge, MN			$99,671	$308,391	$99,671	$308,391	$99,746	$308,426
Cairo, IL			$240,613	$353,614	$237,468	$354,379	$256,082	$354,621
Cin Bunge, OH			$187,554	$276,492	$188,318	$273,890	$202,330	$292,492
Cin Cargill, OH			$100,659	$222,368	$101,762	$223,652	$110,839	$234,203
Creston, IA			$63,235	$350,726	$64,786	$351,426	$62,229	$350,943
Dorchester, NE			$315,678	$423,718	$314,468	$422,907	$325,346	$417,423
Dubuque, IA			$356,150	$400,635	$353,644	$399,031	$379,064	$407,696
Edison, NE			$219,832	$315,261	$219,627	$315,263	$229,194	$314,395
Evansville, IN			$281,568	$354,096	$277,618	$351,731	$290,764	$357,436
Finley, ND			$218,823	$369,386	$216,309	$369,160	$225,089	$369,604
Fremont, NE			$294,845	$1,243,868	$295,466	$1,243,581	$303,448	$1,246,347
Gurley, NE			$437,367	$467,432	$437,761	$465,917	$439,005	$466,964
Hinton, IA			$24,605	$101,411	$25,881	$104,305	$26,328	$107,375
Jamestown, ND			$209,111	$303,014	$213,609	$303,571	$221,810	$301,564
Jasper, MN			$3,291	$28,347	$2,947	$25,201	$3,345	$28,445
Jeffersonville, IN			$258,459	$305,577	$252,877	$302,197	$263,763	$307,391

Table A2. Copula Buy Track/CIF NOLA/Sell FOB/Adaptive/ Risk Average Profit (continued).

	Buy Track & CIF/Sell FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Madison, SD			$65,656	$293,824	$65,454	$293,722	$65,770	$293,877
Marion, SD			$64,025	$205,831	$64,913	$208,891	$58,680	$200,204
Maywood, NE			$350,365	$376,758	$349,705	$376,050	$356,055	$375,830
Mellett, SD			$329,585	$393,228	$327,970	$394,719	$332,147	$397,704
Mitchell, SD			$37,774	$145,882	$36,522	$143,978	$37,970	$146,599
Mound City, IL			$259,764	$359,178	$263,517	$359,684	$272,252	$365,884
Mount Vernon, IN			$266,519	$327,912	$264,920	$326,215	$268,287	$325,535
Muscatine, IA			$218,030	$311,610	$219,898	$314,836	$230,514	$326,434
Nauvoo, IL			$361,071	$415,077	$366,348	$411,627	$368,589	$419,589
Pekin, IL			$277,762	$363,913	$281,079	$362,365	$285,402	$368,312
Pleasant Hill, IA			$49,832	$183,370	$51,986	$188,107	$52,638	$192,808
Red Oak, IA			$45,341	$149,494	$45,341	$149,494	$51,324	$156,813
Wolsey, SD			$202,442	$435,039	$205,162	$439,033	$207,672	$443,277

Table A3. Copula Risk Loving Average Profit.

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$167,990	$249,594	$175,393	$249,818	$171,125	$253,464
Alden, IA	$128,845	$333,938	$134,856	$336,266	$135,624	$336,917
Alton, ND	$295,531	$390,880	$310,511	$396,536	$314,402	$394,300
Aurora, IN	$214,773	$327,409	$223,774	$329,465	$236,765	$330,672
Ayr, ND	$200,786	$282,444	$217,353	$292,721	$220,499	$291,469
Bayard, IA	$87,381	$285,427	$93,222	$291,181	$91,606	$291,570
Beatrice, NE	$200,301	$332,119	$218,671	$342,861	$219,389	$344,178
Bradshaw, NE	$135,865	$401,315	$142,066	$404,436	$139,948	$403,660
Breckenridge, MN	$95,572	$291,148	$96,359	$292,678	$97,097	$292,264
Cairo, IL	$241,514	$358,633	$253,071	$359,173	$255,986	$357,009
Cin Bunge, OH	$161,541	$253,065	$159,921	$253,089	$169,611	$262,659
Cin Cargill, OH	$95,409	$207,163	$93,868	$208,639	$96,129	$213,500
Creston, IA	$61,893	$347,640	$61,186	$348,302	$63,698	$349,217
Dorchester, NE	$283,929	$397,483	$293,216	$407,555	$307,143	$410,594
Dubuque, IA	$313,030	$389,433	$317,008	$391,580	$339,142	$402,331
Edison, NE	$190,286	$306,274	$199,796	$312,288	$205,784	$315,360
Evansville, IN	$212,418	$257,606	$257,637	$347,290	$266,839	$350,331
Finley, ND	$186,765	$350,057	$201,789	$366,721	$209,854	$368,518
Fremont, NE	$278,037	$1,240,766	$282,762	$1,240,562	$289,439	$1,243,622
Gurley, NE	$414,670	$446,333	$423,146	$449,380	$428,070	$454,213
Hinton, IA	$27,259	$103,074	$29,671	$104,568	$25,596	$100,231
Jamestown, ND	$197,609	$301,288	$199,999	$302,142	$206,339	$302,990
Jasper, MN	$2,665	$22,456	$2,665	$22,456	$3,256	$28,289
Jeffersonville, IN	$262,850	$353,812	$249,178	$299,232	$257,988	$298,758
Madison, SD	$62,730	$289,085	$62,723	$289,184	$62,978	$289,209
Marion, SD	$60,546	$198,816	$58,865	$197,945	$58,307	$195,956
Maywood, NE	$302,001	$361,441	$313,427	$364,342	$322,626	$369,962
Mellett, SD	$262,888	$383,287	$272,715	$386,437	$309,646	$391,900
Mitchell, SD	$27,834	$132,850	$27,983	$132,960	$28,195	$133,150
Mound City, IL	$240,691	$353,444	$259,647	$357,488	$261,728	$359,159
Mount Vernon, IN	$238,172	$367,445	$233,172	$314,512	$245,524	$316,493
Muscatine, IA	$213,306	$305,329	$216,134	$303,706	$215,198	$307,278
Nauvoo, IL	$314,645	$423,203	$329,018	$419,337	$334,218	$417,951
Pekin, IL	$241,029	$296,428	$259,847	$357,018	$264,672	$357,952
Pleasant Hill, IA	$46,781	$166,871	$52,365	$182,494	$50,265	$177,418
Red Oak, IA	$39,373	$146,540	$39,194	$138,399	$42,966	$142,417
Wolsey, SD	$187,949	$423,260	$195,933	$425,922	$194,215	$425,921

Table A4. Copula Increase in Shuttle Train Loading Efficiency Average Profit.

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$167,739	$248,676	$171,125	$253,464	$169,442	$252,677	$171,927	$253,514	$171,101	$253,528
Alden, IA	$136,024	$337,350	$135,624	$336,917	$134,385	$335,946	$136,134	$337,383	$134,859	$336,152
Alton, ND	$315,943	$394,655	$314,402	$394,300	$311,455	$394,232	$314,432	$395,325	$314,078	$395,122
Aurora, IN	$238,070	$331,399	$236,765	$330,672	$235,885	$330,392	$236,876	$330,305	$233,976	$329,402
Ayr, ND	$101,360	$140,678	$220,499	$291,469	$351,369	$439,807	$470,089	$585,446	$596,726	$731,447
Bayard, IA	$93,413	$293,195	$91,606	$291,570	$93,145	$293,109	$93,902	$293,718	$93,539	$293,238
Beatrice, NE	$219,760	$346,958	$219,389	$344,178	$220,167	$344,028	$219,669	$344,389	$220,070	$344,227
Bradshaw, NE	$140,285	$405,644	$139,948	$403,660	$140,059	$405,409	$141,327	$405,604	$141,428	$405,650
Breckenridge, MN	$99,393	$303,040	$97,097	$292,264	$95,662	$291,523	$95,836	$291,555	$98,307	$302,405
Cairo, IL	$255,610	$356,678	$255,986	$357,009	$255,493	$357,684	$255,515	$358,146	$253,284	$358,809
Cin Bunge, OH	$167,598	$260,724	$169,611	$262,659	$169,590	$264,066	$170,282	$263,548	$168,781	$261,214
Cin Cargill, OH	$97,497	$215,145	$96,129	$213,500	$96,006	$214,263	$96,006	$214,263	$95,341	$214,135
Creston, IA	$63,663	$349,195	$63,698	$349,217	$63,698	$349,217	$63,698	$349,217	$62,550	$348,572
Dorchester, NE	$311,150	$414,113	$307,143	$410,594	$307,245	$411,295	$305,671	$412,195	$306,356	$409,642
Dubuque, IA	$342,109	$400,438	$339,142	$402,331	$336,871	$400,762	$337,196	$402,154	$336,500	$400,484
Edison, NE	$205,579	$314,024	$205,784	$315,360	$201,176	$313,135	$206,288	$314,218	$200,641	$313,226
Evansville, IN	$268,013	$350,515	$266,839	$350,331	$264,605	$350,054	$264,392	$350,457	$262,169	$350,132
Finley, ND	$210,404	$368,585	$209,854	$368,518	$208,445	$367,937	$209,448	$368,037	$205,515	$366,661
Fremont, NE	$294,154	$1,242,452	$289,439	$1,243,622	$289,780	$1,241,540	$286,972	$1,242,307	$288,508	$1,242,973
Gurley, NE	$423,801	$454,071	$428,070	$454,213	$427,316	$452,245	$426,619	$452,722	$428,826	$454,174
Hinton, IA	$26,517	$103,054	$25,596	$100,231	$27,190	$103,701	$25,537	$100,155	$24,638	$99,039
Jamestown, ND	$207,788	$302,716	$206,339	$302,990	$204,094	$303,129	$204,159	$303,190	$207,852	$304,935
Jasper, MN	$3,256	$28,289	$3,256	$28,289	$3,256	$28,289	$3,256	$28,289	$3,345	$28,445
Jeffersonville, IN	$258,120	$298,787	$257,988	$298,758	$253,615	$297,719	$253,361	$298,367	$254,495	$298,111
Madison, SD	$63,259	$289,293	$62,978	$289,209	$65,274	$293,672	$63,079	$289,283	$62,978	$289,209

Table A4. Increase in Shuttle Train Loading Efficiency Average Profit (continued).

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4Shutlle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Marion, SD	$58,093	$195,909	$58,307	$195,956	$58,307	$195,956	$58,011	$195,897	$58,011	$195,897
Maywood, NE	$325,688	$370,013	$322,626	$369,962	$330,243	$372,955	$326,689	$370,782	$325,303	$369,941
Mellett, SD	$306,519	$381,975	$309,646	$391,900	$300,657	$380,528	$303,323	$384,740	$299,762	$385,424
Mitchell, SD	$28,095	$133,052	$28,195	$133,150	$28,095	$133,052	$28,095	$133,052	$28,195	$133,150
Mound City, IL	$260,483	$359,489	$261,728	$359,159	$266,949	$360,686	$264,781	$360,216	$260,483	$359,489
Mount Vernon, IN	$246,757	$318,822	$245,524	$316,493	$240,685	$317,687	$239,249	$314,672	$239,809	$312,885
Muscatine, IA	$215,223	$307,305	$215,198	$307,278	$217,329	$310,303	$216,185	$306,754	$215,748	$308,912
Nauvoo, IL	$335,154	$419,520	$334,218	$417,951	$335,909	$418,048	$334,143	$418,024	$337,586	$418,950
Pekin, IL	$265,700	$357,632	$264,672	$357,952	$265,257	$358,063	$267,680	$357,359	$268,737	$357,133
Pleasant Hill, IA	$48,005	$167,445	$50,265	$177,418	$50,265	$177,418	$48,005	$167,445	$48,612	$167,755
Red Oak, IA	$44,927	$148,155	$42,966	$142,417	$42,966	$142,416	$42,966	$142,416	$44,927	$148,155
Wolsey, SD	$195,452	$425,711	$194,215	$425,921	$193,022	$423,558	$190,291	$415,500	$195,103	$427,354

Table A5. Copula Base Case and Vertical Integration Average Profit/bu.

	Base Case		VI w/o Ocean		VI w/Ocean		Sell CIF/Buy FOB	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Port PNW							$0.05	$0.08
Port USG							$0.09	$0.15
Albany,IL	$0.09	$0.14	$0.23	$0.34	$0.39	$0.73		
Alden, IA	$0.05	$0.14	$0.10	$0.32	$0.10	$0.47		
Alton, ND	$0.13	$0.17	$0.29	$0.38	$0.47	$0.74		
Aurora, IN	$0.22	$0.25	$0.32	$0.45	$0.69	$0.93		
Ayr, ND	$0.15	$0.25	$0.25	$0.32	$0.47	$0.74		
Bayard, IA	$0.04	$0.13	$0.09	$0.28	$0.11	$0.43		
Beatrice, NE	$0.12	$0.18	$0.24	$0.36	$0.37	$0.71		
Bradshaw, NE	$0.09	$0.18	$0.15	$0.39	$0.30	$0.79		
Breckenridge, MN	$0.02	$0.09	$0.08	$0.31	$0.09	$0.52		
Cairo, IL	$0.16	$0.23	$0.26	$0.41	$0.34	$0.67		
Cin Bunge, OH	$0.12	$0.20	$0.23	$0.41	$0.21	$0.43		
Cin Cargill, OH	$0.07	$0.14	$0.14	$0.28	$0.19	$0.57		
Creston, IA	$0.03	$0.11	$0.06	$0.30	$0.03	$0.20		
Dorchester, NE	$0.20	$0.25	$0.32	$0.41	$0.39	$0.72		
Dubuque, IA	$0.23	$0.28	$0.39	$0.48	$0.65	$0.87		
Edison, NE	$0.12	$0.19	$0.23	$0.35	$0.38	$0.71		
Evansville, IN	$0.26	$0.30	$0.37	$0.56	$0.39	$0.79		
Finley, ND	$0.12	$0.21	$0.23	$0.39	$0.36	$0.71		
Fremont, NE	$0.02	$0.08	$0.21	$0.99	$0.33	$0.84		
Gurley, NE	$0.35	$0.29	$0.47	$0.49	$0.86	$0.92		
Hinton, IA	$0.02	$0.08	$0.05	$0.19	$0.08	$0.44		
Jamestown, ND	$0.12	$0.18	$0.28	$0.44	$0.43	$0.74		
Jasper, MN	$0.00	$0.00	$0.02	$0.12	$0.03	$0.20		
Jeffersonville, IN	$0.21	$0.25	$0.31	$0.38	$0.66	$0.94		
Madison, SD	$0.02	$0.08	$0.08	$0.35	$0.05	$0.24		
Marion, SD	$0.02	$0.08	$0.07	$0.25	$0.07	$0.28		
Maywood, NE	$0.20	$0.23	$0.37	$0.49	$0.65	$0.79		
Mellett, SD	$0.22	$0.25	$0.31	$0.41	$0.11	$0.36		
Mitchell, SD	$0.03	$0.11	$0.07	$0.31	$0.05	$0.27		
Mound City, IL	$0.19	$0.23	$0.30	$0.42	$0.65	$0.93		
Mount Vernon, IN	$0.24	$0.32	$0.34	$0.53	$0.22	$0.59		
Muscatine, IA	$0.13	$0.20	$0.24	$0.36	$0.43	$0.85		
Nauvoo, IL	$0.23	$0.26	$0.35	$0.45	$0.62	$0.93		
Pekin, IL	$0.22	$0.23	$0.35	$0.43	$0.68	$0.90		
Pleasant Hill, IA	$0.02	$0.08	$0.05	$0.20	$0.04	$0.21		
Red Oak, IA	$0.01	$0.04	$0.07	$0.30	$0.08	$0.46		
Wolsey, SD	$0.07	$0.19	$0.15	$0.38	$0.11	$0.38		

Table A6. Copula Risk Loving and Adaptive to Changes in Risk Average Profit/bu.

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$0.21	$0.30	$0.22	$0.31	$0.21	$0.31	$0.22	$0.31	$0.22	$0.30	$0.23	$0.30
Alden, IA	$0.16	$0.40	$0.17	$0.41	$0.17	$0.41	$0.18	$0.42	$0.18	$0.42	$0.18	$0.42
Alton, ND	$0.36	$0.47	$0.37	$0.48	$0.38	$0.47	$0.39	$0.47	$0.39	$0.47	$0.40	$0.46
Aurora, IN	$0.27	$0.40	$0.28	$0.40	$0.29	$0.40	$0.31	$0.40	$0.30	$0.40	$0.32	$0.41
Ayr, ND	$0.24	$0.34	$0.26	$0.35	$0.27	$0.35	$0.28	$0.35	$0.28	$0.35	$0.29	$0.35
Bayard, IA	$0.11	$0.35	$0.12	$0.35	$0.11	$0.35	$0.12	$0.36	$0.13	$0.36	$0.12	$0.36
Beatrice, NE	$0.24	$0.40	$0.27	$0.41	$0.27	$0.41	$0.27	$0.42	$0.27	$0.42	$0.28	$0.41
Bradshaw, NE	$0.17	$0.48	$0.17	$0.49	$0.18	$0.49	$0.18	$0.49	$0.18	$0.49	$0.18	$0.49
Breckenridge, MN	$0.11	$0.35	$0.12	$0.35	$0.12	$0.35	$0.12	$0.37	$0.12	$0.37	$0.12	$0.37
Cairo, IL	$0.31	$0.43	$0.31	$0.43	$0.32	$0.43	$0.30	$0.43	$0.30	$0.43	$0.32	$0.43
Cin Bunge, OH	$0.21	$0.31	$0.21	$0.32	$0.21	$0.32	$0.23	$0.34	$0.23	$0.33	$0.27	$0.43
Cin Cargill, OH	$0.13	$0.27	$0.13	$0.27	$0.12	$0.26	$0.12	$0.27	$0.13	$0.27	$0.14	$0.28
Creston, IA	$0.08	$0.42	$0.07	$0.42	$0.08	$0.42	$0.08	$0.42	$0.08	$0.42	$0.07	$0.42
Dorchester, NE	$0.34	$0.48	$0.35	$0.49	$0.37	$0.49	$0.38	$0.51	$0.38	$0.51	$0.39	$0.50
Dubuque, IA	$0.38	$0.47	$0.38	$0.47	$0.41	$0.48	$0.43	$0.48	$0.42	$0.48	$0.46	$0.49
Edison, NE	$0.23	$0.37	$0.24	$0.37	$0.25	$0.38	$0.27	$0.38	$0.27	$0.38	$0.28	$0.38
Evansville, IN	$0.28	$0.32	$0.32	$0.42	$0.33	$0.42	$0.34	$0.42	$0.34	$0.42	$0.36	$0.43
Finley, ND	$0.22	$0.42	$0.24	$0.44	$0.25	$0.44	$0.26	$0.44	$0.26	$0.44	$0.27	$0.44
Fremont, NE	$0.34	$1.49	$0.34	$1.49	$0.35	$1.49	$0.36	$1.49	$0.36	$1.49	$0.36	$1.50
Gurley, NE	$0.50	$0.54	$0.51	$0.54	$0.52	$0.54	$0.53	$0.56	$0.53	$0.56	$0.54	$0.56
Hinton, IA	$0.03	$0.13	$0.04	$0.14	$0.03	$0.13	$0.03	$0.12	$0.03	$0.13	$0.03	$0.13
Jamestown, ND	$0.24	$0.36	$0.24	$0.36	$0.25	$0.36	$0.25	$0.36	$0.26	$0.36	$0.27	$0.36
Jasper, MN	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03
Jeffersonville, IN	$0.33	$0.42	$0.31	$0.36	$0.32	$0.36	$0.31	$0.37	$0.31	$0.36	$0.32	$0.37
Madison, SD	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35
Marion, SD	$0.08	$0.24	$0.07	$0.24	$0.07	$0.24	$0.08	$0.26	$0.09	$0.26	$0.08	$0.25

Table A6. Copula Risk Loving and Adaptive to Changes in Risk Average Profit/bu (continued).

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Maywood, NE	$0.37	$0.43	$0.38	$0.44	$0.39	$0.44	$0.42	$0.45	$0.42	$0.45	$0.43	$0.45
Mellett, SD	$0.32	$0.46	$0.33	$0.46	$0.40	$0.48	$0.41	$0.48	$0.41	$0.48	$0.42	$0.48
Mitchell, SD	$0.03	$0.16	$0.03	$0.16	$0.03	$0.16	$0.05	$0.18	$0.04	$0.17	$0.05	$0.18
Mound City, IL	$0.30	$0.43	$0.33	$0.43	$0.33	$0.43	$0.32	$0.43	$0.33	$0.43	$0.34	$0.44
Mount Vernon, IN	$0.29	$0.44	$0.30	$0.44	$0.31	$0.45	$0.34	$0.45	$0.34	$0.45	$0.33	$0.39
Muscatine, IA	$0.26	$0.37	$0.27	$0.36	$0.27	$0.37	$0.27	$0.37	$0.27	$0.38	$0.28	$0.39
Nauvoo, IL	$0.39	$0.51	$0.40	$0.50	$0.41	$0.50	$0.44	$0.50	$0.46	$0.49	$0.45	$0.50
Pekin, IL	$0.31	$0.43	$0.32	$0.43	$0.32	$0.43	$0.34	$0.44	$0.35	$0.43	$0.35	$0.44
Pleasant Hill, IA	$0.06	$0.20	$0.06	$0.22	$0.06	$0.21	$0.06	$0.22	$0.07	$0.23	$0.07	$0.23
Red Oak, IA	$0.05	$0.18	$0.05	$0.17	$0.05	$0.18	$0.06	$0.19	$0.06	$0.19	$0.07	$0.20
Wolsey, SD	$0.23	$0.51	$0.24	$0.51	$0.24	$0.51	$0.25	$0.53	$0.25	$0.53	$0.26	$0.54

Table A7. Copula Increase in Shuttle Train Loading Efficiency Average Profit/bu.

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$0.21	$0.30	$0.21	$0.31	$0.21	$0.30	$0.21	$0.31	$0.21	$0.31
Alden, IA	$0.17	$0.41	$0.17	$0.41	$0.17	$0.41	$0.17	$0.41	$0.17	$0.41
Alton, ND	$0.38	$0.47	$0.38	$0.47	$0.37	$0.47	$0.38	$0.47	$0.38	$0.47
Aurora, IN	$0.30	$0.40	$0.29	$0.40	$0.29	$0.40	$0.30	$0.40	$0.29	$0.40
Ayr, ND	$0.24	$0.34	$0.27	$0.35	$0.28	$0.35	$0.28	$0.35	$0.29	$0.35
Bayard, IA	$0.11	$0.35	$0.11	$0.35	$0.11	$0.35	$0.11	$0.35	$0.11	$0.35
Beatrice, NE	$0.27	$0.42	$0.27	$0.41	$0.27	$0.41	$0.27	$0.41	$0.27	$0.41
Bradshaw, NE	$0.18	$0.49	$0.18	$0.49	$0.17	$0.49	$0.18	$0.49	$0.18	$0.49
Breckenridge, MN	$0.12	$0.37	$0.12	$0.35	$0.12	$0.35	$0.12	$0.35	$0.12	$0.37
Cairo, IL	$0.32	$0.43	$0.32	$0.43	$0.32	$0.43	$0.32	$0.43	$0.32	$0.43
Cin Bunge, OH	$0.21	$0.32	$0.21	$0.32	$0.21	$0.32	$0.21	$0.32	$0.21	$0.32
Cin Cargill, OH	$0.12	$0.26	$0.12	$0.26	$0.12	$0.26	$0.12	$0.26	$0.12	$0.26
Creston, IA	$0.08	$0.42	$0.08	$0.42	$0.08	$0.42	$0.08	$0.42	$0.08	$0.42
Dorchester, NE	$0.37	$0.50	$0.37	$0.49	$0.37	$0.49	$0.37	$0.49	$0.37	$0.49
Dubuque, IA	$0.42	$0.48	$0.41	$0.48	$0.41	$0.48	$0.41	$0.48	$0.41	$0.48
Edison, NE	$0.25	$0.38	$0.25	$0.38	$0.24	$0.38	$0.25	$0.38	$0.24	$0.38
Evansville, IN	$0.33	$0.42	$0.33	$0.42	$0.32	$0.42	$0.32	$0.42	$0.32	$0.42
Finley, ND	$0.25	$0.44	$0.25	$0.44	$0.25	$0.44	$0.25	$0.44	$0.25	$0.44
Fremont, NE	$0.36	$1.49	$0.35	$1.49	$0.35	$1.49	$0.35	$1.49	$0.35	$1.49
Gurley, NE	$0.51	$0.55	$0.52	$0.54	$0.52	$0.54	$0.52	$0.54	$0.52	$0.54
Hinton, IA	$0.03	$0.13	$0.03	$0.13	$0.04	$0.13	$0.03	$0.13	$0.03	$0.12
Jamestown, ND	$0.25	$0.36	$0.25	$0.36	$0.25	$0.36	$0.25	$0.36	$0.25	$0.37
Jasper, MN	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03	$0.00	$0.03
Jeffersonville, IN	$0.32	$0.36	$0.32	$0.36	$0.31	$0.36	$0.31	$0.36	$0.31	$0.36
Madison, SD	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35	$0.08	$0.35
Marion, SD	$0.07	$0.24	$0.07	$0.24	$0.07	$0.24	$0.07	$0.24	$0.07	$0.24

Table A7. Copula Increase in Shuttle Train Loading Efficiency Average Profit/bu (continued).

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Maywood, NE	$0.39	$0.44	$0.39	$0.44	$0.40	$0.45	$0.39	$0.45	$0.39	$0.44
Mellett, SD	$0.40	$0.47	$0.40	$0.48	$0.39	$0.47	$0.39	$0.47	$0.39	$0.47
Mitchell, SD	$0.03	$0.16	$0.03	$0.16	$0.03	$0.16	$0.03	$0.16	$0.03	$0.16
Mound City, IL	$0.32	$0.43	$0.33	$0.43	$0.33	$0.44	$0.33	$0.43	$0.32	$0.43
Mount Vernon, IN	$0.32	$0.45	$0.31	$0.45	$0.31	$0.45	$0.31	$0.44	$0.31	$0.44
Muscatine, IA	$0.27	$0.37	$0.27	$0.37	$0.27	$0.37	$0.27	$0.37	$0.27	$0.37
Nauvoo, IL	$0.41	$0.50	$0.41	$0.50	$0.41	$0.50	$0.41	$0.50	$0.42	$0.50
Pekin, IL	$0.32	$0.43	$0.32	$0.43	$0.32	$0.43	$0.33	$0.43	$0.33	$0.43
Pleasant Hill, IA	$0.06	$0.20	$0.06	$0.21	$0.06	$0.21	$0.06	$0.20	$0.06	$0.20
Red Oak, IA	$0.06	$0.19	$0.05	$0.18	$0.05	$0.18	$0.05	$0.18	$0.06	$0.19
Wolsey, SD	$0.24	$0.51	$0.24	$0.51	$0.24	$0.51	$0.23	$0.50	$0.24	$0.52

Table A8. Copula Base Case/Vertical Integration/Adaptive/Probability of Profit.

	Base Case		VI w/o Ocean		VI w/Ocean		Sell CIF/Buy FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Port PNW							100%							
Port USG								100%						
Albany,IL		40%		46%		48%				49%		48%		50%
Alden, IA		19%		18%		10%				30%		30%		29%
Alton, ND	56%	4%	66%	4%	66%	2%			78%	6%	77%	4%	80%	5%
Aurora, IN		61%		55%		81%				56%		56%		59%
Ayr, ND	60%	3%	68%	3%	69%	3%			75%	1%	74%	1%	80%	1%
Bayard, IA		16%		16%		12%				20%		22%		20%
Beatrice, NE	36%	21%	47%	14%	47%	9%			57%	8%	52%	10%	59%	8%
Bradshaw, NE		30%		27%		30%				26%		28%		28%
Breckenridge, MN		6%		11%		8%				14%		14%		14%
Cairo, IL		47%		48%		41%				50%		47%		50%
Cin Bunge, OH		41%		45%		32%				44%		47%		49%
Cin Cargill, OH		33%		34%		23%				30%		29%		31%
Creston, IA		9%		11%		3%				10%		11%		10%
Dorchester, NE	39%	27%	50%	18%	46%	9%			57%	11%	57%	11%	63%	11%
Dubuque, IA		57%		60%		73%				64%		64%		68%
Edison, NE	34%	18%	46%	11%	48%	6%			53%	10%	53%	13%	56%	12%
Evansville, IN		61%		55%		42%				55%		60%		60%
Finley, ND	40%	4%	49%	1%	50%	1%			48%	2%	50%	3%	54%	2%
Fremont, NE	10%	2%	26%	4%	31%	4%			32%	4%	30%	5%	34%	4%
Gurley, NE		82%		77%		95%				78%		78%		78%
Hinton, IA		6%		9%		9%				8%		8%		8%
Jamestown, ND	53%	4%	65%	3%	60%	0%			69%	2%	70%	2%	73%	2%
Jasper, MN		0%		2%		4%				2%		2%		2%
Jeffersonville, IN		57%		57%		74%				53%		54%		55%
Madison, SD		6%		10%		5%				11%		11%		11%
Marion, SD		6%		12%		8%				13%		13%		12%

Table A8. Copula Base Case/Vertical Integration/Adaptive/Probability of Profit (continued).

	Base Case		VI w/o Ocean		VI w/Ocean		Sell CIF/Buy FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Maywood, NE	65%	4%	70%	2%	64%	31%			79%	3%	79%	0%	80%	0%
Mellett, SD		62%		56%		14%				70%		70%		69%
Mitchell, SD		10%		11%		4%				9%		9%		9%
Mound City, IL		60%		57%		77%				54%		56%		55%
Mount Vernon, IN		51%		50%		25%				51%		52%		51%
Muscatine, IA		41%		47%		45%				48%		48%		48%
Nauvoo, IL		64%		61%		72%				72%		76%		74%
Pekin, IL		64%		64%		79%				60%		61%		59%
Pleasant Hill, IA		8%		13%		7%				11%		12%		11%
Red Oak, IA		4%		10%		6%				11%		11%		13%
Wolsey, SD		15%		20%		11%				24%		25%		26%

Table A9. Copula Risk Loving/Increase Loading Efficiency Probability of Profit.

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Albany ,IL		45%		45%		44%		45%		44%		44%		44%		44%
Alden, IA		27%		28%		28%		28%		28%		28%		28%		28%
Alton, ND	68%	6%	70%	4%	71%	4%	71%	4%	71%	4%	71%	5%	71%	5%	71%	5%
Aurora, IN		52%		52%		54%		54%		54%		54%		54%		54%
Ayr, ND	68%	2%	70%	2%	71%	2%	71%	4%	71%	2%	72%	3%	72%	3%	72%	3%
Bayard, IA		19%		20%		19%		19%		19%		19%		19%		19%
Beatrice, NE	49%	12%	50%	17%	51%	13%	51%	12%	51%	13%	51%	14%	51%	14%	51%	14%
Bradshaw, NE		26%		26%		27%		26%		27%		27%		27%		27%
Breckenridge, MN		14%		15%		15%		15%		15%		15%		15%		15%
Cairo, IL		48%		49%		50%		50%		50%		50%		50%		50%
Cin Bunge, OH		46%		46%		45%		45%		45%		45%		45%		45%
Cin Cargill, OH		31%		29%		28%		28%		28%		28%		28%		28%
Creston, IA		12%		11%		11%		11%		11%		11%		11%		11%
Dorchester, NE	49%	16%	52%	17%	54%	15%	55%	15%	54%	15%	54%	16%	54%	16%	54%	16%
Dubuque, IA		60%		59%		61%		62%		61%		61%		61%		61%
Edison, NE	47%	11%	48%	11%	48%	10%	48%	10%	48%	10%	48%	10%	48%	10%	48%	10%
Evansville, IN		56%		57%		56%		56%		56%		56%		56%		56%
Finley, ND	46%	3%	47%	5%	47%	2%	47%	4%	47%	2%	47%	2%	47%	2%	47%	2%
Fremont, NE	25%	5%	27%	4%	28%	4%	27%	4%	28%	4%	27%	4%	27%	4%	27%	4%
Gurley, NE		79%		79%		79%		79%		79%		79%		79%		79%
Hinton, IA		9%		11%		9%		9%		9%		9%		9%		9%
Jamestown, ND	64%	6%	67%	6%	70%	3%	70%	3%	70%	3%	70%	4%	70%	4%	70%	4%
Jasper, MN		2%		2%		2%		2%		2%		2%		2%		2%
Jeffersonville, IN		57%		56%		57%		57%		57%		57%		57%		57%
Madison, SD		12%		11%		11%		11%		11%		11%		11%		11%

Table A9. Copula Risk Loving/Increase Loading Efficiency Probability of Profit (continued).

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Marion, SD		12%		11%		12%		12%		12%		12%		12%		12%
Maywood, NE	73%	0%	75%	1%	76%	0%	76%	0%	76%	0%	76%	0%	76%	0%	76%	0%
Mellett, SD		60%		61%		69%		69%		69%		69%		69%		69%
Mitchell, SD		7%		7%		7%		7%		7%		7%		7%		7%
Mound City, IL		53%		57%		57%		57%		57%		57%		57%		57%
Mount Vernon, IN		46%		48%		50%		50%		50%		50%		50%		50%
Muscatine, IA		48%		51%		50%		50%		50%		50%		50%		50%
Nauvoo, IL		64%		69%		71%		71%		71%		71%		71%		71%
Pekin, IL		57%		58%		59%		59%		59%		59%		59%		59%
Pleasant Hill, IA		12%		13%		13%		13%		13%		13%		13%		13%
Red Oak, IA		9%		10%		11%		11%		11%		11%		11%		11%
Wolsey, SD		23%		24%		24%		24%		24%		24%		24%		24%

Table A10. Normal Base Case and Vertical Integration Average Profit.

	Base Case			VI w/o Ocean			VI w/Ocean		
Origins	Mean	Stdev	1/CV	Mean	Stdev	1/CV	Mean	Stdev	1/CV
Albany,IL	$139,935	$256,634	0.545	$184,121	$259,224	0.710	$315,319	$458,747	0.687
Alden, IA	$109,975	$226,864	0.485	$121,646	$235,300	0.517	$222,474	$435,419	0.511
Alton, ND	$178,439	$258,001	0.692	$237,932	$263,325	0.904	$526,203	$609,151	0.864
Aurora, IN	$207,871	$321,367	0.647	$265,479	$321,412	0.826	$460,895	$562,007	0.820
Ayr, ND	$229,619	$345,453	0.665	$244,591	$261,203	0.936	$539,766	$604,194	0.893
Bayard, IA	$67,853	$184,137	0.368	$71,195	$178,977	0.398	$141,965	$358,356	0.396
Beatrice, NE	$156,860	$252,781	0.621	$186,468	$253,695	0.735	$474,179	$618,944	0.766
Bradshaw, NE	$117,073	$226,052	0.518	$140,311	$227,035	0.618	$251,385	$447,071	0.562
Breckenridge, MN	$71,184	$198,839	0.358	$82,404	$205,809	0.400	$155,672	$398,723	0.390
Cairo, IL	$143,755	$237,516	0.605	$158,264	$236,144	0.670	$320,630	$473,724	0.677
Cin Bunge, OH	$111,705	$219,375	0.509	$127,938	$248,587	0.515	$246,654	$432,743	0.570
Cin Cargill, OH	$108,620	$209,412	0.519	$128,836	$209,718	0.614	$254,616	$410,189	0.621
Creston, IA	$46,041	$148,346	0.310	$45,558	$158,786	0.287	$80,827	$273,294	0.296
Dorchester, NE	$177,341	$287,416	0.617	$221,456	$301,213	0.735	$500,849	$646,645	0.775
Dubuque, IA	$213,652	$339,756	0.629	$276,571	$395,456	0.699	$433,491	$603,180	0.719
Edison, NE	$209,687	$311,457	0.673	$250,598	$314,925	0.796	$514,347	$595,776	0.863
Evansville, IN	$150,120	$291,741	0.515	$177,485	$308,154	0.576	$369,325	$579,023	0.638
Finley, ND	$162,928	$286,813	0.568	$207,484	$294,517	0.704	$463,159	$577,105	0.803
Fremont, NE	$226,906	$418,450	0.542	$260,562	$495,321	0.526	$472,787	$693,303	0.682
Gurley, NE	$305,550	$347,546	0.879	$408,770	$348,140	1.174	$662,205	$592,510	1.118
Hinton, IA	$38,703	$148,516	0.261	$43,398	$161,760	0.268	$81,425	$308,841	0.264
Jamestown, ND	$188,962	$294,137	0.642	$246,088	$287,742	0.855	$516,804	$585,548	0.883
Jasper, MN	$21,834	$100,856	0.216	$13,663	$99,105	0.138	$26,133	$161,816	0.161
Jeffersonville, IN	$193,764	$303,330	0.639	$239,481	$308,878	0.775	$433,712	$554,806	0.782
Madison, SD	$54,823	$170,587	0.321	$47,981	$155,847	0.308	$74,344	$250,205	0.297
Marion, SD	$36,941	$131,924	0.280	$39,535	$142,098	0.278	$88,956	$324,148	0.274
Maywood, NE	$375,517	$484,348	0.775	$461,613	$460,882	1.002	$753,263	$735,779	1.024
Mellett, SD	$91,928	$225,462	0.408	$97,131	$255,359	0.380	$175,647	$476,721	0.368

Table A10. Normal Base Case and Vertical Integration Average Profit (continued).

	Base Case			VI w/o Ocean			VI w/Ocean		
Origins	Mean	Stdev	1/CV	Mean	Stdev	1/CV	Mean	Stdev	1/CV
Mitchell, SD	$55,177	$176,446	0.313	$73,798	$194,002	0.380	$111,405	$303,774	0.367
Mound City, IL	$181,442	$257,926	0.703	$223,997	$273,836	0.818	$445,482	$548,314	0.812
Mount Vernon, IN	$155,000	$305,357	0.508	$167,239	$317,647	0.526	$321,239	$588,514	0.546
Muscatine, IA	$154,226	$272,627	0.566	$186,301	$316,412	0.589	$308,446	$513,450	0.601
Nauvoo, IL	$176,346	$286,463	0.616	$227,266	$345,371	0.658	$425,666	$601,109	0.708
Pekin, IL	$227,474	$312,222	0.729	$298,776	$356,750	0.837	$475,668	$570,997	0.833
Pleasant Hill, IA	$31,231	$114,716	0.272	$30,701	$103,828	0.296	$75,330	$247,684	0.304
Red Oak, IA	$121,659	$303,870	0.400	$116,403	$294,274	0.396	$200,612	$497,534	0.403
Wolsey, SD	$97,615	$236,110	0.413	$127,002	$283,511	0.448	$220,952	$525,354	0.421

Table A11. Normal Buy Track/CIF NOLA/Sell FOB/Adaptive/Average Profit.

	Sell CIF/Buy FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Port PNW	$2,431,571	$2,263,124						
Port USG	$4,182,257	$3,680,641						
Albany,IL			$208,066	$310,033	$191,574	$285,625	$159,224	$219,205
Alden, IA			$120,488	$246,675	$104,890	$219,548	$57,616	$141,265
Alton, ND			$296,863	$344,509	$276,390	$318,612	$212,820	$233,471
Aurora, IN			$275,194	$298,192	$289,397	$303,294	$315,870	$334,932
Ayr, ND			$309,594	$331,604	$284,639	$305,342	$205,031	$208,901
Bayard, IA			$99,936	$212,774	$75,698	$181,857	$43,868	$142,728
Beatrice, NE			$266,006	$337,677	$244,147	$311,429	$172,041	$222,629
Bradshaw, NE			$199,316	$309,284	$174,302	$273,600	$124,336	$232,295
Breckenridge, MN			$140,326	$305,741	$113,394	$260,606	$21,773	$112,844
Cairo, IL			$110,599	$190,602	$112,932	$191,846	$131,302	$212,745
Cin Bunge, OH			$152,927	$285,887	$148,021	$269,153	$142,325	$233,349
Cin Cargill, OH			$172,602	$260,720	$157,147	$242,358	$145,019	$223,870
Creston, IA			$43,801	$171,980	$42,815	$169,065	$44,004	$170,489
Dorchester, NE			$287,684	$338,318	$274,235	$314,194	$219,224	$256,142
Dubuque, IA			$302,891	$429,155	$291,511	$398,750	$257,072	$302,641
Edison, NE			$328,958	$404,076	$301,840	$369,970	$198,882	$238,954
Evansville, IN			$177,523	$301,997	$175,884	$300,252	$188,491	$295,401
Finley, ND			$257,220	$348,507	$237,170	$323,045	$185,443	$248,643
Fremont, NE			$440,451	$632,550	$321,771	$475,071	$74,944	$134,982
Gurley, NE			$428,837	$392,699	$404,911	$350,979	$336,411	$282,681
Hinton, IA			$59,243	$192,975	$48,482	$168,589	$52,157	$161,286
Jamestown, ND			$350,070	$409,037	$306,172	$349,943	$181,473	$198,539
Jasper, MN			$19,517	$86,630	$15,152	$75,642	$18,796	$88,581
Jeffersonville, IN			$275,847	$363,197	$276,066	$353,299	$297,446	$369,509
Madison, SD			$48,472	$146,060	$47,417	$143,217	$67,376	$183,311
Marion, SD			$29,393	$100,849	$24,892	$94,342	$26,888	$103,144
Maywood, NE			$590,836	$590,128	$545,662	$523,292	$305,738	$261,688

Table A11. Normal Buy Track/CIF NOLA/Sell FOB/Adaptive/Average Profit (continued).

	Sell CIF/Buy FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Mellett, SD			$124,724	$263,321	$119,177	$253,984	$70,776	$175,869
Mitchell, SD			$52,226	$160,744	$56,433	$166,820	$69,715	$194,033
Mound City, IL			$223,863	$275,841	$229,541	$271,807	$240,868	$290,014
Mount Vernon, IN			$198,697	$341,333	$196,060	$335,776	$183,598	$323,478
Muscatine, IA			$177,767	$346,336	$174,782	$320,775	$159,494	$253,167
Nauvoo, IL			$237,034	$328,505	$230,757	$312,839	$213,912	$289,471
Pekin, IL			$320,955	$388,499	$318,635	$364,260	$269,613	$273,225
Pleasant Hill, IA			$47,206	$125,852	$39,189	$108,832	$13,131	$47,164
Red Oak, IA			$74,340	$175,017	$76,627	$179,986	$84,951	$200,586
Wolsey, SD			$111,719	$234,633	$117,565	$238,406	$132,275	$258,297

Table A12. Normal Risk Loving Average Profit.

	Risk Measures 10%		Risk Measures 20%		Risk Measures 30%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$173,518	$261,457	$180,196	$271,212	$181,842	$271,332
Alden, IA	$75,362	$158,853	$84,766	$180,783	$96,215	$202,791
Alton, ND	$237,531	$290,305	$248,718	$290,414	$258,494	$286,360
Aurora, IN	$248,553	$297,482	$266,836	$302,149	$289,052	$309,853
Ayr, ND	$250,943	$273,719	$258,539	$276,935	$263,056	$271,282
Bayard, IA	$49,980	$140,551	$61,085	$158,832	$61,260	$161,514
Beatrice, NE	$203,413	$271,505	$214,547	$273,646	$222,908	$275,995
Bradshaw, NE	$143,659	$257,171	$153,997	$261,503	$163,807	$268,768
Breckenridge, MN	$91,347	$235,665	$90,600	$236,898	$80,352	$220,431
Cairo, IL	$124,620	$199,000	$125,781	$198,124	$123,775	$196,629
Cin Bunge, OH	$132,242	$240,381	$135,454	$246,211	$143,704	$257,906
Cin Cargill, OH	$132,502	$215,328	$136,501	$228,706	$147,615	$233,709
Creston, IA	$36,800	$151,175	$35,463	$153,015	$37,972	$162,631
Dorchester, NE	$235,965	$291,234	$248,217	$297,888	$259,007	$293,226
Dubuque, IA	$271,265	$367,029	$277,233	$370,732	$282,040	$376,324
Edison, NE	$246,246	$323,381	$267,593	$334,586	$273,854	$338,571
Evansville, IN	$169,895	$292,487	$176,656	$297,834	$188,305	$310,147
Finley, ND	$217,669	$305,052	$220,513	$300,784	$221,311	$297,786
Fremont, NE	$254,704	$391,902	$256,074	$387,834	$259,585	$388,004
Gurley, NE	$359,959	$326,052	$387,921	$325,017	$406,706	$323,988
Hinton, IA	$42,288	$148,919	$47,482	$159,278	$48,200	$159,946
Jamestown, ND	$231,483	$302,349	$263,063	$309,015	$273,741	$308,903
Jasper, MN	$12,793	$73,585	$12,476	$73,571	$13,436	$74,032
Jeffersonville, IN	$253,603	$321,775	$287,344	$335,177	$291,984	$337,199
Madison, SD	$55,103	$153,668	$58,733	$166,724	$55,867	$154,672
Marion, SD	$23,735	$100,783	$24,054	$101,318	$23,152	$94,282
Maywood, NE	$459,280	$478,781	$488,134	$471,411	$498,922	$460,665
Mellett, SD	$115,581	$238,677	$115,565	$239,967	$110,224	$242,807
Mitchell, SD	$47,307	$160,768	$55,101	$169,074	$59,604	$174,438
Mound City, IL	$203,336	$263,272	$221,170	$267,503	$234,856	$279,218
Mount Vernon, IN	$175,167	$300,467	$180,410	$305,850	$192,216	$323,213
Muscatine, IA	$139,360	$257,095	$149,852	$263,967	$158,723	$277,069
Nauvoo, IL	$191,205	$304,209	$214,106	$318,655	$228,695	$325,832
Pekin, IL	$250,115	$321,284	$270,896	$328,846	$307,013	$334,479
Pleasant Hill, IA	$33,194	$99,006	$31,569	$90,681	$35,175	$95,295
Red Oak, IA	$82,914	$197,842	$84,695	$201,333	$81,273	$184,355
Wolsey, SD	$114,234	$251,406	$117,106	$255,167	$117,386	$256,031

Table A13. Normal Increase in Shuttle Train Loading Efficiency Average Profit.

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$182,243	$269,279	$182,224	$269,291	$182,206	$269,303	$182,187	$269,315	$182,168	$269,327
Alden, IA	$94,759	$200,767	$94,759	$200,767	$94,759	$200,767	$94,759	$200,767	$94,759	$200,767
Alton, ND	$261,505	$296,044	$260,757	$296,162	$259,953	$296,482	$258,034	$297,390	$256,268	$298,645
Aurora, IN	$290,955	$309,647	$289,522	$309,434	$289,080	$309,422	$289,080	$309,422	$288,609	$309,406
Ayr, ND	$132,703	$139,880	$264,493	$280,381	$396,347	$422,211	$526,960	$563,289	$656,708	$704,466
Bayard, IA	$62,604	$163,659	$64,276	$163,866	$62,632	$163,649	$64,170	$163,803	$62,709	$163,622
Beatrice, NE	$227,855	$287,357	$226,293	$288,113	$225,379	$287,202	$223,815	$285,897	$222,251	$285,445
Bradshaw, NE	$160,633	$259,038	$159,870	$259,174	$159,467	$258,747	$159,381	$258,664	$159,381	$258,664
Breckenridge, MN	$86,846	$217,129	$86,846	$217,129	$86,846	$217,129	$86,846	$217,129	$86,846	$217,129
Cairo, IL	$121,424	$199,428	$120,832	$199,254	$121,905	$199,937	$123,140	$201,236	$123,708	$201,903
Cin Bunge, OH	$142,520	$254,468	$143,022	$254,307	$142,308	$253,916	$141,095	$253,711	$139,882	$254,085
Cin Cargill, OH	$150,458	$235,258	$150,456	$235,259	$149,812	$235,500	$149,381	$235,501	$148,949	$235,582
Creston, IA	$40,408	$163,684	$37,646	$161,987	$37,646	$161,987	$37,646	$161,987	$37,646	$161,987
Dorchester, NE	$257,849	$296,776	$257,279	$296,793	$257,062	$296,884	$257,119	$296,899	$256,700	$297,042
Dubuque, IA	$281,246	$386,519	$280,808	$386,545	$280,531	$386,583	$280,524	$386,575	$280,223	$386,409
Edison, NE	$277,900	$340,491	$276,758	$341,061	$276,272	$341,273	$275,905	$341,345	$275,328	$341,418
Evansville, IN	$182,574	$301,011	$181,958	$300,183	$182,682	$300,674	$182,901	$300,878	$182,398	$300,056
Finley, ND	$224,124	$302,825	$222,784	$302,758	$220,660	$302,851	$218,782	$303,516	$218,160	$303,906
Fremont, NE	$257,954	$380,559	$256,437	$379,608	$255,654	$379,336	$255,570	$379,329	$255,486	$379,322
Gurley, NE	$393,526	$322,547	$392,995	$322,455	$392,149	$322,489	$390,602	$322,589	$388,170	$323,271
Hinton, IA	$46,341	$161,271	$46,341	$161,271	$46,341	$161,271	$46,341	$161,271	$46,341	$161,271
Jamestown, ND	$276,024	$307,437	$275,090	$307,551	$274,292	$307,638	$273,495	$307,821	$272,856	$307,980
Jasper, MN	$13,347	$73,158	$13,347	$73,158	$13,347	$73,158	$13,347	$73,158	$13,347	$73,158
Jeffersonville, IN	$282,140	$353,603	$284,000	$352,592	$283,425	$352,390	$283,425	$352,390	$283,887	$352,465
Madison, SD	$62,657	$164,383	$62,657	$164,383	$62,657	$164,383	$62,657	$164,383	$62,657	$164,383
Marion, SD	$24,390	$96,998	$24,390	$96,998	$24,390	$96,998	$24,390	$96,998	$24,390	$96,998

Table A13. Normal Increase in Shuttle Train Loading Efficiency Average Profit (continued).

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Maywood, NE	$501,930	$465,229	$503,725	$464,535	$505,201	$464,425	$505,091	$464,621	$504,621	$464,912
Mellett, SD	$108,273	$239,645	$108,648	$239,950	$108,920	$240,209	$108,911	$240,193	$109,480	$239,982
Mitchell, SD	$59,287	$173,350	$59,287	$173,350	$59,287	$173,350	$59,287	$173,350	$59,287	$173,350
Mound City, IL	$227,264	$273,140	$227,195	$273,115	$227,069	$273,019	$226,840	$272,962	$226,484	$273,018
Mount Vernon, IN	$196,942	$336,102	$196,677	$334,269	$196,681	$334,269	$196,002	$333,307	$195,313	$332,470
Muscatine, IA	$167,013	$299,929	$167,013	$299,929	$165,732	$299,156	$164,966	$298,955	$164,966	$298,955
Nauvoo, IL	$227,313	$306,001	$227,273	$306,003	$224,920	$304,640	$222,522	$305,342	$223,427	$305,351
Pekin, IL	$311,766	$338,857	$308,425	$339,914	$306,425	$339,864	$304,513	$340,111	$303,095	$340,400
Pleasant Hill, IA	$32,318	$91,616	$32,318	$91,616	$32,318	$91,616	$32,318	$91,616	$32,318	$91,616
Red Oak, IA	$81,099	$185,465	$81,094	$185,457	$81,094	$185,457	$81,094	$185,457	$81,094	$185,457
Wolsey, SD	$118,901	$252,435	$118,465	$252,598	$118,455	$252,595	$118,097	$251,818	$118,072	$251,459

Table A14. Normal Base Case and Vertical Integration Average Profit/bu.

	Base Case		VI w/o Ocean		VI w/Ocean		Sell CIF/Buy FOB	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Port PNW							$0.15	$0.14
Port USG							$0.25	$0.21
Albany,IL	$0.17	$0.31	$0.23	$0.32	$0.39	$0.56		
Alden, IA	$0.13	$0.27	$0.16	$0.29	$0.28	$0.54		
Alton, ND	$0.21	$0.31	$0.29	$0.32	$0.64	$0.73		
Aurora, IN	$0.26	$0.39	$0.33	$0.39	$0.58	$0.70		
Ayr, ND	$0.28	$0.42	$0.30	$0.31	$0.66	$0.73		
Bayard, IA	$0.08	$0.22	$0.09	$0.22	$0.18	$0.43		
Beatrice, NE	$0.19	$0.30	$0.23	$0.31	$0.58	$0.74		
Bradshaw, NE	$0.15	$0.28	$0.18	$0.28	$0.33	$0.56		
Breckenridge, MN	$0.09	$0.24	$0.10	$0.25	$0.20	$0.50		
Cairo, IL	$0.18	$0.29	$0.20	$0.29	$0.40	$0.58		
Cin Bunge, OH	$0.14	$0.27	$0.16	$0.30	$0.30	$0.53		
Cin Cargill, OH	$0.13	$0.25	$0.16	$0.26	$0.32	$0.51		
Creston, IA	$0.06	$0.18	$0.06	$0.19	$0.11	$0.35		
Dorchester, NE	$0.22	$0.35	$0.27	$0.36	$0.61	$0.78		
Dubuque, IA	$0.26	$0.41	$0.34	$0.48	$0.54	$0.73		
Edison, NE	$0.25	$0.37	$0.30	$0.38	$0.63	$0.72		
Evansville, IN	$0.19	$0.35	$0.22	$0.37	$0.47	$0.71		
Finley, ND	$0.20	$0.34	$0.25	$0.35	$0.56	$0.69		
Fremont, NE	$0.27	$0.50	$0.32	$0.60	$0.57	$0.83		
Gurley, NE	$0.37	$0.42	$0.50	$0.42	$0.82	$0.72		
Hinton, IA	$0.05	$0.19	$0.06	$0.20	$0.11	$0.39		
Jamestown, ND	$0.23	$0.35	$0.30	$0.35	$0.62	$0.70		
Jasper, MN	$0.03	$0.13	$0.02	$0.12	$0.03	$0.20		
Jeffersonville, IN	$0.24	$0.37	$0.30	$0.38	$0.54	$0.67		
Madison, SD	$0.07	$0.21	$0.06	$0.19	$0.09	$0.30		
Marion, SD	$0.05	$0.17	$0.05	$0.17	$0.11	$0.40		
Maywood, NE	$0.45	$0.58	$0.56	$0.55	$0.92	$0.89		
Mellett, SD	$0.12	$0.28	$0.12	$0.31	$0.22	$0.58		
Mitchell, SD	$0.07	$0.21	$0.09	$0.23	$0.14	$0.37		
Mound City, IL	$0.22	$0.31	$0.27	$0.33	$0.54	$0.66		
Mount Vernon, IN	$0.19	$0.37	$0.21	$0.38	$0.40	$0.71		
Muscatine, IA	$0.19	$0.33	$0.23	$0.38	$0.39	$0.62		
Nauvoo, IL	$0.22	$0.35	$0.28	$0.42	$0.53	$0.73		
Pekin, IL	$0.28	$0.38	$0.36	$0.43	$0.59	$0.70		
Pleasant Hill, IA	$0.04	$0.14	$0.04	$0.14	$0.11	$0.35		
Red Oak, IA	$0.15	$0.37	$0.15	$0.36	$0.26	$0.61		
Wolsey, SD	$0.12	$0.29	$0.15	$0.34	$0.27	$0.63		

Table A15. Normal Risk Loving and Adaptive to Changes in Risk Average Profit/bu.

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$0.21	$0.31	$0.22	$0.33	$0.22	$0.33	$0.25	$0.37	$0.23	$0.34	$0.20	$0.26
Alden, IA	$0.10	$0.20	$0.10	$0.22	$0.12	$0.24	$0.15	$0.30	$0.13	$0.27	$0.07	$0.18
Alton, ND	$0.29	$0.35	$0.30	$0.35	$0.31	$0.34	$0.36	$0.41	$0.33	$0.38	$0.26	$0.28
Aurora, IN	$0.31	$0.37	$0.34	$0.38	$0.36	$0.39	$0.34	$0.37	$0.36	$0.38	$0.38	$0.40
Ayr, ND	$0.30	$0.33	$0.31	$0.33	$0.33	$0.33	$0.37	$0.40	$0.35	$0.36	$0.25	$0.25
Bayard, IA	$0.07	$0.17	$0.08	$0.20	$0.08	$0.20	$0.14	$0.29	$0.09	$0.22	$0.07	$0.22
Beatrice, NE	$0.25	$0.33	$0.26	$0.33	$0.27	$0.33	$0.32	$0.41	$0.30	$0.38	$0.21	$0.27
Bradshaw, NE	$0.17	$0.31	$0.19	$0.31	$0.20	$0.32	$0.24	$0.37	$0.21	$0.33	$0.16	$0.29
Breckenridge, MN	$0.11	$0.29	$0.11	$0.29	$0.10	$0.26	$0.17	$0.37	$0.14	$0.32	$0.03	$0.14
Cairo, IL	$0.16	$0.24	$0.18	$0.28	$0.16	$0.25	$0.14	$0.23	$0.14	$0.24	$0.16	$0.26
Cin Bunge, OH	$0.17	$0.29	$0.17	$0.30	$0.17	$0.31	$0.19	$0.34	$0.18	$0.32	$0.18	$0.29
Cin Cargill, OH	$0.16	$0.26	$0.17	$0.28	$0.18	$0.29	$0.22	$0.32	$0.20	$0.30	$0.18	$0.27
Creston, IA	$0.05	$0.18	$0.04	$0.18	$0.05	$0.20	$0.05	$0.21	$0.05	$0.20	$0.06	$0.21
Dorchester, NE	$0.29	$0.35	$0.30	$0.36	$0.32	$0.36	$0.36	$0.41	$0.34	$0.38	$0.26	$0.31
Dubuque, IA	$0.33	$0.44	$0.34	$0.44	$0.34	$0.45	$0.37	$0.52	$0.36	$0.48	$0.32	$0.37
Edison, NE	$0.30	$0.39	$0.32	$0.40	$0.33	$0.41	$0.40	$0.49	$0.36	$0.44	$0.24	$0.29
Evansville, IN	$0.21	$0.35	$0.22	$0.36	$0.23	$0.37	$0.22	$0.36	$0.22	$0.36	$0.23	$0.36
Finley, ND	$0.26	$0.37	$0.26	$0.36	$0.27	$0.36	$0.32	$0.43	$0.31	$0.40	$0.22	$0.30
Fremont, NE	$0.31	$0.47	$0.31	$0.47	$0.32	$0.47	$0.53	$0.76	$0.39	$0.57	$0.09	$0.16
Gurley, NE	$0.44	$0.39	$0.48	$0.39	$0.49	$0.39	$0.52	$0.47	$0.49	$0.42	$0.40	$0.34
Hinton, IA	$0.05	$0.18	$0.06	$0.19	$0.06	$0.19	$0.07	$0.23	$0.06	$0.20	$0.07	$0.20
Jamestown, ND	$0.28	$0.36	$0.32	$0.37	$0.33	$0.37	$0.42	$0.49	$0.38	$0.42	$0.22	$0.24
Jasper, MN	$0.02	$0.11	$0.01	$0.09	$0.02	$0.09	$0.03	$0.12	$0.02	$0.11	$0.02	$0.11
Jeffersonville, IN	$0.31	$0.39	$0.35	$0.40	$0.36	$0.40	$0.34	$0.44	$0.34	$0.43	$0.37	$0.44
Madison, SD	$0.07	$0.20	$0.07	$0.20	$0.07	$0.20	$0.06	$0.19	$0.06	$0.19	$0.08	$0.22
Marion, SD	$0.03	$0.13	$0.03	$0.13	$0.04	$0.14	$0.04	$0.13	$0.03	$0.12	$0.04	$0.13

Table A15. Normal Risk Loving and Adaptive to Changes in Risk Average Profit/bu (continued).

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Maywood, NE	$0.58	$0.57	$0.59	$0.56	$0.61	$0.55	$0.72	$0.70	$0.67	$0.62	$0.37	$0.31
Mellett, SD	$0.14	$0.29	$0.15	$0.29	$0.13	$0.29	$0.16	$0.32	$0.15	$0.31	$0.09	$0.23
Mitchell, SD	$0.06	$0.19	$0.07	$0.20	$0.07	$0.21	$0.06	$0.20	$0.07	$0.20	$0.09	$0.23
Mound City, IL	$0.25	$0.32	$0.28	$0.32	$0.29	$0.34	$0.28	$0.33	$0.29	$0.33	$0.29	$0.35
Mount Vernon, IN	$0.22	$0.37	$0.23	$0.38	$0.24	$0.39	$0.25	$0.41	$0.24	$0.41	$0.23	$0.39
Muscatine, IA	$0.17	$0.31	$0.18	$0.32	$0.20	$0.34	$0.22	$0.42	$0.21	$0.39	$0.20	$0.31
Nauvoo, IL	$0.24	$0.37	$0.27	$0.39	$0.28	$0.39	$0.30	$0.40	$0.29	$0.38	$0.26	$0.35
Pekin, IL	$0.31	$0.39	$0.34	$0.39	$0.38	$0.40	$0.41	$0.47	$0.40	$0.44	$0.34	$0.33
Pleasant Hill, IA	$0.04	$0.12	$0.04	$0.12	$0.05	$0.14	$0.06	$0.15	$0.05	$0.14	$0.02	$0.06
Red Oak, IA	$0.10	$0.24	$0.10	$0.24	$0.11	$0.24	$0.09	$0.21	$0.09	$0.22	$0.11	$0.24
Wolsey, SD	$0.14	$0.30	$0.14	$0.31	$0.14	$0.31	$0.14	$0.28	$0.15	$0.30	$0.17	$0.32

Table A16. Normal Increase in Shuttle Train Loading Efficiency Average Profit/bu.

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Albany,IL	$0.22	$0.32	$0.22	$0.32	$0.22	$0.32	$0.22	$0.32	$0.22	$0.32
Alden, IA	$0.12	$0.24	$0.12	$0.24	$0.12	$0.24	$0.12	$0.24	$0.12	$0.24
Alton, ND	$0.32	$0.36	$0.32	$0.36	$0.32	$0.36	$0.32	$0.36	$0.31	$0.36
Aurora, IN	$0.36	$0.38	$0.36	$0.38	$0.36	$0.38	$0.36	$0.38	$0.36	$0.38
Ayr, ND	$0.32	$0.34	$0.32	$0.34	$0.32	$0.34	$0.32	$0.34	$0.32	$0.34
Bayard, IA	$0.08	$0.20	$0.08	$0.20	$0.08	$0.20	$0.08	$0.20	$0.08	$0.20
Beatrice, NE	$0.28	$0.35	$0.29	$0.35	$0.28	$0.35	$0.27	$0.34	$0.27	$0.34
Bradshaw, NE	$0.19	$0.31	$0.19	$0.31	$0.19	$0.31	$0.19	$0.31	$0.19	$0.31
Breckenridge, MN	$0.11	$0.26	$0.11	$0.26	$0.11	$0.26	$0.11	$0.26	$0.11	$0.26
Cairo, IL	$0.16	$0.25	$0.15	$0.25	$0.15	$0.25	$0.15	$0.25	$0.18	$0.33
Cin Bunge, OH	$0.17	$0.31	$0.17	$0.31	$0.17	$0.31	$0.17	$0.31	$0.17	$0.31
Cin Cargill, OH	$0.19	$0.29	$0.19	$0.29	$0.19	$0.29	$0.19	$0.28	$0.19	$0.28
Creston, IA	$0.05	$0.20	$0.05	$0.19	$0.05	$0.19	$0.05	$0.19	$0.05	$0.19
Dorchester, NE	$0.32	$0.36	$0.32	$0.36	$0.32	$0.36	$0.32	$0.36	$0.32	$0.36
Dubuque, IA	$0.34	$0.46	$0.34	$0.46	$0.34	$0.46	$0.34	$0.46	$0.34	$0.46
Edison, NE	$0.35	$0.42	$0.34	$0.41	$0.33	$0.41	$0.34	$0.41	$0.34	$0.41
Evansville, IN	$0.22	$0.36	$0.23	$0.36	$0.22	$0.36	$0.23	$0.36	$0.22	$0.36
Finley, ND	$0.27	$0.36	$0.27	$0.36	$0.27	$0.36	$0.27	$0.36	$0.26	$0.37
Fremont, NE	$0.32	$0.46	$0.32	$0.46	$0.31	$0.46	$0.31	$0.46	$0.31	$0.46
Gurley, NE	$0.48	$0.39	$0.48	$0.39	$0.48	$0.39	$0.48	$0.39	$0.48	$0.39
Hinton, IA	$0.06	$0.19	$0.06	$0.19	$0.06	$0.19	$0.06	$0.19	$0.06	$0.19
Jamestown, ND	$0.34	$0.37	$0.33	$0.37	$0.33	$0.37	$0.33	$0.37	$0.33	$0.37
Jasper, MN	$0.02	$0.09	$0.02	$0.09	$0.02	$0.09	$0.02	$0.09	$0.02	$0.09
Jeffersonville, IN	$0.35	$0.43	$0.35	$0.42	$0.35	$0.42	$0.35	$0.42	$0.35	$0.42
Madison, SD	$0.08	$0.21	$0.08	$0.21	$0.08	$0.21	$0.08	$0.21	$0.08	$0.21
Marion, SD	$0.03	$0.12	$0.03	$0.12	$0.03	$0.12	$0.03	$0.12	$0.03	$0.12

Table A16. Normal Increase in Shuttle Train Loading Efficiency Average Profit/bu (continued).

	1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Maywood, NE	$0.61	$0.56	$0.62	$0.55	$0.62	$0.55	$0.62	$0.55	$0.62	$0.55
Mellett, SD	$0.14	$0.29	$0.14	$0.29	$0.14	$0.29	$0.14	$0.29	$0.14	$0.29
Mitchell, SD	$0.07	$0.21	$0.07	$0.21	$0.07	$0.21	$0.07	$0.21	$0.07	$0.21
Mound City, IL	$0.28	$0.33	$0.28	$0.33	$0.29	$0.33	$0.28	$0.33	$0.28	$0.33
Mount Vernon, IN	$0.24	$0.40	$0.24	$0.40	$0.24	$0.40	$0.24	$0.40	$0.24	$0.40
Muscatine, IA	$0.20	$0.36	$0.20	$0.36	$0.20	$0.36	$0.21	$0.36	$0.20	$0.36
Nauvoo, IL	$0.28	$0.37	$0.28	$0.37	$0.28	$0.37	$0.27	$0.37	$0.27	$0.37
Pekin, IL	$0.40	$0.41	$0.38	$0.41	$0.38	$0.41	$0.38	$0.41	$0.38	$0.41
Pleasant Hill, IA	$0.04	$0.12	$0.04	$0.12	$0.04	$0.12	$0.04	$0.12	$0.04	$0.12
Red Oak, IA	$0.11	$0.24	$0.11	$0.24	$0.11	$0.24	$0.11	$0.24	$0.11	$0.24
Wolsey, SD	$0.15	$0.31	$0.15	$0.30	$0.15	$0.30	$0.15	$0.30	$0.15	$0.30

Table A17. Base Case/Vertical Integration/Adaptive/Probability of Profit.

	Base Case		VI w/o Ocean		VI w/Ocean		Sell CIF/Buy FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Port PNW							100%							
Port USG								100%						
Albany,IL		40%		47%		46%				42%		41%		47%
Alden, IA		29%		32%		31%				25%		25%		18%
Alton, ND	50%	7%	65%	4%	69%	3%			63%	1%	63%	2%	65%	2%
Aurora, IN		48%		60%		59%				60%		62%		62%
Ayr, ND	52%	7%	71%	5%	76%	5%			70%	4%	71%	3%	69%	2%
Bayard, IA		20%		19%		21%				24%		19%		13%
Beatrice, NE	38%	13%	47%	11%	56%	10%			48%	12%	48%	16%	47%	11%
Bradshaw, NE		32%		38%		37%				38%		37%		34%
Breckenridge, MN		18%		21%		22%				24%		21%		7%
Cairo, IL		43%		44%		45%				34%		35%		37%
Cin Bunge, OH		36%		35%		37%				38%		37%		40%
Cin Cargill, OH		35%		37%		40%				42%		40%		39%
Creston, IA		13%		12%		12%				10%		9%		10%
Dorchester, NE	36%	14%	46%	13%	54%	12%			48%	20%	48%	21%	46%	20%
Dubuque, IA		45%		54%		52%				53%		53%		56%
Edison, NE	37%	17%	47%	12%	56%	13%			55%	11%	50%	11%	51%	13%
Evansville, IN		39%		43%		45%				42%		42%		42%
Finley, ND	41%	6%	51%	3%	62%	3%			51%	4%	52%	5%	49%	2%
Fremont, NE	30%	13%	37%	10%	46%	9%			42%	10%	43%	12%	28%	5%
Gurley, NE		64%		79%		78%				71%		73%		74%
Hinton, IA		11%		10%		11%				11%		10%		13%
Jamestown, ND	47%	6%	61%	2%	67%	4%			62%	1%	65%	2%	66%	1%
Jasper, MN		6%		4%		4%				7%		5%		5%
Jeffersonville, IN		47%		58%		56%				57%		60%		63%
Madison, SD		14%		12%		12%				13%		13%		16%

Table A17. Base Case/Vertical Integration/Adaptive/Probability of Profit (continued).

	Base Case		VI w/o Ocean		VI w/Ocean		Sell CIF/Buy FOB		Adaptive 80%		Adaptive 90%		Adaptive 100%	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Marion, SD		10%		10%		12%				13%		13%		13%
Maywood, NE	46%	22%	67%	17%	69%	13%			64%	22%	67%	22%	64%	18%
Mellett, SD		20%		18%		19%				26%		24%		19%
Mitchell, SD		15%		17%		17%				14%		15%		17%
Mound City, IL		54%		59%		60%				57%		60%		58%
Mount Vernon, IN		38%		36%		38%				41%		42%		39%
Muscatine, IA		37%		41%		41%				38%		37%		40%
Nauvoo, IL		43%		51%		52%				50%		52%		51%
Pekin, IL		52%		60%		60%				61%		62%		64%
Pleasant Hill, IA		11%		11%		13%				15%		15%		8%
Red Oak, IA		21%		20%		21%				20%		20%		20%
Wolsey, SD		21%		24%		23%				26%		27%		31%

Table A18. Risk Loving/Increase in Loading Efficiency Probability of Profit.

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Albany,IL		40%		40%		42%		42%		42%		42%		42%		42%
Alden, IA		23%		24%		25%		25%		25%		25%		25%		25%
Alton, ND	57%	4%	61%	3%	64%	2%	64%	1%	64%	1%	64%	2%	64%	2%	63%	2%
Aurora, IN		57%		58%		61%		60%		60%		60%		60%		60%
Ayr, ND	63%	5%	65%	3%	69%	3%	69%	4%	70%	3%	69%	3%	69%	3%	69%	4%
Bayard, IA		17%		17%		17%		17%		18%		18%		18%		18%
Beatrice, NE	44%	13%	46%	13%	47%	13%	50%	13%	49%	16%	50%	15%	49%	13%	49%	13%
Bradshaw, NE		34%		37%		37%		36%		36%		36%		36%		36%
Breckenridge, MN		19%		19%		17%		19%		19%		19%		19%		19%
Cairo, IL		37%		38%		38%		36%		35%		35%		35%		36%
Cin Bunge, OH		40%		39%		38%		37%		37%		37%		37%		37%
Cin Cargill, OH		37%		34%		37%		39%		39%		38%		38%		38%
Creston, IA		10%		8%		8%		9%		8%		8%		8%		8%
Dorchester, NE	42%	20%	42%	18%	48%	20%	48%	20%	48%	20%	49%	21%	47%	20%	48%	22%
Dubuque, IA		51%		52%		52%		52%		52%		52%		52%		52%
Edison, NE	44%	12%	46%	16%	50%	14%	49%	14%	49%	15%	48%	14%	49%	13%	50%	14%
Evansville, IN		40%		40%		42%		42%		43%		42%		43%		42%
Finley, ND	44%	5%	47%	6%	49%	6%	51%	6%	50%	3%	50%	4%	50%	5%	48%	4%
Fremont, NE	39%	11%	38%	10%	40%	11%	39%	11%	39%	13%	39%	10%	39%	11%	39%	11%
Gurley, NE		71%		75%		77%		75%		75%		75%		75%		75%
Hinton, IA		11%		11%		11%		10%		10%		10%		10%		10%
Jamestown, ND	53%	2%	61%	1%	67%	1%	67%	3%	66%	3%	66%	1%	66%	1%	65%	1%
Jasper, MN		4%		3%		4%		4%		4%		4%		4%		4%
Jeffersonville, IN		62%		65%		64%		62%		63%		63%		63%		63%
Madison, SD		16%		15%		15%		16%		16%		16%		16%		16%
Marion, SD		10%		10%		11%		11%		11%		11%		11%		11%
Maywood, NE	56%	19%	60%	18%	65%	18%	66%	18%	66%	20%	65%	19%	65%	20%	64%	19%

Table A18. Risk Loving/Increase in Loading Efficiency Probability of Profit (continued).

	Risk Measure 10%		Risk Measure 20%		Risk Measure 30%		1 Shuttle Train		2 Shuttle Train		3 Shuttle Train		4 Shuttle Train		5 Shuttle Train	
Origins	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG	PNW	USG
Mellett, SD		26%		27%		22%		23%		23%		23%		23%		24%
Mitchell, SD		12%		14%		16%		15%		15%		15%		15%		15%
Mound City, IL		58%		63%		61%		59%		59%		59%		59%		59%
Mount Vernon, IN		42%		40%		39%		39%		39%		39%		39%		39%
Muscatine, IA		33%		33%		37%		37%		37%		37%		37%		37%
Nauvoo, IL		45%		49%		50%		51%		51%		51%		50%		50%
Pekin, IL		54%		60%		63%		66%		64%		64%		64%		64%
Pleasant Hill, IA		13%		13%		14%		13%		13%		13%		13%		13%
Red Oak, IA		20%		20%		21%		21%		21%		21%		21%		21%
Wolsey, SD		26%		26%		26%		28%		27%		27%		27%		28%