DETERMINING THE OPTIMAL COMMODITY AND HEDGE RATIO FOR CROSS-HEDGING JET FUEL

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Determining the Optimal Commodity and Hedge Ratio for Cross-hedging Jet Fuel

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ABSTRACT

Airlines are exposed to risks in swings in the price of jet fuel. While there are many different options that they can use to hedge this risk, airlines often underutilize them. This study establishes the minimum variance hedge ratio for an airline wishing to hedge with futures, while also establishing the best cross-hedging asset.

Airlines hedging with futures would create the most effective hedge by using 3-month maturity contracts of heating oil. 3- Month maturity contracts are slightly more effective as hedging tools than the next month, but beyond the 3-Month veil, increased maturity makes heating oil less effective as a cross hedging tool.

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1. INTRODUCTION

1.1. Problem Statement

The total number of air travelers has more than doubled since deregulation of the airline industry in 1978 (Smith and Cox, 2008). However, airlines continue to have a difficult time staying profitable. The airlines industry is crucial to the American economy, accounting for over 10 million jobs and 5.2% of the United States Gross Domestic Product (GDP) in 2009 (FAA, 2011). Yet just four years prior to 2009, four major airlines were under Chapter 11 restructuring. The airline industry was deregulated in 1978 opening it up to market forces. Post deregulation airlines operate in a very competitive market and in the years following 1978 have developed many different ways of trying to develop an advantage. Many airlines adapted efficiency increasing measures, others developed low cost structures, but profit margins for airlines remained low (Smith and Cox, 2008). While airlines are making efforts to increase their profitability, they still face many problems, several of which are unique to the industry.

Airline deregulation did not solve all of the problems for the industry. While there were those who feared that without government regulation airlines would adopt monopolistic pricing, it worked out that pressure from competition has actually helped out passengers. Real airfares dropped 25% between 1991 and 2008 (Smith and Cox, 2008) and are 22% lower than they would be if airlines were still fully regulated (Morrison and Winston, 2000). These lower airfares have worked out as a tremendous advantage for passengers but have not had the same effect on airlines.

The airline industry confronts many exogenous shocks that cannot be easily addressed. These shocks, such as terrorist attacks, political instability, and global diseases have been partly responsible for the loss of growth for the entire decade of the 2000s. The post 9/11 shock of 2001 decreased demand by 20%, and it would not be until after 2010 that demand would return to pre-9/11 levels (Borenstein, 2011). Even during periods of decreased demand, airlines often have large fixed and sticky costs, meaning that they must continue to operate even with lower load factors and reduced revenue per mile (RPM).

US airlines also face intense competition when pricing their tickets. With the advent of websites that can compare multiple airlines' prices for tickets, ticket prices have been forced even more downward. Due to competition, the price premium that airlines are able to charge has fallen 20% over the past two decades (Borenstein, 2011). While increases in efficiency have improved the positions of many airlines, for others breakeven points are still out of reach. These factors have led to the consolidation of many airlines (e.g. Continental – United, Northwest – Delta, American Airlines – US Airways, etc.) in recent years. While consolidation has helped the industry reach breakeven points and better serve economies of scale and density, it has not addressed the underlying issue facing airlines, which is the inability to control costs.

The increased competition has also made it so airlines cannot easily pass on costs to consumers. In conjunction with this, airlines have narrow profit margins implying that airlines have restricted cash flows in the event of a price of an input increasing. The combination of these factors means that for an airline to succeed it must control costs (Carter et al, 2004). Of airlines' many costs, the two largest single areas of cost are labor and jet fuel. Traditionally, labor has been an airline's greatest cost but jet fuel has gradually replaced labor as the single largest cost. The increase in the price of jet fuel has been paired with an increase in the price volatility, meaning that not only have the price swings become larger as a percentage, but they have also become larger in both nominal and real terms. To protect against these swings some airlines have decided to hedge their jet fuel.

Additionally, airlines currently use many different methods to reduce fuel usage. Many airlines are updating fleets and making modifications to aircraft to increase fuel efficiency. Other airlines have gone as far as replacing the seats, television monitors, and even the beverage carts with newer and lighter versions (FAA, 2011). However, these improvements have not been enough for airlines to remain profitable during times of increased jet fuel costs. Because of this, fuel hedging and financial contracts play an important role in fuel cost and risk management. These financial instruments, often futures and options, use other petroleum products as their underlying asset. Airlines are forced to use instruments that use varying underlying assets because there is no large commercial market for instruments with jet fuel as the underlying asset. To hedge in a situation like this airlines cannot use a direct hedge and must use a cross-hedge where the hedging contracts used have commodities that are highly correlated with jet fuel. Airlines are presented with a small array of different commodity options, but the most widely used are West Texas Intermediate - Sweet Crude (WTI), Brent North Sea oil, heating oil, and gasoil.

This study aims at finding risk minimizing reducing hedge ratios for the different contracts by using econometric techniques as well as Monte Carlo simulations. From this, the potential Value at Risk (VaR) will be derived from simulated portfolios. Airlines often feel that they should hedge, but admit that they are not sure of the best way to do so (Mercatus, 2013). Those that do hedge often do not have the most effective or successful hedges (Morrell and Swan, 2006). Much of the existing literature in this area addresses why firms hedge (Halls, 2005; Morrell and Swan, 2006), value creation from hedging (Carter et al, 2006; Jin, 2006; 2007), or transportation operations and hedging (Treanor et al, 2014; Lim and Hong, 2014). There is limited research (Adams and Gerner, 2012) that presents the optimal volatility reducing hedge ratio for airlines. Furthermore, no study has examined the hedge effectiveness of the abovementioned petroleum commodities for jet fuel. While other studies have attempted to provide this answer, they have focused more on the models than the results. This study will determine the ideal method for estimating the optimal hedge ratio as well as showing that if airlines are concerned about potential losses they should hedge.

2. LITERATURE REVIEW

2.1. Background

After the Airline Deregulation Act of 1978 (ADA), airlines in the U.S. were opened up to competitive markets. This ultimate goal for the airline industry was mentioned in the proper name of the legislation; "An Act to amend the Federal Aviation Act of 1958, to encourage, develop, and attain an air transportation system which relies on competitive market forces to determine the quality, variety, and price of air services, and for other purposes." The introduction of competitive markets led to the entrance of 49 new airlines between 1979 and 1983 to join the 29 already in existence (Evans and Kessides, 1993). Before the ADA, there was little to no competition because the routes and who serviced them were established by a federal organization called the Civil Aeronautics Board (CAB). However, the CAB often took long amounts of time to investigate if a new route should be opened, decreasing efficiency. For example, many airlines filed suit against the CAB based on the granting of routes such as *443 F. 2d 745 Continental Air Lines v. Civil Aeronautics Board* and the corresponding suit *497 F. 2d 608 Delta Air Lines v. Civil Aeronautics Board*. In these suits and a number of others, Continental and Delta are fighting over the Houston-Miami route. The time and bureaucratic work needed to establish or contest a route added to inefficiency in the industry. For that and other reasons, it was decided that the airline industry should be deregulated (Smith and Cox, 2008).

Deregulation brought with it many improvements, such as the hub and spoke system, and is generally thought to have brought more benefits than drawbacks (Evans and Kessides, 1993). However, along with the introduction of new airlines came the introduction of low-cost carriers (LCC). These LCCs started to put downward pressure on fares presenting even more challenges for legacy carriers. The effect can be such that when an LCC announces plans to add a new route the incumbent is forced to lower their fares (Goolsbee and Syverson, 2008).

To compete with LCCs some legacy airlines tried to create their own low-cost airline. These airlines were run by the legacy but offered the attractions of a LCC. All of the U.S. airlines attempts at starting a LCC failed. The only successful airline was Go! started by British Airways. The reason why it was successful while none of the others were was that it was able to enter into its own contract negotiations and was held as an independent subsidiary. These attempts managed only to cannibalize business and to lose money for legacies (Morrell, 2005; Pilarski, 2012). While Go! was able to negotiate its own contracts, the other legacies' attempts were not. The "mini-me" (Pilarski, 2012) airlines used the same labor negotiations as the larger airlines, meaning that any advantage that Southwest or other LCCs actually held was lost. Because of LCCs pushing down prices, jet fuel prices hitting record highs, and demand losing a decade's worth of growth, the industry has been unable to make any mistakes and remain profitable.

In the decade after deregulation, the airline industry lost $10 billion (Borenstein, 2011). The following decade, the general economic growth of the 1990s saw the airline industry reclaiming $5 billion only to lose $54 billion dollars in the 2000's (Smith and Cox, 2008; Borenstein, 2011). Much of the loss of the 2000s came as a result of the terrorist activities on September 11, 2001 and the Severe Acute Respiratory Syndrome (SARS) leading to a $23.2 billion loss between 2001 and 2003 (Smith Cox, 2008). Not all airlines felt the effect of this evenly; LCCs were able to avoid much of the problems that larger legacy carriers were not. This could be due to the fact that SARS was an international issue and many LCCs are domestic only. All airlines were affected by the drop in demand that happened in the early 2000s. After the terrorist attack of 9/11, demand for airlines fell 20 percent, and was still 3% lower in 2008 than in 2000 (Borenstein, 2011). During the year 2005, four of the top seven largest domestic airlines in America were under Chapter 11 bankruptcy restructuring (United Airlines, Delta Air Lines, US Airways, and Northwest Airlines). These issues have led some to determine that "there is no conventional long-run equilibrium explanation for an industry that perpetually loses money" (Borenstein, 2011; page 233).

Due to the industry's competitive nature and inability to raise airfare, airlines have very low profit margins. This means that any sort of external shock to their already narrow profit margins could result in a loss for the airline. Because of that, many airlines have created fuel hedging programs in an attempt to limit their exposure to upward swings in the cost of jet fuel. The problem with jet fuel is not specifically the cost but the volatility in the cost because risk does not necessarily depend on the cost of the asset.

2.2. Network Industries

Although railroads and commercial airlines are both network industries, airlines face different problems than the rest of the transportation sector. Network industries are made up of two components: the flows and the grid. The flows are the airplanes or the trains, while the grid is the infrastructure such as the airports, roadways, or railways (Smith and Cox, 2008).

However, of these producers, airlines are having the hardest time making consistent profits. Even though they were deregulated around the same time (airlines: 1978, railroads: 1980), railroads have been able to fair significantly better than airlines with increased productivity and increased financial performance. There are a number of factors that lead to this: more concentrated market, decreased competition caused by the ownership of the grid and the rails, and the ability to pass on fuel expenses. Railroads have been very successful in establishing a fuel surcharge, where the competitive airline markets have not been able to. This means that airlines are fully exposed to shocks in the jet fuel market. Another disadvantage of airlines is that the firms that own the flows (planes) do not own the grid (airports). Railroads are able to own the rails and although it is difficult, they can expand their grid as needed. Airlines are unable to expand the grid because they do not own the airports. The government manages the air travel grid, which can often lead to delays and minimal infrastructure expansion (Smith and Cox, 2008). Because of these differences, the practices of airlines are very different than that of railroad and trucking firms.

The risk that is being hedged by airlines is the unpredictability in the price of jet fuel. If jet fuel costs were constantly rising, then airlines could react appropriately, however because the price will change constantly and erratically, airlines have a harder time planning their expenses. For example, in 2008 the price of jet fuel in the beginning of January was $2.714 per gallon; it rose 54% in six months to $ 4.179 per gallon before falling 71% to $1.202 in December of that year. These price swings are potentially damaging when coupled with the fact that fuel can be over 35% of an airline's costs (Southwest, 2013). While 2008 is by no means an average representation a typical year for jet fuel prices, it is an excellent representation of what can happen. Also, when airlines do face high jet fuel prices, there does not seem to be any possible short term capacity adjustments or way to tackle the sticky and fixed costs (Borenstein, 2011). To protect themselves from adverse price swings many airlines enter into derivative contracts and financial instruments, although, others have used other methods, like the 2012 Delta Air Lines purchase of an oil refinery (Delta Air Lines, 2013).

U.S. airlines often have a difficult time hedging their jet fuel because there is no publicly traded contract for a future purchase of it. Airlines can use an Over the Counter (OTC) contract called a forward that is specifically catered to the airline's needs, but this is often a difficult task for an airline that refuels in many places. The only publicly traded futures contract for jet fuel is available at the Tokyo Commodity Exchange (TOCOM), and the use of this would open an airline up to foreign exchange risk. This means that airlines must undertake a practice called cross hedging. In this practice, an item that is highly correlated with jet fuel is hedged. For airlines, this means that in lieu of using futures contracts for jet fuel, they would use one of a different petroleum product. Airlines are left with the choice of which commodity they would like to use as a cross hedge.

Southwest Airlines is well known for hedging a high percentage of its fuel use and mentions "the Company has found that financial derivative instruments in other commodities, such as West Texas Intermediate (WTI) crude oil, Brent crude oil, and refined products, such as heating oil and unleaded gasoline, can be useful in decreasing its exposure to jet fuel price volatility" (Southwest, 2013; page: 25). However, the use of instruments with underlying assets that differ from those actually used leads to a potential situation where the two commodities are not perfectly correlated. The difference between the spot and futures price is called the basis. For firms that cross hedge, there is an increase in the size of the basis, leading to an increased amount of basis risk.

Fuel hedging or cross hedging may not be deemed suitable to each and every airline. US Airways goes unhedged because "There can be no assurance that, at any given time, we will have derivatives in place to provide any particular level of protection against increased fuel costs or that our counterparties will be able to perform under our derivative contracts" (US Airways, 2014; page 20). US Airways also mention the loses from hedging due to downward price swings and the potential need for large amounts of capital to settle debts. The annual report for the SEC, Form 10-K, also mentions that reformed laws could potentially make it harder for airlines and any firm that uses derivatives to hedge. Another problem with jet fuel hedging is that there is no way to be sure of the connection between the two assets. Southwest notes that "the correlation between WTI crude oil prices and jet fuel prices during recent periods has not been as strong as in the past, and therefore the Company can no longer demonstrate that derivatives based on WTI crude oil prices will result in effective hedges on a prospective basis" (Southwest, 2014; page 27). Even with the trouble that cross-hedging can give an airline; most U.S. airlines still choose to participate (Lim and Hong, 2014). Airlines do not have successful hedging strategies (Morrell and Swan, 2006; Mercatus, 2013) and this study will assess and measure the risks of cross-hedging while identifying suitable commodities for use in hedging.

2.3. Introduction to Risk

Airlines face many sources of risk. These risks can often be mitigated by entering into contracts and using financial instruments. This study examines the current uses and the potential uses of contracts and financial instruments to mitigate risk for airlines. The largest area of risk for an international airline is commodity price risk. For an airline the commodity most used is jet fuel (or jet kerosene), which can represent over 30% of the airlines costs. Other financial risks that airlines face are lesser than that of jet fuel, but still present a credible threat to operations. These would include interest rate risk and foreign currency risk. Interest rates are very important to airlines, which are often very heavily debt financed and have a more difficult time attracting equity (Loudon, 2004). Thus, an advantage or disadvantage in borrowing costs could carry through to the rest of the airline's operations. The commodity risk presented to airlines in the form of jet fuel is an important issue. As the number of passengers grows each year and as ticket prices do not grow accordingly, airlines risk losing their already narrow profit margins. However, by hedging airlines could better protect the profit margins in times when the price of fuel is sporadic or increasing.

Casually risk and uncertainty have taken similar definition, but there still exists a distinction between the two. Uncertainty is the state of not knowing future events and/or not being able to measure the probability of such events happening. Risk is the state of knowing the likelihood or probability of an event happening in the future. This would mean that risk is measurable uncertainty (Knight, 1921). The role of risk in a firm is a dynamic one. Due to the nature of risk versus uncertainty, firms are able to mitigate risk at a certain level of confidence, protecting themselves from the source of risk. The other trait of risk is that profit can be defined as a reward or a premium for perusing a risk. By taking a risk, investors may be able to increase their return compared to if they did not take the risk at all. This is most easily seen through the most basic example of comparing a portfolio to a treasury bill. A portfolio may be able to offer a higher return rate, but it also runs the risk of giving the investor a low one, or even losing the investor's money. A treasury bill, however, is a zero-risk investment where the investor receives a low rate of return but is guaranteed that rate of return. The risk that this study will focus on is a financial risk. Airlines face many other risks, such as crashes or terrorist attacks, but they mitigate those risks in different ways.

2.4. Financial Risk

Financial risk is a general term used to discuss many types of risk that involve money. The previous example comparing a portfolio to a treasury bill is an example of financial risk. However financial risk also includes other types of risk. Some of the most common types of financial risks fall into the category of Market Risk. As the name implies, these risks exist because there is a market that sets prices and these prices are always changing.

2.4.1. Default/Counter Party Risk

Counter party risk is a situation in which risk is caused by the actions of the other party in the contract. This risk exists in some form or another in all contracts. The main source of risk is the uncertainty as to if the other party will either abandon their agreement or would no longer be able to meet the agreement. This risk can often be mitigated with a well written contract and is not always a problem between two large firms. For airlines especially, there is always a risk that the airline and the unions will not reach agreeable terms for a contract and the unionize workers could strike. Default risk is very similar to counter party risk except that it not that the opposite party in the contract is unwilling to honor the agreement it is that they are unable to. If the firm with which the airline had a contract goes bankrupt then there isn't much a well written contract would do to help the airline.

The problem could also be that the airlines would be the defaulting party. Airlines have to worry if they will have the future liquidity and collateral to meet counter party demands (US Airways Group, 2012).

Another example of counter party risk for airlines are unions. Airlines always run the risk that a negation between firm and employees will not be reached, resulting in the loss of its workforce. Airlines also worry about if credit card processors will continue to honor purchases made. Although it is unlikely to happen, airlines do mention that "under certain conditions, to hold an amount of our cash (referred to as a "holdback") equal to some or all of the advance ticket sales that have been processed by that company" (US Airways, 2012; page 18).

2.5. Market Risks

2.5.1. Interest Rate Risk

Interest rate risk is when a firm selects a type of interest rate, but is unsure as to where the market will take the interest rate in the future. A firm has two different options, a fixed rate or a floating rate. A fixed rate is where the firm would lock into a rate and it would stay the same over the life of the loan. The risk in this scenario is the uncertainty of the rate; if the interest rate were to drop over the life of the loan, the firm would be paying more than if it had opted for a floating rate. A floating rate loan is one where the rate changes along with the London Interbank Offered Rate (Libor) which helps to determine the interest rate. This uncertainty is that the interest rate may increase, and the firm would have to pay more than if it had opted for a fixed rate loan. As mentioned earlier, airlines are mainly financed through debt due to the high cost of equity (Loudon, 2004). Although part of the Modigliani-Miller (MM) Theorem of capital structure states that financing through debt or equity should not affect the firm, in practical applications parts of the MM theorem can be assumed away (Dufey and Srinivasulu, 1983). The macroeconomic effect that happens along with interest rate changes can also prove to be very influential to airlines' operations. Increases and decreases in interest rates can represent a larger economic issue, which could affect the airline both financially and operationally (Morrell and Swan, 2006).

2.5.2. Equity Risk

Equity risks are associated with the movement of values of stocks in the stock market. While this risk is most often experienced by investors that does not mean that firms are unaffected by it. Management at firms makes choices that are designed to reduce equity risk and make the firm's stock more desirable to the investor. Equity risk can also be deconstructed into the commodity risk, interest rate risk, and foreign currency exchange risk (Adler and Dumas, 1984). This can be accomplished because the value of equity is based on the perceived value of the company. For example, if investors feel that a firm is more exposed to petroleum, its stock value will be more sensitive to increases and decreases in the petroleum markets. Airlines often have volatile earning, which can be less attractive to investors. This can be seen by the lower than average price-earnings ratios that are found in the airline industry (Loudon, 2004). While airlines cannot use a specific financial instrument to manage equity risk, it can be reduced by a series of different financial and operational decisions.

2.5.3. Commodity Risk

Commodity risk deals with the uncertainty in the future price of a good in the market. The commodity markets tend to be more sensitive to price changes leading both producers and consumers to enter into derivative contracts. Commodity risk is the largest risk for airlines. Even with the increased efficiency of airplanes, jet fuel can still be over 30% of an airline's operating cost. There is much literature that exists on this subject and the majority is connected with how hedging affects airlines. The reason for this debate is that while there are the risks for changes in the price, airlines that use fuel hedging to control commodity price risk do not always have lower operating expenses (Lim and Hong, 2014). Delta Air Lines decided to mitigate potential commodity risk by purchasing an oil refinery in 2012. This act of vertical integration shows that some airlines do not think that financial instruments are optimal in controlling commodity risk. Fuel represented 36% of Delta's operating expense in 2012 increased from 30% in 2010, over that same period average fuel price per gallon increased from, $2.33 to $3.25, or 39% (Delta Air Lines, 2012). Wild swings in commodity prices can decrease the profitability of airlines, and due to the nature of competition in the airline sector, outside of hedging, there is little airlines can do to pass on these costs.

2.5.4. Currency Risk

Foreign exchange risk is the variability of a firm's cash flows caused by uncertain changes in the exchange rate. The variability in cash flows leads to a change in the value of the firm. Along with exchange risk there are measures of foreign currency exposure. Exposure is a measure of the amount that the firm is affected to foreign currency changes. Exposure exists in four different measures. Translation exposure is the exposure of the firm when it formally converts a foreign currency to its functional currency. Transaction exposure is the exposure of a firm that has assets, debt, or contractual obligations denominated in a foreign currency. Tax exposure depends upon the country's tax laws and how losses or gains in foreign currency are recorded. Finally, operating exposure is the amount which exchange rates and therefore prices affect the firm. Operating exposure is also a component of inflation risk. Inflation risk is the risk that inflation will affect the purchasing power of the currency adversely.

Transaction exposure affects many firms, but non-American international airlines are especially sensitive to it. For example, Singapore Airlines generates a surplus in all foreign currencies except for the United States Dollar (USD). This is because "most capital expenditure, fuel costs and aircraft leasing costs" are denominated in USD (Singapore Airlines, 2012). This means that they have to convert from Singapore Dollars to US Dollars to cover expenses.

2.5.5. Basis Risk

Basis risk is the difference between the price on the contract and the price that the firm actually paid for the item it used. Normally, for a firm this would include transportation costs of the asset and any imperfect correlation between the asset and the futures price. For an airline, this basis risk includes not only the difference in the cost from the underlying asset to the price that they actually pay for the jet fuel used, but the fact that they are cross hedging increases the basis risk. For example, if an airline uses WTI crude to hedge their jet fuel exposure it most likely will not follow jet fuel exactly. This difference in relationship is part of hedge effectiveness but it also is considered to be part of the basis risk. This is evident in Figure 2.1, which shows the price of jet fuel graphed along with the jet fuel crack spread. The spread represents the cost of refining jet fuel and graphed along with the cost of jet fuel. The pattern can be seen that there are other factors that influence the relationship. For hedgers, airlines especially, this means that the basis and relationship between the assets are always changing. This means that a hedge ratio should be recalculated.

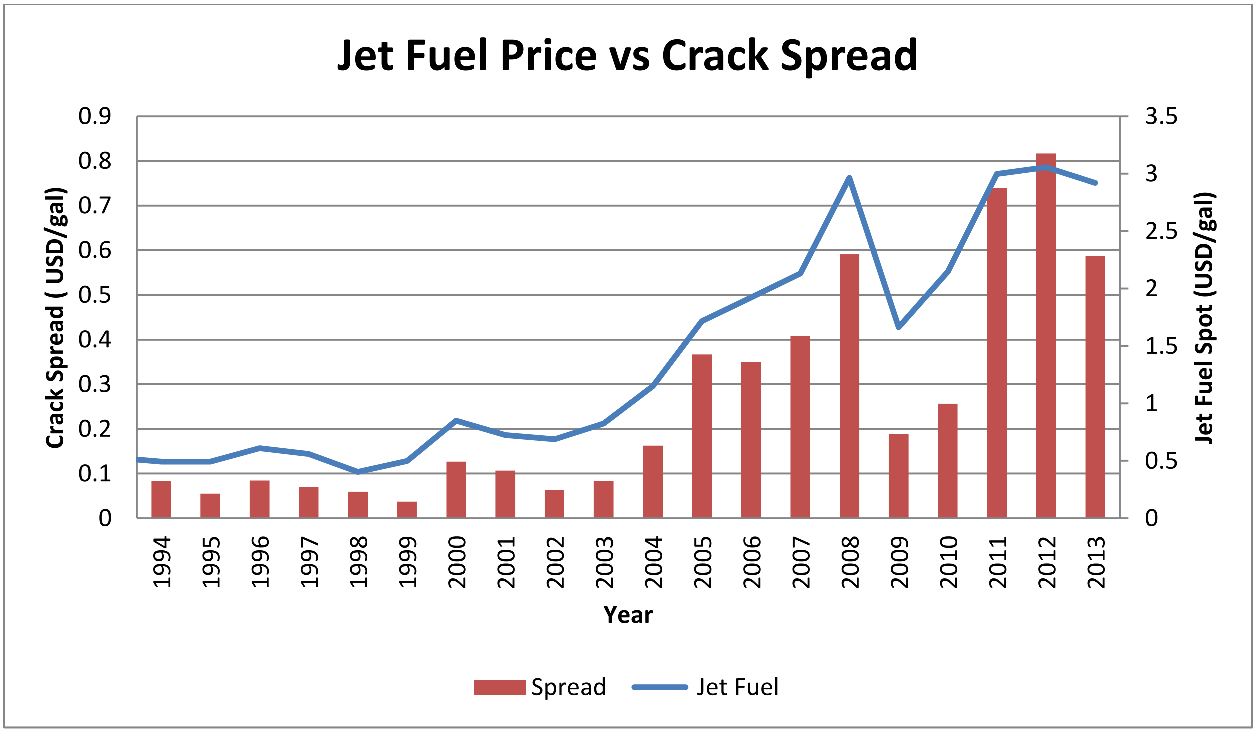

Figure 2.1. Comparison of Jet Fuel Price and Crack Spread
Source: EIA

2.6. Value at Risk

Value at risk (VaR) is a measurement of downside risk. A more specific definition from Wilson et al (2007) defines VaR as "a single, summary statistic indicating the portfolio loss that will be exceeded with a probability of 1-c, during a given period of time (t), under normal market conditions, where c is the specified confidence level." This means that VaR should be interpreted as a value which, at a certain confidence level (90%, 95%, 99%), the portfolio will lose no more than. For example, a one week $5 million VaR at a 95% confidence level means that in one week, the portfolio will not lose an excess of $5 million. The concept of VaR was originally made popular by J.P. Morgan & Co. when it was said that the chairman of the firm wanted to know with confidence what the maximum amount that could be lost that day was (Hallerbach and Menkveld, 1999). From there, the measure was made easily available in the *Risk Metrics* program of J.P. Morgan & Co.

2.6.1. Benefits of VaR

VaR is beneficial for a number of reasons. First, VaR is easily describable. The result is given without statistical terms and could be considered more intuitive because it is given in a dollar amount or percentage. This is one reason why firms will post it in their annual reports. Airlines will often have a sentence mentioning the cost to the firm of a one dollar increase in the price per gallon of jet fuel. Along with this, it focuses on downside risk giving an easy to understand worst case scenario. Another benefit to VaR is that it is that it can be used for different time periods. For example, a monthly VaR may be used by a firm that feels it would need a month to respond, while day traders could use a daily VaR. This is beneficial because it is highly unlikely that an airline or any firm would be able to entirely liquidate a position in a day. Finally, VaR can be calculated by assuming a normal distribution or other distribution of prices. By using a Monte Carlo simulation the VaR can determined with any distribution as well making Monte Carlo the preferred method of determining VaR (Wilson et al, 2007).

2.6.2. Expected Shortfall (ES)

Expected Shortfall (also known as Conditional Value at Risk (CVaR)) is a measure similar to the traditional VaR, but can measure the potential losses outside of normal market conditions. It can also be used to measure the VaR of individual parts of the portfolio. Because ES has the property of subadditivity, the whole should equal the sum of the parts. However, the traditional measure of VaR lacks this property and thus is it potentially possible for the VaR of a portfolio to exceed the sum of the VaR of the weighted average of the assets (Harris and Shen, 2005). Another benefit of ES is that it is more sensitive to the skewedness and kurtosis of the distribution of losses, allowing the value at risk to be quantified at different rates.

2.6.3. Flaws of VaR

Due to the fact that VaR often assumes a normal distribution, there can be many problems. For example, using the wrong distribution or assuming the wrong kurtosis/skewedness can lead to a misrepresentation of VaR (Barry et al., 2009). Another potential problem with VaR is that there are different ways of computing it. While this is not a major problem, it does lead to debate over the best method (Manfredo and Leuthold, 1999), and it can lead to the potential misunderstanding of which method was used as some methods lead to an over/underestimation of the value at risk. There are also criticisms of the decomposition based VaR.

2.6.4. Methods of Calculating VaR

As mentioned earlier, there are many different techniques to calculate VaR, and each one has its own benefits and drawbacks. The first method is the parametric method also called the variance/covariance method. This term is applied to methods that cover historical volatility, implied volatility, and other conditional time series models (Manfredo and Leuthold, 1999). JP Morgan's *Risk Metrics* is an example of parametric technique that uses exponentially weighted moving averages to measure a time sensitive volatility. The criticism of the parametric technique is that it assumes normality, which would cause problems in leptokurtosis and non-normal distributions. Another criticism is that the parametric method is not suitable for long term forecasting, because of scaling. The other main way of establishing VaR is from simulations. These methods, called Full-Valuation methods, include historical simulations, Monte Carlo simulations, and bootstrapping. Non parametric VaR "attempts to model the entire return distribution instead of providing a point estimate of volatility." (Manfredo and Leuthold, 1999) These simulations methods provide a fuller picture of the VaR but they are often lengthy to create and do not always account for trends. Another criticism of Monte Carlo is they "do not have the ability to obtain an explicit variance/covariance matrix" (Manfredo and Leuthold,1999). However, modern software packages are able to overcome this obstacle.

2.7. Hedging

Hedging is taking the opposite position of what the firm normally faces. For example, an airline which receives revenue in Japanese Yen would sell the Yen at a specified rate, thus closing out its position and mitigating the translation risk. Anytime more than the revenue is hedged, the firm starts to speculate and therefore cannot use hedge accounting (FAS 133). A hedge should not be considered a speculative move, which would be a firm using it to increase profit. A hedge is an attempt to smooth out the peaks and troughs in prices. The idea of zero sum means that over time a hedged firm should be worth the same as an unhedged firm (Morrell and Swan, 2006).

Hedging can also be described as a way of making what was once the undesired outcome desirable. For airlines, this is especially true for fuel prices. By purchasing derivatives, an airline owns a contract that becomes more valuable as the fuel prices increase. This means that as fuel price increases, the increased cost is offset by the increased value in the airline's contract portfolio. This is met with the other possible outcome where fuel prices drop. While the contract that they took out is now losing the firm money, by being worth less than they paid for it, that is met by the fuel that they use being cheaper.

2.8. Financial Instruments

Financial instruments are perhaps one of the most widely utilized mechanisms to mitigate risk. A derivative hedge is a system that allows a firm to lock in at a certain price for an asset that it needs in the future. The hedge uses derivative or a contract/agreement to purchase an underlying asset in the future at an agreed upon price. Derivatives contracts are for standardized amounts of standardized assets. These traits make it easily traded, which is another reason why they are so popular. This means that if for any reason either party wants to no longer be in the contract, they will have an easy time canceling out its position. For airlines, the most popular are swaps and futures.

2.8.1. Forwards

A forward contract is an agreement between two parties to buy/sell an asset in the future. These contracts can be tailored to fit either party's needs (i.e. an uncommon amount of the asset or an uncommonly traded asset.) These contracts are less liquid as they are specific to the needs of the parties, making it harder for either party to renege. This type of contract would mainly be used if an option or a futures contract was not available for the asset or quantity. If either party in a forward contracts is unable to meet the agreement then there is little that can be done, unless a measure is written into the contract that deals with such an event. Finally, while some small airlines use forwards, it is uncommon for a larger airline to use them. This is due to the difficulty of taking physical deliveries of the commodity at many different locations. However for a smaller airline, a fuel forward could guarantee that the airline knows the exact cost for fuel for the contracted time period.

2.8.2. Futures

A futures contract is an agreement for one party to purchase an underlying asset for an agreed upon price at an agreed upon date, called the maturity date. For a futures contract, the benefits of standardization make them appealing to both users of the assets and speculators on the price of the asset. Because delivery of the asset has to be taken with a future, they are often sold very closely to their maturity date, but are often not executed for delivery by speculators or financial firms.

For a futures contract, the agreement is handled by a clearing house. Along with this, each party must put up an amount of money that will be traded in the event of a price change on the underlying asset. This account is called a margin account and the amount of money that is put in a margin account is determined by the maximum likely amount of which the underlying asset's price could change. This prevents either party from completely ignoring the contract as the funds in their margin account are already changing along with price flows. Another benefit of the clearing house is that the broker of the sale is the member of the clearing house. This means that a broker is less likely to sponsor someone who he or she thinks is likely to default.

2.8.3. Options

The final common derivative is called an option. It is so called because it gives the holder the option to exercise or not exercise the contract at its maturity date, for a European contract, while an American contract allows for the holder of the contract to exercise it at any point before or on the maturity date. The holder of a call option holds a contract that gives them the right to purchase the underlying asset at the agreed upon price. The holder of a put option has the ability to sell the underlying asset at the agreed upon price.

Because an option is not going to be exercised if it is not profitable, there is no need to worry about a party not fulfilling the agreement. However, because there is that option to not exercise, the party that is issuing the option receives a premium on top of the agreed upon price. Aptly named the "Option Premium," this fee means that even if the party decides not to exercise the contract, the issuer is not entirely without gain.

There are many different types of combinations of longing/ shorting call/put options that an airline may take out at the same time. For example, by "shorting" or selling a put option at the same time a "longing" or purchasing a call option for different strike prices, an airline can create a boundary in which it knows its fuel cost will be. Also, it can create a collar which uses the Option Premium from the shorted option to cover the option premium of the longed option, creating what it called a "costless collar".

2.8.4. Swaps

Swaps are an agreement between two firms to trade a fixed rate and a floating rate at a mutually beneficial rate. Suppose Firm A wants a fixed rate loan but was quoted too high a rate, while the floating rate they were quoted was a low rate. Also suppose Firm B wants a floating rate loan, but their quote was too high, while their fixed rate loan quote was low. These two firms could get together and swap loans, with there being a small premium paid by the firm that is receiving the better interest rate. Even with that small premium, both firms receive the type of loan they want at an interest rate that is lower than they were quoted. Swaps are used by airlines as well as firms in many different industries.

Although interest rate swaps are the most common across most markets, the airline industry takes advantage of commodity swaps (Alaska Air Group, 2014). Also known as fixed price swaps, these allow an airline to trade paying the floating rate of fuel for a fixed rate of fuel. The underwriter of the swap would get paid a fixed rate by the airline, and in return would be paid if the price of the underlying commodity rose above the fixed rate. This is much like the example above, except in lieu of the Libor, the traded commodity's price is used.

2.8.5. Natural Hedge

A natural hedge occurs when the potential undesirable outcome is matched with a desirable outcome without the use of derivatives. Delta's purchase of the Trainer refinery has developed a natural hedge. As costs increase for the airline's fuel, the revenue from the refinery would increase at the same time. As long as the products remain correlated during the changes in price, the refinery's revenue should be inversely proportional to the fuel costs of the airline.

2.9. Advantages of Hedging

Hedges provide many benefits. The first of these is that it can smooth cash flows for firms by protecting them from peaks and troughs in the market. The second advantage is that firms that hedge have better control over when profits are realized. Another possible benefit is that firms which hedge are worth more. The final suggested benefit is that a firm near bankruptcy would be able to perform better if it were to hedge.

2.9.1. Smooth Cash Flows

Of the many proposed benefits that befall a firm which hedges, first and foremost is the idea of smooth cash flows. It is an understood assumption that a firm hedges to prevent volatility in cash flows from market shocks. However, this assumption is not necessarily correct. Copeland and Joshi (1996) found that foreign currency hedging did not and could not reduce cash flow volatility. By comparing the volatility of 198 comparable firms that were hedged and unhedged over a 10-year period they came to the conclusion that the monthly volatility of a firm was not significantly different enough to warrant a foreign currency hedge. Along with this, the authors also simulated the effect of an optimal hedge on specific firms. With the benefit of hindsight, they came to the conclusion that even the best hedge would only reduce quarterly cash flow volatility by 10%. Morrell and Swan (2006) answer the question of "Does hedging reduce volatility?" with a simple

"Sometimes." Writing on airline jet fuel hedging they suggest that the firm should only hedge when one time shocks to the market are likely. This means that if there is likely to be turmoil in an oil producing region than an airline should hedge its fuel costs, however, if these events are unlikely then it should not.

Morrell and Swan (2006), though, go on to give anecdotal evidence as to how hedging could indeed make cash flow more volatile. The idea behind a hedge is that if the oil price increases, while operating costs go up, the value of the derivative contract increases, offsetting the fuel price increase. The other outcome in a hedged scenario is that the price of the fuel input decreases. While the fuel contract is worth less than it was, that does not matter because the operating costs are now cheaper. As mentioned, the authors see a flaw with this kind of thinking. They create a scenario where the price of oil increases because it is demand driven and not supply driven. In this event, when the world Gross Domestic Product (GDP) increases the oil price will be high at the same time that air travel demand is strong. This means that an airline would have increased cash flows from both an increase in travel and an increase in hedge value. At this point the hedge is no longer offsetting potential losses but has doubled the potential gains. However, if there is a slump in GDP growth or a recession, the price of oil could decrease at the same time as there is a lull in demand for air travel. If this were the case, the hedge would be worth less and although the operating costs for fuel are down, the cash flow from travel would also be down. This case would describe how Morrell and Swan imagine hedging to make cash flow more volatile.

2.9.2. Profit Realization

Along with volatility dampening, there is an idea that hedging is beneficial to a company because it allows the firm to choose when the gains from the hedge are realized. Anecdotally speaking this means that if the firm were to have a bad quarter, it could liquidate some of its hedge to make the quarter look more profitable than it actually is. The same could be done with a very successful quarter if hedge losses needed to be hidden. However, going beyond that very basic example there are many opportunities to firms. Smith and Stulz (1985) explain that a hedge can be used to control the tax costs of a firm. By using methods similar to those described earlier, a firm would potentially hide gains in a hedge if it thought it was likely to have to pay a lot in taxes. However, they do note that such a procedure could potentially hurt investor confidence due to the fact that investors often times see the before-tax income. To prevent firms from doing this the tax code was updated in 1998 by the FASB with FAS 133 which makes it so firms must show their position on hedges and value the hedge at the market rate. This practice, called mark-to-market, creates an increase in transparency for the investor into the firm's actions.

Morrell and Swan (2006) also point out that investors like and often value predictability, so even if a firm could manipulate its cash flow to take advantage of the tax code, it may also be damaging its relationship with investors. They also mention that another supposed benefit from controlling when hedging is declared is that a firm could potentially have an increase in cash flows during an industry down turn. The authors describe a situation much like Southwest often takes advantage of, where having a surplus or liquidity at the right moment allows the firm to take advantage of purchasing assets at distressed prices. However, it seems that with a downturn in the industry most larger airlines are also cutting back on capital investment. Disatnik, Duchin, and Schmidt (2013) found that hedging can affect cash flows in a way that could lead to an increased line of credit from a bank. They found that if a firm can successfully control cash flows then that can lead to increased debt limits from banks and potentially lower bond rate when releasing debt.

2.9.3. Value Creation

Another disputed benefit of hedges is that they add value to the firm. This claim is one of the most controversial claims of the benefits of hedging. The most influential paper on the subject is by Allayannis and Weston (2001). In this paper, they look at the value of a firm that uses foreign currency derivatives to hedge. Using Tobin's Q as a proxy for firm value, they establish that a hedging premium, or value added by having a hedging program, is nearly 5%. Tobin's Q is a combination of the market value of the equities and the liabilities divided by the book value of equity and liabilities. Allayannis and Weston did this by looking at 720 nonfinancial firms from a period of 1990-1995. The potential problem with measuring value with the proxy of Tobin's Q is that in their paper they do not establish value as a function of firm characteristics or actions. This makes it harder to connect value creation with the firm's policy of hedging. However, Jin and Jorion (2006) found that the increase in value does not seem to happen when oil and gas producers hedge. The following year, Jin and Jorion (2007) looked at gold mining to see if hedging added any value to those firms. They for the second time found no connection between firm value and hedging. Much like in the oil industry Jin and Jorion suspect that because these commodities are so easily traded, investors do not value a hedging program. If investors did value it, they could easily establish their own hedge within their portfolio.[1]

Carter et al (2006) found that the firm value of airlines could increase by as much as 10% due to a hedging program. The authors are clear to point out that such a premium exists due to the program, and that an airline cannot increase the value of the firm by just increasing the jet fuel hedge

[1] The assumption that corporate finance affects firm's value contradicts the Modigliani-Miller theorem, which states that in well-functioning markets with neutral taxes and rational investors; corporate structure does not matter. The MM theorem can be assumed away in real markets (Dufey and Srinivasulu, 1983). This is due to the advantage a firm has over an investor in hedging. An investor faces entry barriers in real markets caused by the expense of derivatives and the availability of them for investors. The firm also has an advantage in information. Managers are better informed about the firm than investors, meaning that they are better qualified to mitigate the risk. However, it is evident (Morrell and Swan, 2006; Mercatus, 2013) that airline managers lack expertise in fuel hedging.

ratio. However, they link this to the idea that airlines would be able to increase capital investment during downturns, which as is mentioned earlier is unlikely, and that investors value hedging. This latter possibility goes against the opinions of Morrell and Swan (2006) who state that perhaps investors do not value a hedge as greatly as some may think. They cite easyJet's stock price which rose three percent after the announcement that they would start to hedge after being previously unhedged. However, three days later the stock price had returned to the levels prior to the announcement. The authors then rule out any significance by this blip in stock price by pointing out it was lower than the typical blip of a traffic announcement.

2.9.4. Bankruptcy

While there are many conflicting opinions about the potential benefits for a firm by hedging, there is a general consensus about the benefits to a nearly bankrupt firm. The reasoning behind this assumption is that a firm which is near bankruptcy would benefit greatly both by knowing part of the operating costs for the firm at the start of the year and also by avoiding swings in the market. For a firm that is nearly insolvent, it may not be around long enough to experience the opposite swing of the market, so hedging becomes even more valuable. Copeland and Joshi (1996) call this benefit an extension of the "time to ruin." They bring up the fact that large firms that are not likely to enter into insolvency are able to self-insure and do not need or use hedges. However, smaller firms might need to use a different form of insurance against the same risk. They go on to add that as long as the correlation between operating cash flows and foreign currency cash flows are high, a foreign currency hedge would be beneficial to a small firm or one which has a short "time to ruin."

Morrell and Swan (2006) discuss a different potential benefit for cash strapped firms with hedges. They cite the 2004 move by Delta Air Lines to sell profitable hedges early to increase liquidity. The gain of $83 million allowed Delta to enter into other fuel hedges for later dates. The authors also mention that the earlier mentioned practice of allowing a firm to hide profits and losses from a hedge is even more valuable to a nearly insolvent firm. This is because a normal firm would only be able to hide the result from the hedge for so long before it became public. However, for a nearly bankrupt firm, there is no need to worry about the future. Morrell and Swan (2006) discuss that this could be used by a firm that is about to enter into labor negotiations with a union. The firm would not want to look more profitable to unions than it really is, even if it means misleading stock holders.

Smith and Stulz (1985) take hedging and bankruptcy a step further when they discuss how firms can actually hedge the costs of bankruptcy. By creating a hedging portfolio that would increase in value as the firm became bankrupt, the firm could appear more stable to investors. This would be especially attractive to investors who are looking to buy the firm's bonds. Due to the order of payout on debt from a bankrupt firm, with first taxes being taken from the firm and then bond holders and then shareholders, if a firm can secure enough money to pay all of these investors back at the time of insolvency, then they could potentially increase their current cash flows. However, it should be stated that all benefits that hedging could provide to a nearly bankrupt firm are questionable because it is often times unlikely that a firm would have that much liquidity to be entering into hedges.

Wei and Starks (2013) look at the sensitivity of a firm's stock price to exchange rates. The authors look at how related exchange rate exposure elasticity and the likelihood of financial distress, growth opportunities, and product uniqueness. By using a multi-stage regression they were able to find out that firms in distress were more likely to have a stock price that was sensitive to foreign exchange exposure. They mention that this is especially important because although the benefits of a distressed firm hedging are widely known, the ability to hedge in those dire straits is often not possible.

2.10. Disadvantages of Hedging

There are many disadvantages of hedging. One of which is that the hedge may prevent an existing mechanism that was already protecting the firm. Also, hedges can be difficult to design leading to potential issues that exist in cross-hedging. Furthermore, it can be argued that because hedging should over time have zero gains and losses, it should not be done. Finally, there are many different methods to use in hedging, leading to conflicts as to which method to choose.

2.10.1. Loss of Natural Hedge

While the potential benefits to hedging have been established, there are some potential faults too. One such fault is that a derivative hedge can sometimes be created where there is already a natural hedge. Copeland and Joshi (1996) discuss a situation between a European airline and an American airplane producer. In the description of the problem it is discussed that the airline creates a derivative hedge to protect itself from foreign currency risk. However, there was already a natural hedge that protected the firm from that risk. Much like the oil situation described by Morrell and Swan (2006), by creating a hedge it made it so the good times were better and the bad times were worse. But because the airline did have costs in both Euros and US dollars, a strengthening in either currency would have not disrupted cash flows. However, with the derivative hedge and the loss of the natural hedge, there is now a risk.

2.10.2. Difficult to Design

Another potential problem caused by hedging is the ability to easily create a hedge. Going beyond the costs of creating a hedge, how hedge-able is the firm's cost or output and should that even be hedged? After the success of Southwest Airlines' fuel hedge in the early 2000s, many other passenger airlines have started to hedge their fuel costs. However, as Halls (2005) discusses, a fuel hedge is not as straightforward as it may seem. He starts off by exposing potential problems with hedging. One such problem is that for fuel hedging, the actual asset is not associated with a widely traded derivative. Since jet fuel is only traded on the Tokyo Commodities Exchange (TOCOM) a foreign firm cannot easily hedge its fuel use without creating more risk from foreign currency fluctuations. This means that there will have to be some cross price hedging, where the firm hedges a different commodity to the one it actually uses, but figures that the price will correlate to the commodity it uses. For fuel there are many options from Brent, West Texas Intermediate (WTI), heating oil, and even gasoil. While Brent is often used because it closely follows jet fuel, which does not mean it is the natural choice. As Halls (2005) mentions anecdotally the story of a banker who pointed out that while some firms used heating oil, there could be great losses in those hedges because at times heating oil and jet fuel didn't track each other at all. But even with that, on a simple regression he found that over a period of two years heating oil was around 90% correlated and crude was about 80%.

When Adams and Gerner (2012) looked at cross hedging with error correction model and GARCH models, they found that gasoil would be the closest to jet fuel for a period of less than three months and beyond that Brent or WTI would be a better substitute. However, even with this information, there are still unknown variables that could cause the correlation to change, like a change in the cost of the jet fuel differential. The differential is a premium for further refining of the fuel that is needed; however, it can change by large amounts for seemingly unknown reasons. Another possible issue with this study is that they included forwards as an option of the cross hedge. Because the nature of forwards is that the contract is written specifically for the party, thus making it very illiquid, it does not seem practical that an airline would engage in cross price fuel hedging with forwards. Also, the authors note that forwards rates are determined by investment banks which include the futures rate in addition to their margin, or as the authors put it "the pricing on the OTC market crucially depends on the liquidity of the standard futures contracts as investment banks need to re-hedge their OTC commodity positions." Southwest Airlines does a blend of different petroleum commodities to diversify and help prevent the problem of one commodity not being 100% correlated to jet fuel (Southwest, 2012). However, while the Adams and Gerner paper, which was focused more around European designated jet fuel risk, this study is focused around U.S. jet fuel risk. Although this may seem like a subtle difference, it could explain why they found gasoil to be the superior hedging instrument for contracts with near-term maturities.

Another potential problem with cross-hedging is that that even if a suitable commodity can be found, will investors and shareholders value it. Both of the Jin and Jorion papers (2006, 2007) came to the same conclusion; that commodity hedging doesn't necessarily add value to a company. Compared to the other works on the subject this seems to be counter intuitive. It has been assumed that investors like risk reducing practices, however, the two industries that Jin and Jorion (2006, 2007) looked at were both commodity industries. This means that investors likely chose to invest in these industries to be exposed to the commodity price risk.

Dufey and Srinivasulu (1983) make the argument that while corporate management of foreign exchange risk may not matter in theory, it makes a difference in the real world. The crux of their argument is that the assumptions that have to be made for certain theories to work make them impractical in actual application. Starting with the idea that the Purchasing Power Parity (PPP) should be represented in foreign currency exchange, then any management move wouldn't matter. If the value of the currency relative to a different currency is establish by their purchasing power, the nominal amount doesn't matter as much, because it has the same buying power. However, as the authors point out, things can be mispriced making it so that the law of one price doesn't always hold. Also, the changes in a currency's valuation lag behind the purchasing power. This means that while they should ideally catch up, there will be a time that the exchanged currency does not have the same purchasing power. The next arguments they make are against the idea of the zero sum. To combat the arguments that say hedging isn't worthwhile because in the long run everything will cancel out. The authors make the point that creditors value predictability and smooth cash flows, and that some firms are not in the position to ride out the bumpy cash flows. Finally they address the Modigliani-Miller theorem's argument that the investor can do anything the firm can and undo anything the firm does that they do not like. Dufey and Srinivasulu point out that again, in the real world, this is not practical. Private investors face barriers like costs and availability that firms do not face, or that they are more easily able to afford. Also, private investors are likely to be less informed than their corporate counterparts.

2.10.3. Don't Always Work

A different area that people question if hedging is worth it is in foreign currency transactions. Looking at global equity portfolios, Chincarini (2008) found that a currency hedge during the Asian crisis would have been inefficient. With the benefit of hindsight Chincarini (2008) creates a number of likely hedges for the time period of 1999-2006 and finds that all of these potential and possible hedges did not reduce monthly volatility of the portfolio nor did it improve the risk-adjusted return performance. He goes on to add anecdotally that the best course of action for this time period would have been to remain unhedged. This could be due to the fact that he found a 0.249 correlation across all currencies so it is likely that a firm working with a global basket of currencies would likely be very well diversified. This goes against the findings of Glen and Jorion (1993) who found that a currency hedge in the period of 1979-1990 significantly improved the performance of portfolios, especially those with unhedged bonds. They also found that certain hedging strategies were able to get substantially higher yields without increased risk. However, Jorion (1994) specifies that while useful, hedging that includes "overlay strategies" is inefficient because they do not account for the possible relationship between the underlying asset's value change and the change in currency.

Another problem is that over time the traditional benchmark used for hedging, WTI, has started to follow jet fuel less closely than it did in the past. Previously, the price movements for WTI and other crude oils moved along similar to the movements of jet fuel. However, recently the movements have become less correlated. As the gap between crude and jet fuel prices increases, it will significantly hurt those who hedge with WTI futures. While there are many reasons for the gap increases, one potential reason is that the U.S. is exploiting new sources of crude oil, which is lowering the price (IATA, 2014).

2.10.4. Zero Sum

With all of this being said, there is still no general consensus on if firms should even hedge. Morrell and Swan (2006) argue that a permanent hedging policy is not worth it for airlines. They are not opposed to short hedges if there is a risk of a natural disaster or a man made one. But with the exception of unforeseen circumstances, they do not believe that a firm should hedge. This is matched by different industry leaders who acknowledge that in the long run, hedging should not be expected to save money, but just smooth out cash flows. It is often said that hedging over a long period of time is not worth it because it is likely that the market will swing back the other direction but the firm will not be able to reap the benefits of that swing. Although he is writing about the use of derivatives at the time, Stulz (2004) argues that if investors wanted to have a firm hedge, then they, the investor, could do it themselves. He notes that any investor who would find a firm's hedging practices that important would be able to make their own hedge in their portfolio.

2.10.5. Derivative Use

This leads to the final problem of hedging: how it should be done. There are many different options a firm has to reduce risk besides the use of financial instruments. One such way would be to build a plant in the same country as the product is being sold. By doing this, many Japanese auto manufacturers have been able reduce exposure between the US dollar (USD) and the Japanese Yen (JPY). Other firms have used backwards and forwards integration to cover risk exposure. However, for many industries, such as airlines, that is not a practical solution. This has led to the use of derivatives and other financial instruments to hedge risk. Looking at past examples Copeland and Joshi (1996) find that foreign currency hedging with derivatives did not reduce cash flow volatility. They go on to add that in general, derivatives are inefficient in managing foreign exchange risk. This information goes along well with the anecdotal evidence of hedging where it seems that a successful hedge year is often followed by an unsuccessful one. However, Lee (2012) found the opposite to be true. He found that on average futures were an efferent means of hedging and became even more efficient as the duration of the contract increased. Stulz (2006) argues that derivatives only make hedging easier, so they do not create any more of a problem. He argues that if firms desired to, they could recreate the derivatives hedges with elaborate portfolios. This means that the use of derivatives is actually helpful as it is more efficient and convenient

2.11. Fuel Hedging and the Airline Industry

Different airlines utilize different hedging strategies based upon their respective risk aversion. All strategies must meet a certain requirement to be considered hedging. This requirement is determined by the Financial Accounting Standards Board (FASB), whose standards are then used by the Securities and Exchange Commission (SEC). The rule for hedge accounting is FAS 133 *Accounting for Derivative Instruments and Hedging Activities*. To meet the FAS 133 requirements and be considered for hedging accounting, the instrument must be highly correlated and efficient at offsetting changes in fair value or cash flows. While the rule does not make any numeric definition, the rule-of-thumb is that the hedge ratio should be between 80% and 125% (CME Group, 2012). FAS 133 also requires a firm to declare any derivatives held and value them at the price they are worth at the time of declaration. This process is called "mark-to-market." By requiring firms to mark-to-market, the FASB prevents firms from inflating (deflating) losses (profits). Because of these requirements, as well as others that define hedging accounting, not every airline implements it. The choice to implement hedging accounting affects the cash flows of the firm. By implementing hedging accounting, a firm may post losses and gains from hedging along with the corresponding asset and cash flow. By not implementing hedging accounting, a firm has more control over what it deems as a suitable hedging instrument; however it faces different tax and SEC regulations as the income is considered earnings. The benefit of hedge accounting is that firms can post losses or gains from the hedge along with the losses or gains from the hedged asset. For airlines this would mean that they could match their hedging activities with their fuel expenditures. If they do not qualify or use hedge accounting, the gains and losses from a hedge are declared as income.

Another aspect of hedging is risk aversion (Lien and Wang, 2001). Risk aversion is a measure of how exposed the airline wishes to be to price swings. Different airlines have different levels of risk aversion, which are evident in their different amounts of expenditure hedged as well as their hedging strategies. Republic Airways Holdings, the parent firm of Frontier Airlines, uses forwards to hedge 100% their jet fuel exposure (Republic Airways Holdings, 2013). By doing this the airline entirely remove their exposure to fluctuations in the price of jet fuel. This strategy is the most risk adverse strategy because by using forwards rather than futures, the airline has also removed any basis risk. Another risk adverse airline is Southwest Airlines. For the year of 2013, it had 51% of its fuel use hedged and currently has hedged 43% of the expected 2014 fuel use (Southwest, 2014). Unlike

Frontier, Southwest uses forwards to reduce jet fuel exposure. By using forwards, Southwest has increase liquidity compared to Frontier and is able to use hedging accounting[2]. However, Southwest is exposed to basis risk as well as the risk of losing hedging accounting. Recently, one of the instruments Southwest uses to hedge, WTI, has not been as highly correlated with jet fuel and it runs the risk of failing to meet the correlation requirement of FAS 133 (Southwest, 2014).

Other airlines are not as risk averse as Frontier or Southwest. For example, US Airways and Allegiant Air currently operate without any hedge. US Airways hedged in the past but switched to being entirely exposed to the swings in jet fuel price. After a series of losses from a hedging program, the airline decided to go unhedged because they felt that hedging does not guarantee any protection (US Airways, 2014). The airline also mentioned the potential implications of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 and Commodity Futures Trading Commission (CFTC) decisions. This act and the CFTC oversee and set requirements on the use of financial derivatives. US Airways is exempt from some of the regulations because they are a non-financial firm, but they worry that their counterparties will be subject to the reforms and could pass on costs (US Airways, 2014). Also mentioning the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 and the CTFC is Allegiant Air. For similar reasons as US Airways, Allegiant Air remains unhedged despite having 48.7% of their operating costs being jet fuel (Allegiant Travel Company, 2013).

The airlines that decide to hedge also have to determine how much of the fuel use they will hedge and how far out into the future they will hedge. There are many determinants of these choices including risk aversion and financial liquidity. US Airways does not hedge for the reasons already mentioned, but also because they are worried about other risks that stem from being too illiquid (US

[2] Forwards require fulfillment of a contract, and because they are not traded publicly, require more liquidity than other types of contracts. However, forwards are directly linked to the price of jet fuel, meaning that they are correlated enough to be considered for hedge accounting.

Airways, 2014). Other airlines such as Alaska Airlines feel that the illiquidity is acceptable. Traditionally, Alaska Airlines hedged out 3 years, but recently has reduced the time frame to 12 months. Also, in the past the airline had 50% of jet fuel use hedged 1 year out but this has been reduced to 6 months (Alaska Air Group, 2014). Southwest Airlines hedged a similar amount of their fuel consumption, at 51% in 2013 and 43% for 2014. Southwest has contracts in place for the next four years, however they do not mention illiquidity as a potential source of risk for the business (Southwest, 2014). American Airlines hedged 21% of its 2013 fuel requirements and 19% of its estimated 2014 requirements. However, American Airlines announced that once it has merged with US Airways, it will cease hedging and allow currently held contracts to reach maturity (American Airlines, 2014). Finally, Frontier has 100% for the next year and has less liquidity than other airlines, due to the use of forwards. Because forwards are two party contracts, and are not publicly traded, it is harder to liquidate a forward, whereas the other airlines that use futures still have the ability to liquidate their holdings.

Hedging strategies also differ between airlines. Southwest uses a selection of different contracts (i.e. options and fixed price swaps) for multiple underlying assets (WTI, Brent, heating oil and unleaded gasoline) (Southwest, 2014). American Airlines would use crude and refined oils in its hedge of jet fuel, mainly using collars so that the airline could have an approximate guess as to how much it would spend on fuel for the year (American Airlines, 2014). Alaska Airlines uses similar practices to the other airlines, but also focus on commodity swaps more than the other airlines (Alaska Air Group, 2014). The benefit of a commodity swap for the airline is that it has no premium, while the deterring factor is that it affects future cash outlays by locking the airline into a set price. As mentioned earlier, Frontier (subsidiary of Republic) enters into a forward contract so that it has its entire price risk removed (Republic Airways Holdings, 2013). Many of the airlines mention that an updated, fuel efficient fleet is part of the strategy against increases in fuel prices (Alaska Air Group, 2014; Southwest, 2014).

Table 2.1. Airlines' Hedging Practices

Airlines	Time Period Covered	Hedged Every Year?	Other Remarks
American Airlines	2000-2012	Yes	
Continental Airlines	2000-2009	No	Acquired by United in 2010.
Delta Airlines	2000-2007	No	Acquired Northwest in 2008.
Delta Airlines (Post Merger with Northwest)	2008-2012	Yes	Combined reporting after October 29, 2008.
Northwest Airlines	2000-2008	No	Acquired by Delta in 2008.
United Airlines	2000-2009	No	Acquired Continental in 2010.
United Continental	2010-2012	Yes	Combined reporting after October 2010.
US Airways	2000-2004	No	Acquired by America West in 2005
US Airways (America West Post Merger)	2006-2012	No	America West-US Airways combined reporting began in 2006.
America West	2000-2005	Yes	Acquired US Airways in 2005.
Southwest Airlines	2000-2010	Yes	Acquired Air Tran in 2010.
Southwest Airlines (Post Merger)	2011-2012	Yes	Combined reporting after May 2, 2011.
JetBlue	2000-2012	Yes, except 2000[1]	
AirTran	2000-2010	Yes	
Frontier Airlines	2000-2008	No	Acquired by Republic in 2009.
Allegiant	2005-2012	No	
Alaska Air	2000-2012	Yes	
Hawaiian Airlines	2000-2012	Yes	
Great Lakes Airlines	2000-2012	No	
Republic Airways	2004-2008	No	Acquired Frontier. Combined reporting after October 1, 2009.
Republic Airways (Post Merger)	2009-2012	Yes	
Skywest Airlines	2000-2012	No	
Spirit Airlines	2010-2012	Yes	

Notes: [1] Fuel hedging implementation began in 2001

Source: Lim and Hong (2014)

In addition to a fuel efficient fleet and the use of contracts, Delta Air Lines recently vertically integrated in an attempt to hedge jet fuel price exposure. The 2012 purchase of the Trainer refinery gives many benefits to Delta. First, it will help to protect against swings in all petroleum commodity prices. Delta has contracts in place to exchange the non-jet fuel distillates and products to BP and Phillips 66 for jet fuel (Delta Air Lines, 2013). Additionally, the purchase of the refinery included the assets needed to use the jet fuel refined at Trainer to supply Delta's operations in Northeastern US, including LaGuardia and John F. Kennedy International Airport (Delta Air Lines, 2013). However, the purchase of the refinery exposes the airline to the additional risks that arise from operating a refinery.

Different hedging strategies (including unhedged) have led to airlines paying different prices for jet fuel. Table 2.2 shows the average prices paid for fuel by airlines.

Table 2.2. Average Price per gallon of Jet Fuel

Average Price per Gallon of Jet Fuel (including hedge effects)							
Year	American Airlines	Delta Air Lines	US Airways	United Airlines	Southwest Airlines	Alaska Airlines	Allegiant Air
2013	3.09	3.00	3.04	3.13	3.16	3.30	3.20
2012	3.20	3.25	3.17	3.27	3.30	3.37	3.18
2011	3.01	3.06	3.11	3.06	3.19	3.18	3.07
2010	2.31	2.33	2.24	2.35	2.50	2.37	2.30
2009	2.01	2.15	1.74	1.75	2.12	2.05	1.76
2008	3.03	2.33	3.17	3.54	2.44	2.52	2.98
2007	2.12	2.21	2.20	2.19	1.80	2.48	2.30
2006	2.01	2.10	2.08	2.13	1.64	1.98	2.12
2005	1.74	1.79	1.77	1.79	1.13	1.53	1.87
2004	1.22	1.16	1.13	1.25	0.92	1.40	1.41
2003	0.88	0.82	0.89	0.94	0.80	0.95	1.12
2002	0.76	0.67	0.75	0.78	0.68	0.88	1.05
2001	0.81	0.69	0.80	0.87	0.71	0.77	
2000	0.72	0.67	0.89	0.81	0.79	1.18	
1999	0.50	0.50	0.52	0.51	0.53	0.80	
1998	0.50	0.57	0.46	0.51	0.46	0.53	
1997	0.62	0.66	0.61	0.67	0.62	0.72	
1996	0.63	0.59	0.64	0.72	0.65	0.81	
1995	0.54	0.54	0.53	0.60	0.55	0.70	
1994	0.54	0.55	0.53	0.59	0.54	0.60	

Source: 10-K filings

Over the years covered by this study, fuel costs have grown as a percentage of total expense. Table 2.2 shows that even though fuel cost varies for each airline, it is increasing for the industry, and as shown in table 2.3 is the largest single cost for most airlines.

Table 2.3. Fuel Cost as a Percentage of Operating Expense

Fuel Cost as a Percentage of Operating Expense							
Year	American Airlines	Delta Air Lines	US Airways	United Airlines	Southwest Airlines	Alaska Airlines	Allegiant Air
2013	35	33	34	34	35	34	39
2012	35	36	36	37	37	35	42
2011	33	36	36	36	38	34	42
2010	26	30	29	31	33	27	37
2009	24	29	24	27	30	21	44
2008	32	38	33	39	35	36	46
2007	27	26	31	26	30	27	42
2006	30	25	30	26	28	26	42
2005	27	23	29	23	21	20	42
2004	21	16	15	17	18	19	33
2003	15	13	12	15	17	15	25
2002	12	13	9	12	15	13	20
2001	14	12	12	13	16	14	
2000	14	12	14	14	17	17	
1999	11	11	9	9	13	13	
1998	11	12	8	11	11	11	
1997	13	14	11	13	15	15	
1996	14	13	11	14	16	16	
1995	11	12	9	12	14	14	
1994	12	12	9	12	14	12	

Source: 10-K filings

2.12. Producer Hedging

Risk management practices, such as hedging, differ when the costs of the input prices are highly correlated with the output prices (Wilson et al, 2007). The theory is that airlines, like other producers, are able to pass on costs from inputs on to consumers of the output. Airline ticket prices are highly correlated with the increase in jet fuel, meaning that changes in the input (jet fuel) price will be reflected as changes in the output (ticket) price. However, there is a lag between the changes in fuel cost and the change in ticket price. This lag has an effect of reducing the correlation and means that producers (airlines) should hold hedges for the duration of the lag (Jackson, 1980; Wilson et al, 2007). Firms in this position are should also hedge based on what the competition is doing (Wilson et al, 2007; Hull, 2008). Meaning that either the entire industry should hedge or none of the firms should.

For the time period discussed in this study, jet fuel prices and ticket prices are highly correlated, over 90%. Using a Granger Causality test, the null that jet fuel does not cause ticket prices is rejected, while the reversed null that airfare does not cause jet fuel price cannot be rejected with confidence.[3]

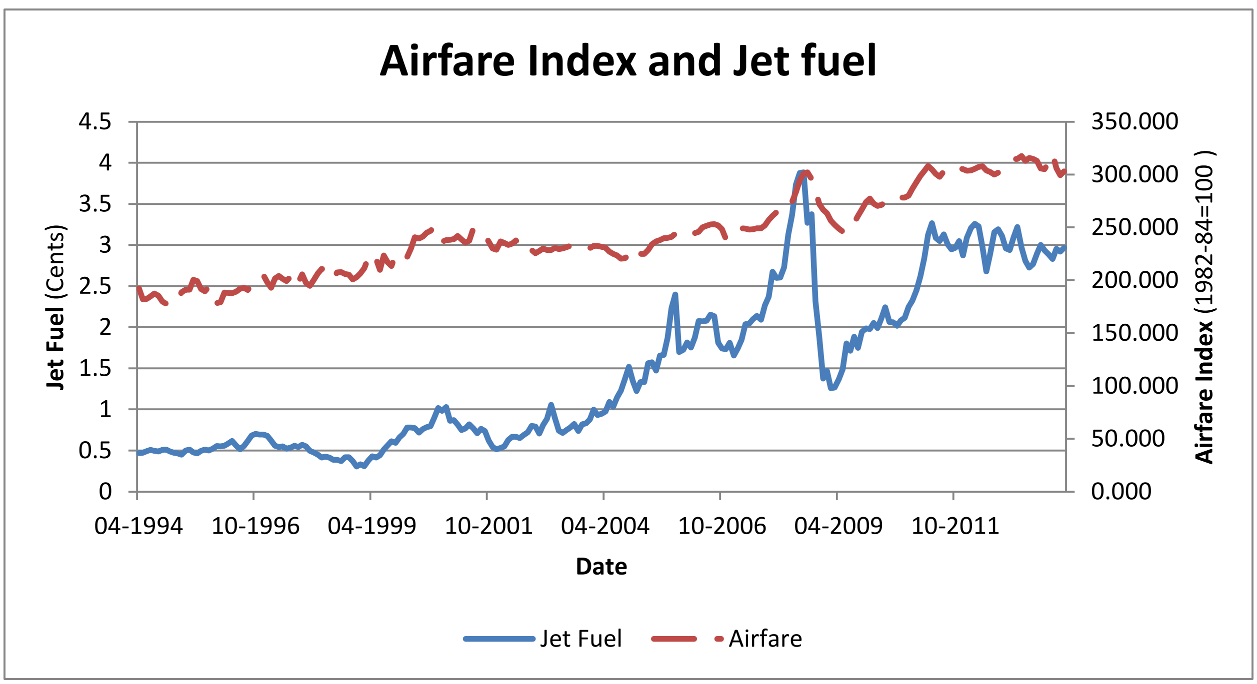

Figure 2.2. Airfare Index and Jet Fuel Price
Source: EIA and St. Louis Fed Airfare CPI

[3] Results are in the Appendix

While there are periods in which airlines seemed unable to pass along the changes in cost of jet fuel on to ticket prices, over time, the airline industry as a whole generally has been able to have the consumer charged for the cost with a lag. However, the operating profit and expenses for airlines suggest a different relationship between fuel costs and revenue. Airlines measure production in available seat miles (ASM) which is a measure of the number of seats per mile. This is obtained by multiplying the number of seats in the aircraft by the number of miles flown, so an aircraft with 100 possible seats on a 1,000 mile route would have 100,000 ASM. Airlines use this measure as a per unit cost and revenue source, meaning that while it is important to know how much each specific flight earns, it is more important to know what the revenue was for the total number of seats per mile. The difference in revenue with the cost of fuel and without the cost of fuel show that over time, increased revenue has not matched times of increased fuel costs. After the year 2007, operating profit ceased having a constant relationship with fuel costs. As you can see in Figure 2.3 in more recent years airlines have not been able to pass on fuel costs entirely.

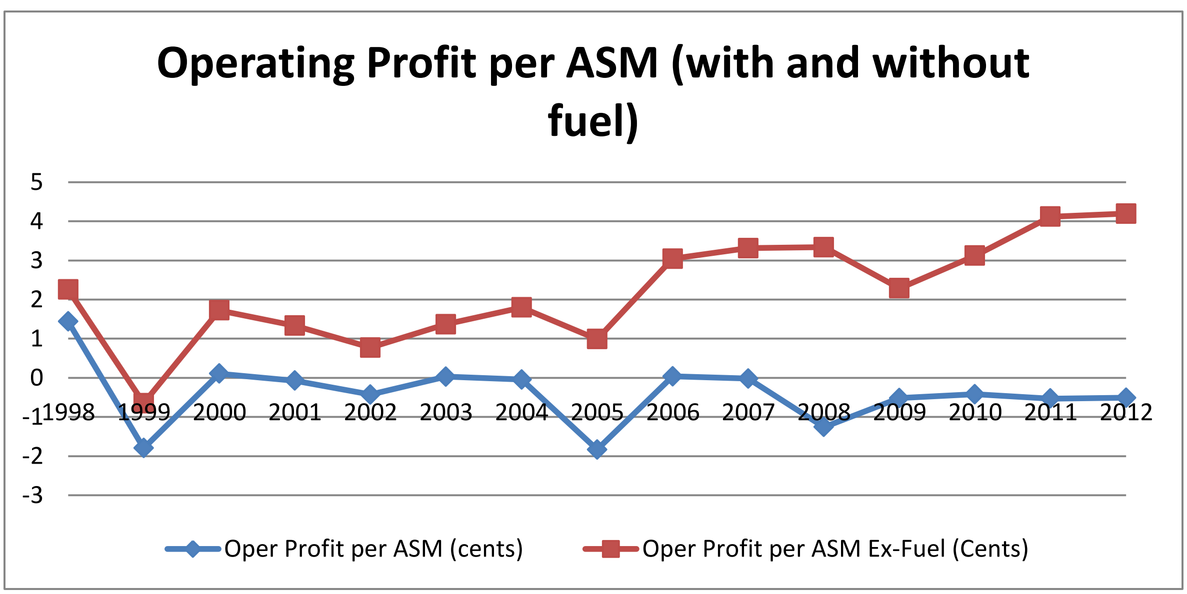

Figure 2.3. Operating Profit per Available Seat Mile
Source: Bloomberg

3. METHODOLOGY AND DATA

3.1. Models

Let S_t represent the log spot price of jet fuel at time t and F_t represent the log price of a petroleum commodity futures. Assuming that the variance-covariance matrix of the returns, R_t, to a portfolio is constant over time. We write

$$R_t = \Delta S_t - \beta \Delta F_t, \tag{3.1}$$

where β is the time invariant ratio of the number of futures contracts needed to hedge jet fuel and is independent of contract size; ΔS_t represents the change in spot price, known as the first difference, at time t; ΔF_t represents the first difference of the futures price. The variance of R_t is

$$\sigma_{R_t}^2 = \sigma_S^2 + \beta^2 \sigma_F^2 - 2\beta\sigma_{SF}, \tag{3.2}$$

where $\sigma_{R_t}^2$ denotes the variance of the portfolio R_t; σ_S^2 denotes the variance of the change in spot price, ΔS_t; σ_F^2 denotes the variance of the change in futures prices, ΔF_t; and σ_{SF} denotes the covariance of ΔS_t and ΔF_t. The minimum variance of R_t is obtained by taking the first derivative of equation (3.2) and setting it equal to 0:

$$\frac{d\sigma_{R_t}^2}{d\beta} = 2\beta\sigma_F^2 - 2\sigma_{SF} = 0. \tag{3.3}$$

The terms in equation (3.3) can be rearranged such that

$$\beta^* = \frac{\sigma_{SF}}{\sigma_F^2}. \tag{3.4}$$

The parameter β^*in equation (3.4) is the optimal hedge ratio. It is optimal because it minimizes the variance of the returns (risk) to the portfolio, R_t. The optimal hedge ratio can be determined by many different methods, such as a linear regression estimated with ordinary least squares (OLS). Because β^* is time invariant, it does not respond to news about the fuel market or the economy. The correlation coefficient of ΔS_t and $\Delta F_t$is

$$\rho = \frac{\sigma_{SF}}{\sigma_S \sigma_F}, \tag{3.5}$$

and is assumed to be time-invariant. The optimal hedge ratio in equation (3.4) is equivalent to

$$\beta^* = \rho \frac{\sigma_{\Delta S}}{\sigma_{\Delta F}}. \tag{3.6}$$

This study considers the β^* estimated from different econometric models to determine which $\widehat{\beta^*}$ is closest to the true β^*.

3.1.1. Ordinary Least Squares (OLS)

The relationship between S_t and F_t can be modeled as:

$$S_t = \alpha + \beta F_t + \varepsilon_t, \tag{3.7}$$

where ε_t is assumed to be homoskedastic, serially uncorrelated, and independently and identically distributed over time. However, these assumptions do not hold for The OLS model mentioned in equation (3.7) is insufficient and inappropriate for the data in this study, as the data in this study is non-stationary in levels. This can be remedied by the taking the first difference of the log prices, as will be described in greater detail further, creating equation (3.8).

$$\Delta S_t = \alpha + \beta \Delta F_t + \varepsilon_t. \tag{3.8}$$

Because the OLS model minimized the sum of the squared residuals, $\sum {\varepsilon_t}^2$, the β in (3.8) represents the variance minimizing hedge ratio; that is, $\hat{\beta}$ minimizes the volatility of the portfolio returns (Ederington, 1979). However, the equation is insufficient for the data of this study due to the complexities of time series data the OLS method is often not appropriate (Brooks, 2004). When $Var(\varepsilon_t|\Delta \log F_t)$ is not constant, the error term for the series can be serially correlated through time.

3.1.2. Error Correction Model

Because an OLS model is insufficient for this study, an error correction model (ECM) is included. The ECM can be used when there is a long term cointegration factor for both of the series. The ECM improves upon the OLS correcting for the cointegration relationship between the two series.

$$\Delta S_t = \alpha + \beta_1 \Delta f_t + \beta_2 (S_{t-1} - \gamma F_{t-1}) + u_t, \tag{3.9}$$

where $(S_{t-1} - \gamma F_{t-1})$ is a cointegration term and γ represents the cointegration coefficient. For this study the cointegration term will be written as ε_{t-1}, as it is the error term from equation (3.7).

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \beta_2 \varepsilon_{t-1} + \sum_{k=1}^{K} \omega_k \Delta F_{t-k} + \sum_{l=1}^{L} \delta_l \Delta S_{t-k} + u_t. \tag{3.10}$$

Under this model, the statistical tests are valid. This model can be used to model long run cointegration while still accounting for temporary deviations from that trend. For that reason, the cointegration term is lagged. The cointegration term represents the response to disequilibrium in the prior period (Brooks, 2004). More plainly, the model can only correct for the deviation once the deviation has happened, meaning that it must have occurred in a prior time period; β_2 should be interpreted as the speed of adjustment back to the long run cointegration and measures the amount of correction made (Brooks, 2004).

The improvements of equation (3.10) over (3.9) include the addition of autoregressive terms for the two variables. Also, the inclusion of the first difference of the log prices will transform the data to a stationary process.

3.1.3. Autoregressive Conditionally Heteroskedastic Model

For many of these models, there still exists heteroskedasticity in the error term. To account for this, the autoregressive conditionally heteroskedastic (ARCH) model is used.

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \sum_{k=1}^{K} \omega_k \Delta F_{t-k} + \sum_{l=1}^{L} \delta_l \Delta S_{t-k} + u_t, \tag{3.11}$$

$$u_t = v_t \sigma_t, \qquad v_t \sim N(0,1),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2.$$

The heteroskedasticity in the error term means that the standard errors are likely to be incorrect, but even more importantly, ARCH models can account for volatility clusters (Brooks, 2004). Volatility in the prices of financial assets are likely to be found in clusters, caused by some exogenous event, meaning that if the prices had a high volatility the day before they are likely to have a high volatility the next day. Accounting for the conditional volatility gives more efficient estimate of the hedge ratio. One of the assumptions for an OLS is homoskedasticity or that $E(u_t) = 0$, thus

$$\sigma_t^2 = Var(u_t | u_{t-1}, u_{t-2}, \ldots) = E[u_t^2 | u_{t-1}, u_{t-2}, \ldots]. \tag{3.12}$$

However, in the presence of heteroskedasticity, equation (14) is no longer true, so an ARCH term can be added. An ARCH term allows for a conditional variance in the error term.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_p u_{t-p}^2. \tag{3.13}$$

3.1.4. Generalized Autoregressive Conditional Heteroskedasticity Model

Another model used in this study is an improved ARCH model called generalized autoregressive conditionally heteroskedastic (GARCH) model. The GARCH model is more efficient and avoids over fitting the data (Brooks, 2004).

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \sum_{k=1}^{K} \omega_k \Delta F_{t-k} + \sum_{l=1}^{L} \delta_l \Delta S_{t-k} + u_t, \tag{3.14}$$

$$u_t = v_t \sigma_t, \qquad v_t \sim N(0,1),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \sigma_{t-1}^2.$$

A GARCH model adds that the volatility is depended upon a constant, the variance of the error term from the previous period, like an ARCH model, but the GARCH adds that the current conditional variance is dependent upon the variance of the period prior.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{3.15}$$

where $\sum_{i=1}^{q} \alpha_i u_{t-i}^2$ would be referred to as the ARCH term and $\sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$ is the GARCH term. The generalized form in equation (3.15) is of order GARCH(q,p). These ARCH and GARCH models overcome the problems of OLS (Engle, 2001) and are solved with the maximum likelihood procedure. The GARCH model that will be used in this study is of order GARCH(1,1), meaning that there will be one ARCH term and one GARCH term.

3.1.5. Error Correction Model with GARCH Term

The final econometric model used will be a combination of the ECM and the GARCH model (Adams and Gerner, 2012).

$$\Delta \log S_t = \alpha + \beta_1 \Delta \log F_t + \beta_2 \varepsilon_{t-1} + \sum_{k=1}^{K} \omega_k \Delta \log F_{t-k} + \sum_{l=1}^{L} \delta_l \Delta \log S_{t-k} + u_t, \tag{3.16}$$

$$u_t = v_t \sigma_t, \qquad v_t \sim N(0,1),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \sigma_{t-1}^2.$$

The ECM with GARCH model adds the benefits of accounting for conditional variance to the improved error corrected model. Because of the benefits of the ECM-GARCH, it is predicted that the hedge ratio from this model will be the most accurate hedge ratio from all of the econometric models.

3.2. Measuring Hedge Effectiveness

The measure of hedge efficiency for previous papers has often been left out. Traditionally the hedge effectiveness for an OLS model has been the R^2. However, with the increase in the terms and the complexity of the models, the use of measuring hedge effectiveness with R^2 no longer seems proper. Some studies have used adjusted R^2 to determine which hedge ratio is a better estimate

(Ghosh, 1996), others have used the log likelihood measure (Adams and Gerner, 2012) to determine which model and therefore hedge ratio is superior. Due to the worry of the R^2 or log likelihood misrepresenting the effectiveness of the hedge, this study computes a hedge effectiveness for each model. The R^2 can be computed separately for the models based on a "R^2 Analogue" (Juhl et al, 2011):

$$R^2 Analogue = 1 - \frac{SSE^*}{SST^*}. \tag{3.17}$$

Unlike the R^2 that will be generated by the econometric programs, where SSE^* is the total variation in the time series $(\Delta S_t - \beta \Delta F_t)$, where β is the hedge ratio determines by the model. The SST is the total variation in the time series for (ΔS_t) about its mean. This measure would allow the comparison across models in a more accurate measure of hedge effectiveness than the previous studies.

3.3. Monte Carlo Simulation

The goal of a hedge is risk reduction. While this study has generated many different hedge ratios and potential portfolios that an airline could use to hedge, these ratios should be tested to ensure accuracy. Other studies have used back testing and forecasting to test proposed hedge ratios (Adams and Gerner, 2012). However, for many activities, especially VaR, simulations are the preferred method (Wilson et al, 2007). Thus, a Monte Carlo simulation will be run generating many different outcomes. These outcomes will be random draws from a distribution that is matched to the data. The distributions will further have a covariance matrix meaning that the outcomes from the random draw should recreate possible occurrences. The hedge effectiveness of the estimated hedge ratios will be tested against the simulated data. The simulated data provides an image of how the hedge ratios would fare in a realistic scenario, which is outside the data sample.

3.3.1. Optimization by Software

The final method of estimating a hedge ratio was an optimization run by the program @Risk. This optimization maximized the hedge effectiveness based on the hedge ratio. Over thousands of trials, the software determined the maximum effectiveness of the hedge and reported the ratio that could achieve the maximum effectiveness for the data. This was done by using the measure of hedge efficiency in (3.18), or:

$$R^2 Analogue = 1 - \frac{\sum[(\Delta S_t - \beta \Delta F_t)^2]}{\sum[(\Delta S_t - \overline{\Delta S_t})^2]}, \tag{3.18}$$

where the program then maximized the value of the R^2 analogue by changing the value β, thus optimizing hedge effectiveness.

3.4. Value at Risk with Monte Carlo Simulation

A Monte Carlo simulation is not only ideal for testing the hedge ratios and to determine effectiveness, it also has the ability to determine value at risk. As mentioned earlier, a Monte Carlo simulation is the preferred method of calculating VaR. For this method, the rate of return for the prices will be taken. Then, these rates will be fitted to a distribution that will have a covariance matrix tying all of the prices together. This prevents a random draw from the far left tail of one happening at the same time as a random draw from the far fight tail of the other. Along with a VaR by asset, a sensitivity analysis will be done to determine the optimal percentage of fuel use to hedge.

For the VaR, distributions were fitted to the data. Then, multiple portfolios were created for a fictional airline which needs jet fuel and owns contracts in petroleum products. These portfolios were designed to have different percentages of fuel use hedged as well as using the different assets as cross-hedging commodities. The amount of fuel that the airline used was taken from Southwest Airlines (Southwest, 2014) and then scaled down to a daily usage. The hedge ratio was then multiplied by the amount of fuel hedged which was then divided by the unit of the contract, to determine how many contracts were needed to cross hedge.[4]

The equation for the portfolios was $R = \Delta S - \beta \Delta F$, where ΔS and ΔF are selected from a fitted distribution, such as a Laplace or logistic. The values for ΔS would be drawn from $\Delta S \sim Lap(\alpha, \beta)$, where α represents shape and β location (mean). While the values for ΔF would be drawn from $\Delta F \sim Logi(\alpha, \beta)$, where α represents scale and β location (mean). For each random draw of ΔS and ΔF, R will have a different value. These values then form a distribution themselves, such as $R \sim \mathrm{N}(\mu, \sigma^2)$,[5] where σ^2 is the scale and μ is the location (mean). This process will be done 5000 times (iterations) to be sure that there are enough observations to create a well formed distribution. From this distribution, the value of the 5% level on the left tail represents the VaR at 5%, meaning that with 95% confidence, this value (loss) will not be exceeded. For example, the portfolio represents the cost for fuel paid by an airline, thus the VaR should be interpreted as the amount which 95% of the time, their daily fuel costs with hedge will not exceed.

3.5. Data

Jet fuel (technically jet kerosene) makes up around 9.7% of what is refined from a barrel of crude oil. The breakdown of crude oil between 1993 and 2013 is around 46% to motor gasoline (including diesel), 25% to distillate fuel oil (including No. 2 heating oil), 9.7% to jet kerosene, 4% to liquid petroleum gases, 5% to coke, 4% to residual fuel oil, with the remaining 6% to different types of naphtha, lubricants, waxes, and asphalt.[6] During the period 1993-2013, the percentage of crude oil dedicated to jet kerosene has been kept between the low and high extremes of 8.5% in September 1993 and 11.4% in January 1996, with an average of 9.7% over the 20 year span. The implication of

[4] As gasoil is sold by metric tonne conversion was used based on conversion sheet provided by the EIA
[5] For more on distributions that would result see (Nadarajah and Kotz, 2007).
[6] Based on Refinery Yield from the U.S. Energy Information Administration.

that is that the supply relationship between crude and jet kerosene should remain the same, keeping the same long run relationship between petroleum products. If refiners decided to change the percentage of crude that would go to jet fuel, it could impact the hedging relationship as well.

The potential cross hedging instruments considered are West Texas Intermediate- sweet crude (WTI) and its European crude oil counterpart North Sea Brent. There are also more refined oils that are publicly traded. These oils would be No. 2 heating oil, traded as New York Harbor ultra-low sulfur No. 2 diesel, formerly called heating oil, and gasoil, which is the same asset but traded in Europe. For example WTI, No. 2 heating oil, and natural gas are traded on the New York Mercantile Exchange (NYMEX) while Brent and gasoil are traded on the Intercontinental Exchange (ICE). The pricing information was retrieved from Bloomberg Professional service. The futures price data were obtained with 3, 6, 9, and 12 month rolling contracts for each commodity. The underlying physical asset for WTI is 1,000 barrels of sweet crude delivery at the hub in Cushing, Oklahoma. The underlying physical asset for Brent is 1,000 barrels delivered at the Sullom Voe. The underlying physical asset of heating oil is 1,000 barrels the delivery at the port of New York. The underlying physical asset for gasoil is a barge of 100 metric tonnes, delivered at the Antwerp, Rotterdam, and Amsterdam (ARA).

Finally, the jet fuel spot is the U.S. Gulf Coast 54 jet fuel spot price. This was chosen because it represents the most popular measure of jet fuel. Another benefit is that it is less volatile and lower priced than West Coast jet fuel (Alaska Air Group, 2014). The time span of the data is from April 1994 through February 2014.This time span includes a number of shocks and recessions, such as the terrorist attacks of September 11th 2001, the SARS epidemic of 2003, and the recessions of 2001 and 2008. Shocks create extreme volatilities (large and unequal variances) which separate models will account for differently. This study will look at the use of different models in determining hedge ratios.

Table 3.1. Contract Descriptions

Asset Name	Symbol	Venue	Contract Units	Price Quotation	Minimum Fluctuation	Delivery	Description
West Texas Intermediate Crude Oil	CL	NYMEX	1,000 Barrels (42,000 gallons)	U.S. Dollars and Cents per barrel	$0.01 per barrel	Cushing, Oklahoma	*Also known as Texas light sweet, WTI is the most commonly traded commodity in the world. It is a sweet crude, containing .24% sulfur.*
New York Harbor Heating Oil	HO	NYMEX	42,000 gallons (1,000 barrels)	U.S. Dollars and Cents per Gallon	$0.0001 per gallon	New York, New York	*Heating oil, also known as No. 2 fuel oil, is a low viscosity distillate. As the name suggests, it is often used in residential and commercial heating.*
Brent Crude Oil	CO	ICE	1,000 Barrels (42,000 gallons)	U.S. Dollars and Cents per barrel	$0.01 per barrel	Sullom Voe, Scotland	*Brent is a sweet crude from the North Sea. It is sourced from the Brent, Oseberg, Forties, and Ekofisk fields. 'Sweet' crude is defined as having a sulphur content of less than 0.5%. Brent contains about .37% sulfur.*
Gasoil	QS	ICE	100 metric tonnes of gasoil	U.S. Dollars and Cents per tonne	$0.25 per tonne	Any port within Antwerp, Rotterdam, Amsterdam area	*Gasoil is the same as No. 2 fuel oil, but is the European designation for the product.*

Source: CME and NYMEX

Table 3.2. Summary Statistics

Summary Statistics Table

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera Statistic	Distribution
Jet Fuel Spot	146.76	104.30	417.88	24.15	98.34	0.63	2.03	**519.2251**	Exponential
Brent 1-Month	51.87	33.46	146.08	9.64	35.85	0.66	2.02	**560.9935**	Exponential
Brent 3-Month	51.84	32.69	147.05	10.16	35.87	0.63	1.97	**548.2227**	Exponential
Brent 6-Month	51.68	31.51	148.13	10.92	35.95	0.60	1.91	**542.483**	Exponential
Brent 9-Month	51.45	30.63	148.54	11.36	35.94	0.57	1.86	**542.1659**	Log Normal
Brent 12-Month	51.19	29.71	148.21	11.70	35.87	0.56	1.82	**544.5048**	Log Normal
WTI 1-Month	50.51	36.88	145.29	10.72	31.77	0.58	2.03	**471.5232**	Exponential
WTI 3-Month	50.75	35.65	146.13	11.33	32.19	0.54	1.96	**472.3479**	Exponential
WTI 6-Month	50.71	34.15	146.85	12.06	32.56	0.52	1.89	**481.8863**	Exponential
WTI 9-Month	50.52	33.09	146.86	12.45	32.72	0.50	1.84	**490.1864**	Exponential
WTI 12-Month	50.29	32.25	146.32	12.81	32.78	0.49	1.81	**497.9488**	Log Logistic
Heating Oil 1-Month	145.05	101.70	410.60	29.52	96.95	0.64	2.04	**531.0333**	Exponential
Heating Oil 3-Month	145.81	98.15	418.00	30.76	97.73	0.62	2.00	**527.0762**	Exponential
Heating Oil 6-Month	146.12	91.19	426.70	33.16	98.61	0.61	1.98	**525.0918**	Exponential
Heating Oil 9-Month	145.90	92.05	421.15	35.96	98.93	0.59	1.93	**527.8644**	Log Normal
Heating Oil 12-Month	145.52	87.48	413.25	37.46	98.83	0.56	1.84	**541.3268**	Log Normal
Gasoil 1-Month	451.79	313.75	1325.25	91.25	307.65	0.66	2.10	**529.61**	Exponential
Gasoil 3-Month	451.90	297.25	1340.50	94.25	307.87	0.64	2.06	**524.4263**	Exponential
Gasoil 6-Month	452.66	277.50	1353.25	101.75	309.10	0.62	2.02	**518.553**	Exponential
Gasoil 9-Month	452.57	269.25	1341.75	109.00	309.97	0.59	1.96	**519.0424**	Log Normal
Gasoil 11-Month	452.19	262.75	1332.25	112.50	310.16	0.58	1.91	**523.5342**	Log Normal

Note: Distributions based on the Anderson-Darling test

3.5.1. Tests

Due to the nature of time series, a number of tests should be run on the data before it is used in a model. These tests are used to establish if the data is stationary or non-stationary. A time series is stationary if its probability distribution does not change over time. If time series Y_t has a joint distribution of (Y_{s+1}, Y_{s+2}, …, Y_{s+T}) and it does not depend on *s* regardless of the value of T, then the data is stationary. If Y_t does depend on *s*, the data is non-stationary (Stock and Watson, 2012). This can be elaborated further as to having one constant mean, constant covariance and constant autocovariances for each lag (Brooks, 2002). Stationarity of a series is important for many reasons. Use of non-stationary data can lead to spurious regression, one which would appear as a fit model, but would actually be worthless (Brooks, 2002; Adams and Gerner, 2012). With a stationary series, shocks, or severe unexpected changes, will gradually have a smaller and smaller effect. However, with non-stationary data the persistence of shocks can be infinite, and a shock in one time period will continue to influence each and every time period without ever reducing in effect (Brooks, 2002). The final problem with non-stationary data is that the distribution assumptions are no longer true, meaning that all t-statistics and f-statistics will be incorrect. This means that is there is no valid way to test a hypothesis with non-stationary data. In an attempt to model and work with non-stationary data, a few models have been developed. With market data and other time series data that could be non-stationary, there could be the existence of a trend. A trend is a long term movement through the data which the values of the variable fluctuate around. For example, the following chart of jet fuel spot prices would be an example of a linear trend line around which prices fluctuate.

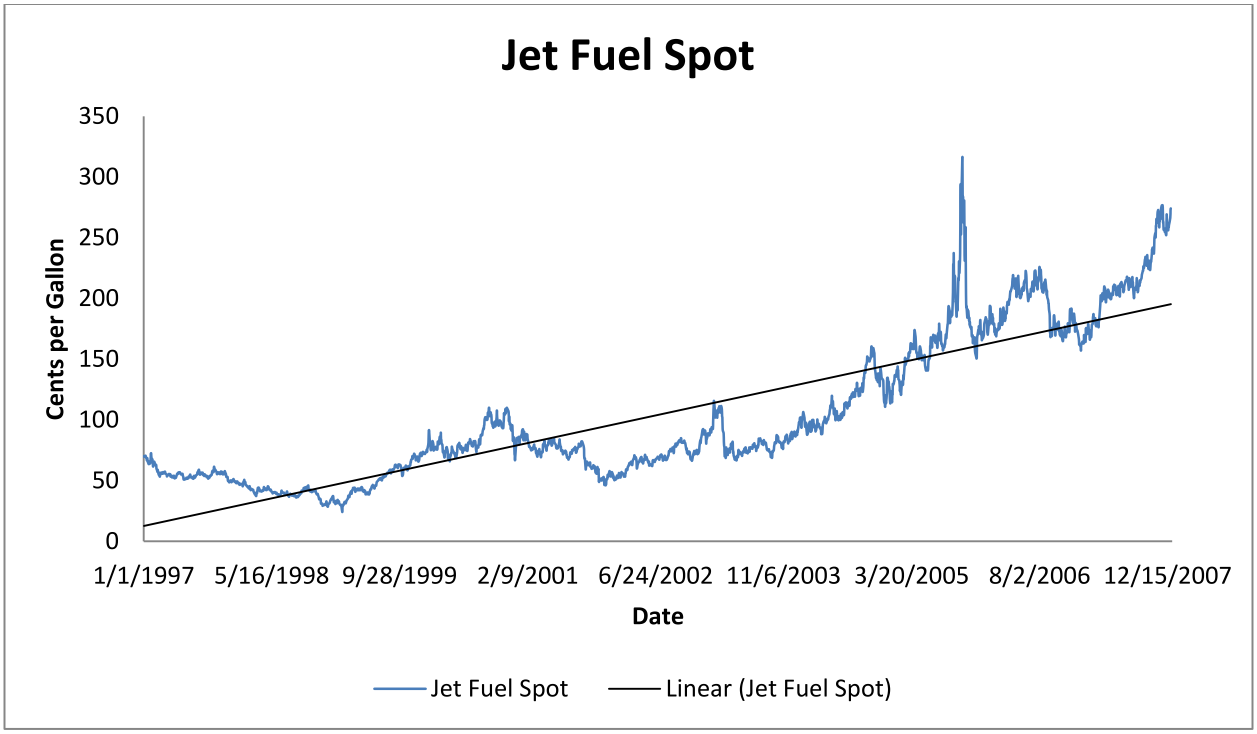

Figure 3.1. Jet Fuel Spot Price with Trend

Trends can be broken down further into two different categories. The first is a deterministic trend. A deterministic trend is a nonrandom function of time. This means that the increases in the price of jet fuel move around a certain linear increase over time. The other type of trend is a stochastic trend. A stochastic trend is one where the trend is random and varies over time. This is perhaps the more realistic of the two trends, as it can explain an increase for one section of time but also a decrease for a different section of time. A stochastic trend can be used to model data that may have periods of increase followed by periods of decrease. One example of a stochastic trend is a random walk. A random walk is where the value of the dependent variable in time T is dependent upon the value in the previous time period (T-1). This can be modeled as $Y_t = Y_{t-1} + u_t$. For a more improved model of a random walk, a drift term can be included such as β_0 so the model becomes $Y_t = \beta_0 + Y_{t-1} + u_t$. Trends are important for checking to see if the data is stationary or non-stationary. If the series follows a random walk, then it is non-stationary. This is because the u_t term, representing the errors of the equation, is conditionally distributed and depends on the time period and is serially uncorrelated. Because of these problems, tests should be done for stationarity of a series.

3.5.1.1. Stationarity Tests

The tests that have been run on this paper are the Augmented Dickey-Fuller (ADF) test, the Phillps-Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The ADF and the PP tests check for a unit root in the series, while the KPSS checks for stationarity. While a single test could be used to determine stationarity, it is best to use a combination of a unit root test and a stationarity test. There are potential problems with just using a unit root test that could lead to increased type-II errors (Brooks, 2002). The ADF test checks for a unit root, and therefore stationarity in the series. It does this by checking for a stochastic trend, in this case called a unit root of 1, in the series. The null is that the series has a unit root (of 1); the alternative is that the series is stationary. Because this test depends on the number of lags included, a Schwartz Information Criterion (SIC) value is used to determine the optimal amount of lags. The next unit root test that was performed on the data was the PP test. The PP test is very similar to the ADF but it includes a measure to see if there is autocorrelation in the residuals. It shares the same null hypothesis as the ADF. The results for both the ADF and the PP tests were that the level data is non-stationary. Table 3.3 shows that the ADF test results and 3.4 shows the PP test results.

Table 3.3. Augmented Dickey-Fuller Results

Augmented Dickey Fuller Test

Null: Series has a Unit Root

Significance : 10%= -3.12, 5%= -3.41, 1%= -3.96

Level

	1-Month	3-Month	6-Month	9-Month	12-Month
Brent	-2.78997	-2.82727	-2.73825	-2.66415	-2.60289
WTI	-3.31185	-3.09819	-2.92883	-2.79475	-2.57627
Heating Oil	-2.96841	-2.78416	-2.64758	-2.57648	-2.54316
Gasoil	-2.60407	-2.52316	-2.42044	-2.35933	-2.32768

First Log Difference

	1-Month	3-Month	6-Month	9-Month	12-Month
Brent	**-73.2365**	**-73.8427**	**-74.8344**	**-76.2115**	**-77.0994**
WTI	**-52.4492**	**-71.5747**	**-73.6609**	**-75.0722**	**-76.1667**
Heating Oil	**-71.5908**	**-72.0581**	**-73.6955**	**-75.7795**	**-77.2332**
Gasoil	**-69.0067**	**-70.0595**	**-71.4536**	**-72.7268**	**-73.9508**

Table 3.4. Phillips-Perron Results

Phillips-Perron Test

Null: Series has a Unit Root

Significance : 10%= -3.12, 5%= -3.41, 1%= -3.96

Level

	1-Month	3-Month	6-Month	9-Month	12-Month
Brent	-2.7903	-2.73189	-2.69656	-2.63817	-2.59113
WTI	-3.16176	-3.03136	-2.85705	-2.74641	-2.6378
Heating Oil	-2.87464	-2.79985	-2.63242	-2.58461	-2.53211
Gasoil	-2.70111	-2.6929	-2.64638	-2.56616	-2.52623

First Log Difference

	1-Month	3-Month	6-Month	9-Month	12-Month
Brent	**-73.3249**	**-73.9124**	**-74.902**	**-76.3094**	**-77.298**
WTI	**-71.4042**	**-71.6707**	**-73.7584**	**-75.2065**	**-76.3613**
Heating Oil	**-71.9385**	**-72.1125**	**-73.7186**	**-75.8348**	**-77.5159**
Gasoil	**-68.9895**	**-70.0576**	**-71.459**	**-72.7441**	**-73.9821**

Unit root tests have been criticized for failing to distinguish between non-stationary data and stationary data with unit roots close to 1 (Brooks, 2002). This is why the KPSS test was included. The KPSS is a test for stationarity, with the alternative hypothesis being non-stationarity. This means that a series with a unit root close to 1 would still be considered stationary. Due to the opposite nulls and alternative hypothesis, a series should be declared stationary by both types of tests to be sure of stationarity. The results for the KPSS test were rejection of the null for the level data, meaning non-stationarity, as seen in Table 3.5.

Table 3.5. Kwiatkowski–Phillips–Schmidt–Shin Results

Kwiatkowski–Phillips–Schmidt–Shin					
Null: Series is Stationarity					
Significance :	10%= 0.119, 5%= 0.146, 1%= 0.216				
Level					
	1-Month	3-Month	6-Month	9-Month	12-Month
Brent	**0.836192**	**0.84371**	**0.877039**	**0.899394**	**0.934429**
WTI	**0.580759**	**0.636792**	**0.704538**	**0.756442**	**0.800508**
Heating Oil	**0.717966**	**0.735573**	**0.77841**	**0.823428**	**0.897189**
Gasoil	**0.699087**	**0.73166**	**0.763449**	**0.814673**	**0.851831**

First Log Difference					
	1-Month	3-Month	6-Month	9-Month	12-Month
Brent	0.037581	0.046689	0.060643	0.074785	0.089656
WTI	0.031706	0.040247	0.054948	0.070314	0.087275
Heating Oil	0.038673	0.047027	0.061569	0.079929	0.092502
Gasoil	0.046151	0.055058	0.072852	0.089721	0.099646

If a time series follows a non-stationary process then the log first difference will be taken of the series. This transformation converts the level data, which is non-stationary, into a stationary series. This means that the tests for stationarity and unit root of 1 should be conducted on both level data and log difference data. This can be seen in Table 1, which shows that the log differenced data is stationary according to all three tests and the level price data is non-stationary in all of the tests. An earlier graph of level price data (Figure 3.1) shows an example of a linear trend and it also shows an example of non-stationarity. A graph of the same data after the transformation of the first log difference can be seen in Figure 3.2. Included in Figure 3.2 is a linear trend line to show that the data, once transformed, is stationary. The results for the log first difference of the data were rejection of the null for the ADF and PP tests and failure to reject the null for the KPSS meaning that the data is stationary.

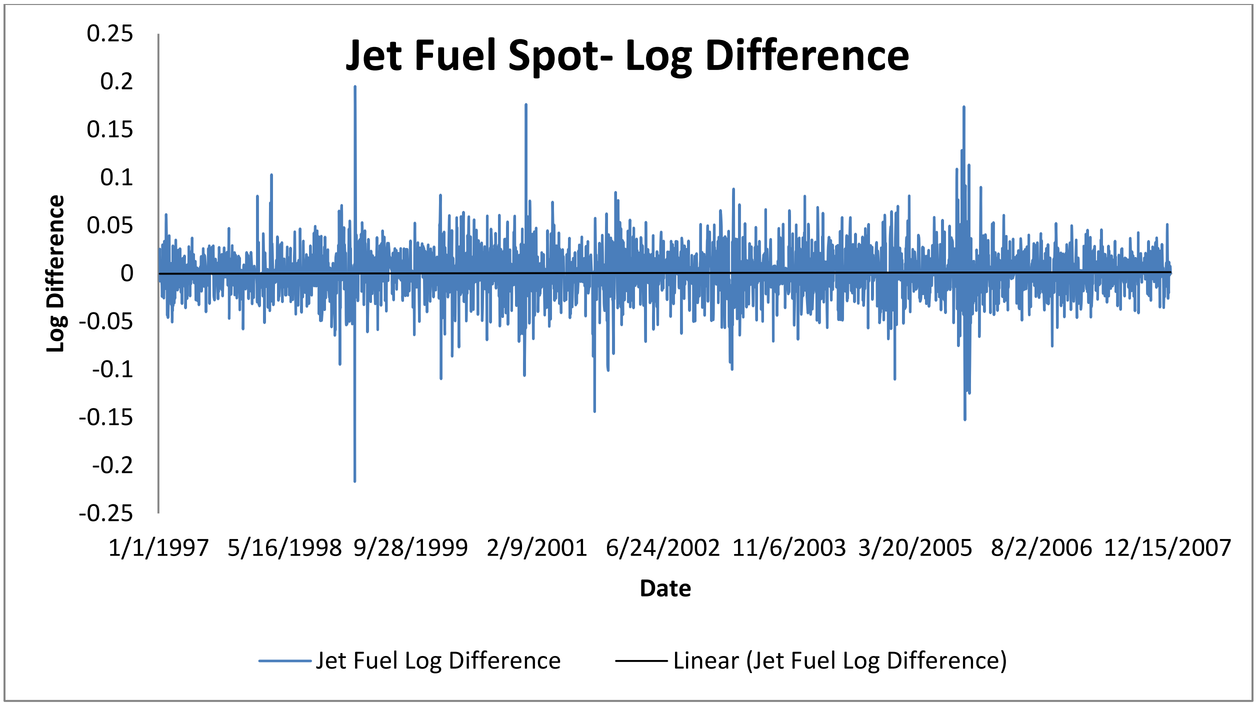

Figure 3.2. Log Difference of Jet Fuel Price

3.5.1.2. Cointegration Tests

After determining the stationarity of the series, it has to be determined if the series are cointegrated with jet fuel. Cointegration means that two different series "move together" over time. This relationship exists as the two price series are related and have similar influences, meaning that though the prices (and therefore relationship) may vary in the short run, the series will return to being related in the long run. There are many tests for cointegration, including the Engle-Granger test and the Johansen cointegration test. The Engle-Granger test looks at the error term of an OLS between two time series, with the null that there is no cointegration. The combination of two non-stationary variables would yield stationary error terms if the series were cointegrated. The test used to check for stationarity in the error term the ADF test is used. The results for Engle-Granger test, shown in Table 3.6, were that the non-stationarity in the error terms was rejected, meaning that the spot price of jet fuel is cointegrated with the futures prices.

The Johansen cointegration test is specified in a vector autoregression (VAR) model. The model runs the two series to measure the number of cointegration relationships that may exist. Because the Johansen test does not have the ADF or a separate unit test, it is possible to include a constant and/or a trend. The results for the Johansen cointegration test were the same as the Engle-Granger test. The null hypothesis of zero cointegration terms was rejected with a failure to reject the second null of at most one cointegration term; this can be seen in Table 3.6. The Johansen test was run with the inclusion of both a constant and a trend, based upon SIC values for the potential models.

Table 3.6. Cointegration Test Results

Johansen Cointegration Test		
Contract	None	At most 1
Brent 1-Month	**93.79879**	8.291175
Brent 3-Month	**86.59311**	7.002707
Brent 6-Month	**60.64995**	5.755637
Brent 9-Month	**45.71152**	5.030281
Brent 12-Month	**38.77651**	4.509726
WTI 1-Month	**92.0087**	9.15905
WTI 3-Month	**71.66035**	8.062919
WTI 6-Month	**50.07577**	6.237567
WTI 9-Month	**38.20476**	5.066876
WTI 12-Month	**32.07936**	4.266998
Heating Oil 1-Month	**174.9687**	8.868992
Heating Oil 3-Month	**109.5238**	7.472865
Heating Oil 6-Month	**50.31963**	6.208997
Heating Oil 9-Month	**41.10974**	5.712081
Heating Oil 12-Month	**40.82031**	5.103538
Gasoil 1-Month	**141.6637**	7.478849
Gasoil 3-Month	**90.75148**	6.439682
Gasoil 6-Month	**52.41219**	5.395362
Gasoil 9-Month	**43.68192**	4.997079
Gasoil 11-Month	**42.31945**	4.775469

Note: Bolded numbers are significant at the 1% level and lower according to MacKinnon-Haug-Michelis (1999) p-values.

Engle-Granger	
Contract	Tau-Statistic
Brent 1-Month	**-9.065518**
Brent 3-Month	**-9.693689**
Brent 6-Month	**-7.241888**
Brent 9-Month	**-6.077096**
Brent 12-Month	**-5.441673**
WTI 1-Month	**-7.375705**
WTI 3-Month	**-8.149583**
WTI 6-Month	**-6.833997**
WTI 9-Month	**-5.893029**
WTI 12-Month	**-5.286977**
Heating Oil 1-Month	**-12.93099**
Heating Oil 3-Month	**-10.53726**
Heating Oil 6-Month	**-6.432806**
Heating Oil 9-Month	**-5.48416**
Heating Oil 12-Month	**-5.119681**
Gasoil 1-Month	**-12.04221**
Gasoil 3-Month	**-9.276612**
Gasoil 6-Month	**-6.579423**
Gasoil 9-Month	**-5.568938**
Gasoil 11-Month	**-5.21672**

Note: Bolded numbers are significant at the 1% level and lower according to MacKinnon (1996) p-values.

4. RESULTS

4.1. Hedge Ratio

The econometric models estimated in this paper were OLS, ECM, ARCH(1), GARCH(1,1), and ECM-GARCH. Included with these was a hedge ratio generated by optimizing hedge effectiveness, and the traditional method of determining the hedge ratio using equation (3.4) which will now be referred to as the "covariance" method. These results are reported in Table 4.1.

The results of the study determine the best asset for a jet fuel cross hedge and to conclude the best method of determining the hedge ratio. As discussed earlier, there are different ways of determining the best hedge. It was expected that the ECM-GARCH would have the most effective hedge as it removed the homoskedasticity in the errors. The ARCH LM test which is posted with the results has the null of no homoskedasticity, this means that when the null is rejected then there is homoskedasticity, however if the null cannot be rejected the errors are not serially correlated. Most often the GARCH(1,1) and the ECM-GARCH models did not have homoskedasticity, but that did not transfer over into the model having the most effective hedge ratio.

The first results presented in Table 4.1 are the hedge ratios generated from the different models. These results show that the OLS estimate for the optimal hedge ratio is very similar to the optimization's estimate of the ratio. This means that of all of the models the OLS estimated a hedge ratio that is closest to the hedge ratio generated by an optimization of hedge effectiveness. Consistent with the prior studies, the OLS has a lower hedge ratio than the ECM and the ECM-GARCH, leading to the conclusion that the OLS underestimates the hedge ratio (Ghosh, 1996). As time till maturity increases so does the hedge ratio, matching similar studies (Ripple and Moosa, 2007).

Table 4.1. Hedge Ratio

WTI	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	0.7270	0.9228	1.0277	1.0839	1.1199
ECM	0.7349	0.9256	1.0288	1.0860	1.1240
ARCH(1)	0.7852	0.9229	1.0250	1.0826	1.1207
GARCH(1,1)	0.7728	0.9093	1.0013	1.0458	1.0736
ECM-GARCH(1,1)	0.7746	0.9100	1.0016	1.0459	1.0733
Covariance	0.8946	1.0423	1.1096	1.1537	1.1885
Optimization	0.7271	0.9228	1.0277	1.0839	1.1199

Brent	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	0.8074	0.9428	1.0359	1.0755	1.0949
ECM	0.8100	0.9431	1.0372	1.0798	1.1016
ARCH(1)	0.8380	0.9587	1.0515	1.0992	1.1187
GARCH(1,1)	0.8415	0.9425	1.0130	1.0488	1.0681
ECM-GARCH(1,1)	0.8436	0.9435	1.0138	1.0494	1.0683
Covariance	1.0206	1.1010	1.1515	1.1801	1.2132
Optimization	0.8074	0.9428	1.0359	1.0754	1.0949

Heating Oil	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	0.8963	1.0408	1.1238	1.1922	1.2216
ECM	0.9047	1.0429	1.1257	1.1979	1.2330
ARCH(1)	0.9688	1.0437	1.1141	1.1808	1.2284
GARCH(1,1)	0.9585	1.0103	1.0606	1.1087	1.1469
ECM-GARCH(1,1)	0.9624	1.0127	1.0607	1.1084	1.1474
Covariance	0.9684	1.0504	1.0825	1.1222	1.1508
Optimization	0.8963	1.0408	1.1238	1.1921	1.2215

Gasoil	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	0.6659	0.7894	0.8569	0.8973	0.9056
ECM	0.7679	0.8947	0.9521	0.9815	0.9845
ARCH(1)	0.7925	0.9438	0.9987	1.0213	1.0217
GARCH(1,1)	0.7937	0.8976	0.9343	0.9581	0.9576
ECM-GARCH(1,1)	0.8062	0.9042	0.9373	0.9611	0.9605
Covariance	0.9047	1.0117	1.0467	1.0734	1.0835
Optimization	0.6660	0.7894	0.8570	0.8974	0.9057

4.2. Model Results

While all of the results will be posted in the appendix, presented in the following section will be the results from all of the models for contracts with WTI as the underlying asset. The first table is the hedge ratio generated by the "covariance" method, equation (3.21). These results are how textbooks (Hull, 2008) determine the hedge ratio. However, due to the design of OLS, it is can also be used to determine the variance minimizing hedge ratio, as seen in Table 4.3

Table 4.2. WTI Covariance Results

Covariance					
	1-Month	3-Month	6-Month	9-Month	12-Month
Hedge Ratio	0.894632	1.042307	1.109551	1.1537	1.188468
R-Squared	0.45625	0.513421	0.512523	0.506451	0.498395

Table 4.3. WTI OLS Results

OLS					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.727026**	**0.922761**	**1.027705**	**1.083942**	**1.119921**
	(0.010819)	(0.011916)	(0.013631)	(0.014988)	(0.016159)
Adjusted R-Squared	0.475353	0.546125	0.532828	0.512048	0.490771
Log-Likelihood	12992.9	13353.99	13282.04	13173.59	13067.23
ARCH-LM (5)	**31.6613**	**28.82523**	**25.31712**	**24.00661**	**21.1315**

(Bolded means significance at 5% or below)

The OLS model yields the variance minimizing hedge ratio as the coefficient on the term representing the change in log futures prices. However, the ARCH-LM test is rejected, meaning that there is heteroskedasticity in the errors. An OLS also does not account for the long run relationship between the series, so an ECM was used. The ECM results are posted in Table 4.4

Table 4.4. WTI ECM Results

ECM					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.734887**	**0.92564**	**1.028823**	**1.085951**	**1.124014**
	(0.01078)	(0.011845)	(0.013562)	(0.014932)	(0.016117)
ΔF_{t-1}	0.017025	0.015983	**0.041837**	**0.066494**	**0.084701**
ΔF_{t-2}	**0.063161**	**0.066022**	**0.061419**	**0.063926**	**0.06227**
ΔF_{t-3}	0.010044	0.014429	-	-	-
ΔF_{t-4}	**0.041975**	0.031843	-	-	-
ΔS_{t-1}	-0.01926	-0.01454	-0.00914	-0.00611	**-0.0016**
ΔS_{t-2}	**-0.06657**	**-0.06855**	**-0.06217**	**-0.05902**	**-0.05418**
ΔS_{t-3}	0.004907	-0.006	-	-	-
ΔS_{t-4}	-0.02327	-0.01512	-	-	-
e_{t-1}	**0.029877**	**0.026806**	**0.019471**	**0.014741**	**0.011719**
Adjusted R-Squared	0.484273	0.553161	0.538947	0.518255	0.497362
Log-Likelihood	13028.05	13385.07	13311.42	13202.06	13096.31
ARCH-LM (5)	**654.7391**	**582.1442**	**575.4598**	**565.4451**	**567.1922**

(Bolded means significance at 5% or below)

The Results from the ECM show a higher hedge ratio, as earlier mentioned, it has been said that OLS under estimated the hedge ratio. The lag length was chosen based on SIC values, for the 1-Month and 3-Month contracts 4 lags were used, for the other maturities only 2 lags were used. While the adjusted R^2 and the log-likelihood ratios are both higher than the OLS, the presence of heteroskedasticity is still shown by the ARCH-LM test. Due to that, the ARCH(1) model was run, and its results are presented in Table 4.5.

Table 4.5. WTI ARCH(1) Results

ARCH(1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.785211**	**0.92293**	**1.025006**	**1.082595**	**1.12072**
	(0.005234)	(0.007161)	(0.008563)	(0.00934)	(0.009979)
ΔF_{t-1}	**-0.01453**	-0.00807	**0.038353**	**0.06315**	**0.090892**
ΔF_{t-2}	**0.022729**	**0.038038**	0.011408	0.018258	0.019244
ΔS_{t-1}	**0.012045**	**0.01603**	0.002025	0.004894	0.001853
ΔS_{t-2}	**-0.03643**	**-0.04575**	**-0.0254**	**-0.02692**	**-0.02414**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.493823**	**0.465587**	**0.43854**	**0.432948**	**0.425977**
Adjusted R-Squared	0.472991	0.546908	0.533752	0.514128	0.493906
Log-Likelihood	13602.53	13909.59	13816.93	13677.08	13536.75
ARCH-LM (5)	**44.2231**	**46.59432**	**54.69169**	**58.6381**	**64.45046**

(Bolded means significance at 5% or below)

The results from the ARCH(1) show that the ARCH term is significant, and with this the ARCH-LM test has lower values. Although there is still heteroskedasticity in the model, the ARCH(1) and its ARCH term are closer to accounting for the heteroskedasticity than previous models. The number of lags, two, used for both the futures and the spot prices was chosen based on SIC values. As mentioned earlier, the model does not fully account for heteroskedasticity, so a GARCH(1,1) model was used and its results are posted in Table 4.6.

Table 4.6. WTI GARCH(1,1) Results

	GARCH(1,1)				
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	**0.00**	**0.00**	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.772771**	**0.909336**	**1.001273**	**1.045815**	**1.073586**
	(0.006799)	(0.008243)	(0.009418)	(0.009993)	(0.010562)
ΔF_{t-1}	0.00517	-0.00507	0.017243	0.030208	0.035034
ΔF_{t-2}	0.018423	0.010919	0.009382	0.011021	0.013445
ΔS_{t-1}	0.000805	0.004674	0.005452	0.012519	0.021384
ΔS_{t-2}	**-0.04216**	**-0.04563**	**-0.04562**	**-0.04486**	**-0.04374**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.116236**	**0.11517**	**0.11076**	**0.106773**	**0.104185**
GARCH	**0.88356**	**0.884967**	**0.890158**	**0.894626**	**0.897583**
Adjusted R-Squared	0.473899	0.5463	0.533187	0.513024	0.49242
Log-Likelihood	14067.54	14418.65	14341.25	14204.68	14072.88
ARCH-LM (5)	8.129499	4.712533	7.086755	8.426825	10.39599

(Bolded means significance at 5% or below)

The results from the GARCH(1,1) show that the model has a high log-likelihood and also has removed the heteroskedasticity from the errors. The number of lags is two, based on SIC values, for both spot and futures lagged data. Both the ARCH and the GARCH term are significant and the ARCH-LM test for the first time cannot be rejected with 95% confidence or greater. The successes of the GARCH(1,1) suggested that an ARCH and a GARCH term were needed to account for the heteroskedasticity in the errors, but the model still does not account for the long run relationship. To accommodate both of these factors an ECM model with GARCH terms was run, and the results for the ECM-GARCH can be found in Table 4.7.

Table 4.7. WTI ECM-GARCH(1,1) Results

ECM-GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.774559**	**0.909959**	**1.001557**	**1.045872**	**1.073283**
	(0.006745)	(0.008206)	(0.009441)	(0.010031)	(0.010576)
ΔF_{t-1}	-0.00311	-0.01158	0.012603	0.026771	0.032197
ΔF_{t-2}	0.010549	0.005296	0.005595	0.00812	0.010901
ΔS_{t-1}	0.007782	0.010024	0.009697	0.01583	0.024205
ΔS_{t-2}	**-0.03537**	**-0.04064**	**-0.0417**	**-0.04165**	**-0.04093**
e_{t-1}	**-0.01425**	**-0.0115**	**-0.00868**	**-0.00687**	**-0.00566**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.116814**	**0.115621**	**0.111364**	**0.107089**	**0.104078**
GARCH	**0.882275**	**0.88438**	**0.889477**	**0.894218**	**0.897611**
Adjusted R-Squared	0.479771	0.550248	0.536089	0.515367	0.494412
Log-Likelihood	14085.6	14432.37	14351.04	14212.27	14079
ARCH-LM (5)	7.850179	4.850799	7.248721	8.535928	10.40054

(Bolded means significance at 5% or below)

The results from the ECM-GARCH model are that the model has the highest log-likelihood value, there is no heteroskedasticity in the errors, and that the hedge ratio includes a long term relationship between the series. However, the actual effectiveness of the hedge ratio generated is not judged by any of the values presented in the table. This led to the use of a hedge effectiveness measure that will be mentioned in future sections.

4.3. Measure of Log-Likelihood

While many of the models give similar ratios, they cannot all be the best estimate of the true optimal hedge ratio. Based upon the Adams and Gerner (2012) the log-likelihood can be used to measure how well the model explains the occurrences. The higher the log-likelihood the better the model. For Adams and Gerner (2012), they concluded that the better the model, the better the hedge ratio and the asset. While this study does not fundamentally agree with this, the log likelihoods of the models were used

For every asset, the log-likelihood of the ECM-GARCH model was the highest. These values were taken for each asset and graphed to show, based upon log-likelihood, which asset should be used based on the contract length. The results in Figure 4.1 show that based upon log-likelihood the best asset to hedge jet fuel is heating oil and the shorter the contract duration the better. These results are similar with other studies that find shorter maturity contracts for refined products to be the best cross hedge.

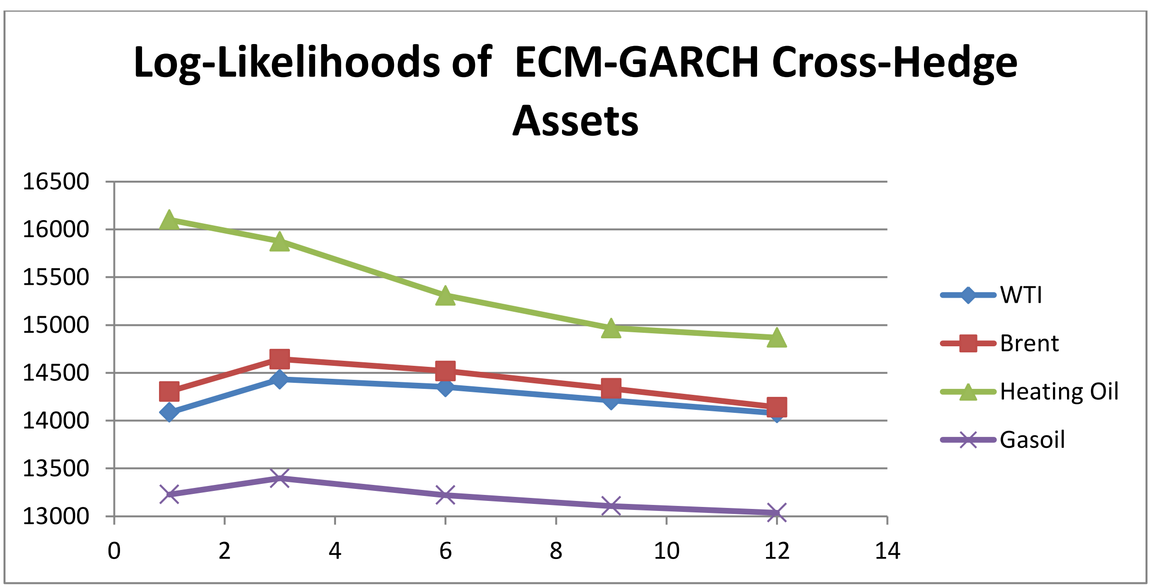

Figure 4.1. Log-Likelihood Results for ECM-GARCH Models

4.4. Measure of Hedge Effectiveness

These results however, do not include the actual measure of hedge effectiveness. The argument that an OLS is insufficient is predicated by the assumption that an adjusted R^2 (Ghosh, 1996) or a log-likelihood (Adams and Gerner, 2012). These measures that have been used in other studies are measures of how well the model fits, not measures of the accuracy of the hedge ratio. For this, the model in equation (3.21) is used, the "R^2 Analogue" (Juhl et al, 2011). This looks at the position of the hedged portfolio and divides it by the unhedged position, with all of that subtracting from 1. This means that the smaller the effect of the hedge, the larger the ratio, and therefore the lower the number after the ratio has been subtracted from one.

The results of the test show that, as expected, the similar hedge ratios yield similar effectiveness values. Table 4.8 presents the results of the hedge effectiveness test, with the highest effectiveness value in bold. However, the optimal hedge ratio that preformed the best for the time period sampled was the OLS hedge ratio. Technically, the ratio generated by the software optimization was the most effective, but it was designed specifically for this data, so it was not considered. The OLS method generates the best estimate contrary to past studies. The past studies used measures that judged how well the model fit the data, while this study uses a proper measure of hedge effectiveness.

Table 4.8. Results of Hedge Effectiveness

WTI	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	**0.475441**	**0.546214**	**0.532922**	**0.512146**	**0.490873**
ECM	0.475386	0.546209	0.532922	0.512144	0.490867
ARCH(1)	0.472402	0.546214	0.532919	0.512145	0.490873
GARCH(1,1)	0.473564	0.546098	0.53257	0.511513	0.490033
ECM-GARCH(1,1)	0.473414	0.546108	0.532577	0.511515	0.490022
Covariance	0.450186	0.537048	0.529541	0.510023	0.489032
Optimization	0.475441	0.546214	0.532922	0.512146	0.490873

Brent	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	**0.49377**	**0.530689**	**0.516716**	**0.487935**	**0.461986**
ECM	0.493765	0.530689	0.516715	0.487927	0.461968
ARCH(1)	0.493064	0.530538	0.516598	0.487695	0.461766
GARCH(1,1)	0.492889	0.530689	0.516464	0.487636	0.461709
ECM-GARCH(1,1)	0.492778	0.530689	0.516483	0.48765	0.461714
Covariance	0.45934	0.515734	0.510276	0.483307	0.456587
Optimization	0.49377	0.530689	0.516716	0.487935	0.461986

Heating Oil	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	**0.666851**	**0.665577**	**0.615343**	**0.588811**	**0.56933**
ECM	0.666793	0.665574	0.615342	0.588798	0.56928
ARCH(1)	0.662495	0.665572	0.615298	0.588758	0.569312
GARCH(1,1)	0.663646	0.665004	0.613398	0.585926	0.567205
ECM-GARCH(1,1)	0.663228	0.665092	0.613407	0.585908	0.567236
Covariance	0.662539	0.66552	0.614513	0.586785	0.567424
Optimization	0.666851	0.665577	0.615343	0.588812	0.56933

Gasoil	Contract Maturity in Months				
Model	1	3	6	9	12
OLS	**0.294521**	**0.330774**	**0.306812**	**0.28985**	**0.278142**
ECM	0.287616	0.324889	0.303035	0.287304	0.276034
ARCH(1)	0.283883	0.318125	0.298426	0.284318	0.273579
GARCH(1,1)	0.283678	0.324565	0.304317	0.288522	0.277227
ECM-GARCH(1,1)	0.281463	0.323776	0.304118	0.288388	0.277123
Covariance	0.256655	0.304541	0.291776	0.278695	0.26741
Optimization	0.294521	0.330774	0.306812	0.28985	0.278142

4.5. Monte Carlo Simulation

The comparison made of the R^2 analogue that is shown in Table 4.8 is that it is only for the time period and the data from which it was drawn. To have a more practical measure of which model creates a more accurate hedge ratio, the ratios that were developed here were tested against simulated data. Many other studies use back testing and forecasting to determine how well the hedge ratios generated would minimize variance. However, this study decided to use Monte Carlo simulations to forecast, to work outside the data. First, it was required that a potential 100 day period on which to test the hedge ratios estimated was created. The generated 100 day period was created from results drawn from a fitted distribution to the rates of change. The software used was @Risk., which is not only able to fit the distributions but is also able to generate a covariance matrix so that the random draws are correlated in an appropriate manner. The distributions that were fitted to the series based on AIC are presented in Table 4.9 (Palisade, 2014).

Table 4.9. Monte Carlo Distributions

Fitted Distribution	Contract or Asset	Fitted Distribution	Contract or Asset
Laplace	Jet Fuel	Logistic	Heating Oil 1-Month
Laplace	WTI 1-Month	Logistic	Heating Oil 3-Month
Logistic	WTI 3-Month	Logistic	Heating Oil 6-Month
Logistic	WTI 6-Month	Logistic	Heating Oil 9-Month
Logistic	WTI 9-Month	Logistic	Heating Oil 12-Month
Logistic	WTI 12-Month	Laplace	Gasoil 1-Month
Laplace	Brent 1-Month	Logistic	Gasoil 3-Month
Laplace	Brent 3-Month	Logistic	Gasoil 6-Month
Laplace	Brent 6-Month	Logistic	Gasoil 9-Month
Laplace	Brent 9-Month	Logistic	Gasoil 11-Month
Laplace	Brent 12-Month		

Table 4.10. Results of Monte Carlo Hedge Effectiveness

WTI	Contract Maturity in Months				
	1	3	6	9	12
OLS	0.524587	0.533679	0.57157	0.562763	0.52564
ECM	0.525016	0.533624	0.571683	0.562952	0.526003
ARCH(1)	0.525103	0.533676	0.571291	0.562635	0.525712
GARCH(1,1)	**0.525509**	**0.533793**	0.568562	0.558582	0.520743
ECM-GARCH(1,1)	0.525468	0.533792	0.568597	0.558589	0.520706
Covariance	0.509423	0.522403	**0.576968**	**0.567465**	**0.530217**
Optimization	0.524591	0.533678	0.57157	0.562762	0.525638

Brent	Contract Maturity in Months				
	1	3	6	9	12
OLS	**0.486452**	0.551762	0.461267	0.459526	0.446571
ECM	0.486377	0.551776	0.461184	0.459605	0.446673
ARCH(1)	0.484886	**0.552276**	0.460108	**0.459783**	**0.446788**
GARCH(1,1)	0.484609	0.551751	**0.462532**	0.458728	0.445839
ECM-GARCH(1,1)	0.484436	0.551792	0.462493	0.458754	0.445849
Covariance	0.445142	0.543866	0.446985	0.457448	0.443669
Optimization	0.486451	0.551762	0.461271	0.459525	0.446569

Heating Oil	Contract Maturity in Months				
	1	3	6	9	12
OLS	0.699531	0.704488	0.635248	0.624217	0.589934
ECM	0.700269	0.704674	**0.63536**	**0.624424**	**0.59001**
ARCH(1)	0.702357	0.704742	0.634616	0.623726	0.589992
GARCH(1,1)	**0.702445**	0.70116	0.629607	0.618163	0.586953
ECM-GARCH(1,1)	0.702431	0.701465	0.629622	0.618135	0.586991
Covariance	0.702363	**0.705314**	0.631966	0.619527	0.587218
Optimization	0.699533	0.704486	0.635244	0.624214	0.589933

Gasoil	Contract Maturity in Months				
	1	3	6	9	12
OLS	**0.259351**	**0.227745**	**0.217819**	**0.186618**	**0.190372**
ECM	0.246444	0.211382	0.205388	0.171864	0.180356
ARCH(1)	0.241239	0.199999	0.196629	0.162945	0.174164
GARCH(1,1)	0.240961	0.210784	0.208271	0.176514	0.18425
ECM-GARCH(1,1)	0.237997	0.209359	0.207798	0.175942	0.183859
Covariance	0.207172	0.180297	0.185761	0.149422	0.161746
Optimization	0.259345	0.227736	0.21781	0.186606	0.190363

The results from the Monte Carlo simulation in Table 4.10 suggest that there is not one model that consistently estimates a more precise hedge ratio. In Table 4.8 and Table 4.10 the bolded values represent the highest and therefore the most effective hedge. While some models never generated the best hedge ratio, there were not any models that always generated the best hedge ratio for all assets. The exception is the OLS estimates from gasoil. For gasoil the OLS estimates for the hedge ratio were the optimal ratios for all contracts.

Figure 4.2 shows the average effectiveness of all of the models for the four different commodities. This is a graphical representation showing which commodity hedge is the most efficient cross hedge, and which contract maturity should be used. As you can see on Figure 4.2, the best cross hedge commodity is heating oil for all maturities. Again, this is a logical conclusion as heating oil is a refined petroleum product and is therefore likely to be highly correlated with jet fuel, an even more refined petroleum product.

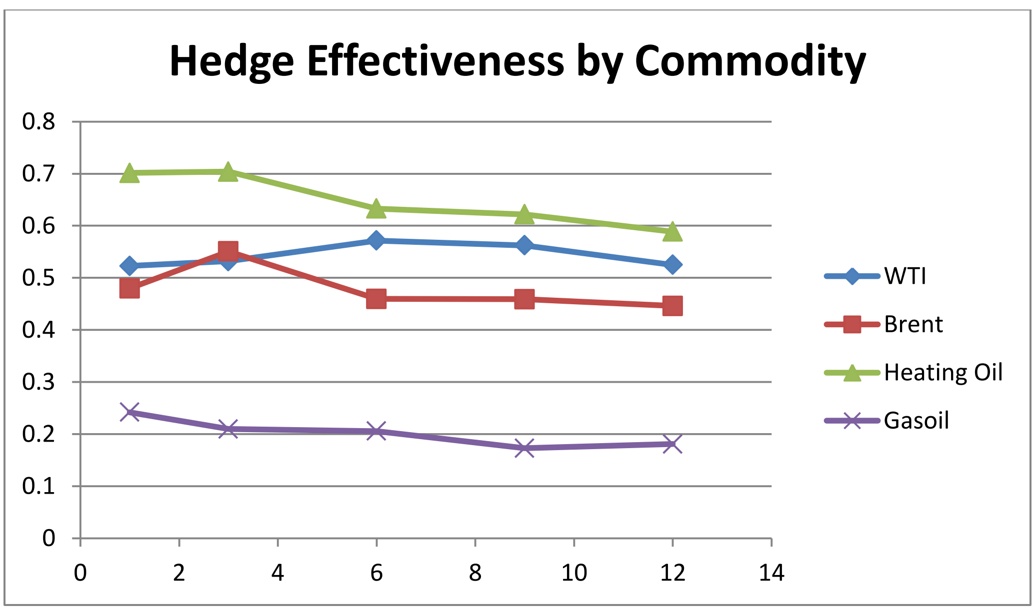

Figure 4.2. Hedge Effectiveness by Commodity from the Simulated Results

Equally noticeable from Figure 4.2 is that gasoil is the least suitable cross-hedging asset. This could have in part to deal with the commodity contract being in a different unit of measure than the other contracts and also due to the minimum fluctuation being $0.25 per tonne, while the other commodities are $0.01 per barrel. Also important is that Brent and WTI were similar in effectiveness, but as maturity increased, WTI became the superior cross hedging asset. These results are similar with Adams and Gerner (2012), who found that past a six month maturity WTI was the best asset with which to hedge. However, based on the results shown in Figure 4.2, the best asset use in cross-hedging is heating oil.

4.6. Value at Risk

The final part of this study looks at the value at risk generated by jet fuel for an airline. This will look at the daily VaR, which is the most an airline could lose due to fuel in a day. Figure 4.3 shows that the optimal strategy to reduce Value at Risk is to use heating oil contracts to hedge 50% of estimated daily fuel usage. It is assumed that because airlines have fixed costs and difficulty starting and stopping routes, they can fairly accurately estimate their own fuel usage.

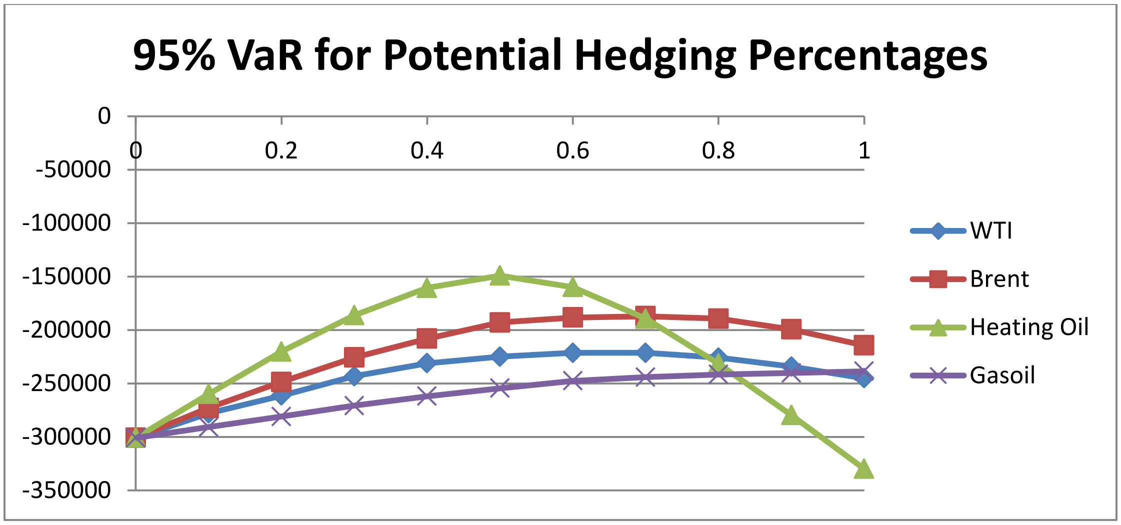

Figure 4.3. VaR for Potential Hedge Percentages [7]

The Monte Carlo simulation for VaR is by creating different portfolios with payoffs that correspond to different hedging positions. First, Distributions are fitted to the rates of change, the software has the ability to do all of the series at once to create a covariance matrix, allowing for more realistic simulations. Then, to create a realistic daily amount of fuel usage, the average annual consumption of similarly sized airlines was determined and was divided by 365. That was a large value in terms of jet fuel, so in order to determined how many contracts were needed gallons were converted into barrels and barrels converted into contracts.

Knowing how many contracts were needed based on estimated fuel consumption, portfolios could be designed representing the potential stances a hedger could have. The portfolios tested the amount hedged by the airline in 10% increments from 0, completely unhedged by futures, to 100, completely hedged fuel use by futures. The results for the 95% VaR are posted in Figure 4.3 and are given in normal dollar amounts. It is interpreted that with 95% confidence, the firm will pay no more than [X] amount for fuel.

[7] Numeric results are presented in the Appendix, along with a 99% VaR

5. CONCLUSIONS

Airlines have had mixed results with hedging and the general feeling from both scholars and airline managers themselves is that airlines are unsure of how to hedge their jet fuel exposure. This study has presented both the arguments for and against hedging. While the study did not intend to prove that airlines should hedge, it has shown that if an airline wishes to reduce its value at risk, a well-constructed hedge portfolio can significantly reduce VaR. Furthermore, if the airline wishes to construct a cross-hedging portfolio, the optimal hedge ratio generated from an OLS is not inappropriate. While some papers have suggested that due to the shortcomings of an OLS, a more advanced model should be used, this study does not reach the same conclusions. While other models, such as ECM and GARCH(1,1) generate similar hedge ratios to the OLS, after simulations the results were that no model clearly and consistently generates a better hedge ratio than the other models. This means that due to the ease of understanding the OLS and the R^2 as a measure of efficacy, an OLS is still an appropriate model to use.

Other findings of this study are that cross-hedges created with futures should use heating oil as the underlying commodity. As heating oil is a refined petroleum product, its price follows jet fuel closer than the other petroleum products. Moreover, the relationship between heating oil will likely stay the same while oil booms could affect the price of WTI and Brent (Southwest, 2014). While some airlines continue to use Brent and WTI crude oil contracts, the hedge portfolios with the lowest VaR and the highest effectiveness had heating oil as the underlying asset.

This study also determined that for the data used, airlines would not qualify for hedge accounting if they used forwards. While heating oil contracts would decrease airlines' fuel VaR, the contracts are not correlated enough to qualify for the benefit of hedge accounting. Airlines could overcome this hedge accounting problem by switching to a different type of contract, such as a forward, but they would then lose the benefits of using futures contracts.

This study has provided many solutions to problems that exist in the airline industry, however there are still drawbacks. The main drawback of this study is that it used daily data, providing both a daily VaR and daily hedge ratio. To have a fuller solution to the questions of hedging and model usage, weekly or monthly data should be used providing respective VaR and hedge ratios. Also, the VaR calculated was for jet fuel use by an airline. It would be an interesting examination of an airline if a component VaR was used, including interest rate, foreign exchange, and equity risks along with commodity risk.

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APPENDIX. MODEL ESTIMATIONS

Table A.1. Results of the Airfare/Jet Fuel Granger Causality

Pairwise Granger Causality Tests
Sample: 1994M04 2014M02
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
JETFUELPRICE does not Granger Cause CPI_AIRFARE	237	12.2145	9.E-06
CPI_AIRFARE does not Granger Cause JETFUELPRICE		2.02397	0.1345

Table A.2. Correlation Matrix for Airfare/Jet Fuel

	CPI Airfare	Jet Fuel
CPI Airfare	1	0.905128
Jet Fuel	0.905128	1

Table A.3. WTI Test Results[8]

WTI Covariance					
	1-Month	3-Month	6-Month	9-Month	12-Month
Hedge Ratio	0.894632	1.042307	1.109551	1.1537	1.188468
R-Squared	0.45625	0.513421	0.512523	0.506451	0.498395

WTI OLS					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.727026**	**0.922761**	**1.027705**	**1.083942**	**1.119921**
	(0.010819)	(0.011916)	(0.013631)	(0.014988)	(0.016159)
Adjusted R-Squared	0.475353	0.546125	0.532828	0.512048	0.490771
Log-Likelihood	12992.9	13353.99	13282.04	13173.59	13067.23
ARCH-LM (5)	**31.6613**	**28.82523**	**25.31712**	**24.00661**	**21.1315**

WTI ECM					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.734887**	**0.92564**	**1.028823**	**1.085951**	**1.124014**
	(0.01078)	(0.011845)	(0.013562)	(0.014932)	(0.016117)
ΔF_{t-1}	0.017025	0.015983	**0.041837**	**0.066494**	**0.084701**
ΔF_{t-2}	**0.063161**	**0.066022**	**0.061419**	**0.063926**	**0.06227**
ΔF_{t-3}	0.010044	0.014429	-	-	-
ΔF_{t-4}	**0.041975**	0.031843	-	-	-
ΔS_{t-1}	-0.01926	-0.01454	-0.00914	-0.00611	**-0.0016**
ΔS_{t-2}	**-0.06657**	**-0.06855**	**-0.06217**	**-0.05902**	**-0.05418**
ΔS_{t-3}	0.004907	-0.006	-	-	-
ΔS_{t-4}	-0.02327	-0.01512	-	-	-
e_{t-1}	**0.029877**	**0.026806**	**0.019471**	**0.014741**	**0.011719**
Adjusted R-Squared	0.484273	0.553161	0.538947	0.518255	0.497362
Log-Likelihood	13028.05	13385.07	13311.42	13202.06	13096.31
ARCH-LM (5)	**654.7391**	**582.1442**	**575.4598**	**565.4451**	**567.1922**

[8] Bolded numbers mean significance at 5% and below for all result tables

Table A.3. WTI Test Results (continued)

WTI ARCH(1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.785211**	**0.92293**	**1.025006**	**1.082595**	**1.12072**
	(0.005234)	(0.007161)	(0.008563)	(0.00934)	(0.009979)
ΔF_{t-1}	**-0.01453**	-0.00807	**0.038353**	**0.06315**	**0.090892**
ΔF_{t-2}	**0.022729**	**0.038038**	0.011408	0.018258	0.019244
ΔS_{t-1}	**0.012045**	**0.01603**	0.002025	0.004894	0.001853
ΔS_{t-2}	**-0.03643**	**-0.04575**	**-0.0254**	**-0.02692**	**-0.02414**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.493823**	**0.465587**	**0.43854**	**0.432948**	**0.425977**
Adjusted R-Squared	0.472991	0.546908	0.533752	0.514128	0.493906
Log-Likelihood	13602.53	13909.59	13816.93	13677.08	13536.75
ARCH-LM (5)	**44.2231**	**46.59432**	**54.69169**	**58.6381**	**64.45046**

WTI GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	**0.00**	**0.00**	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.772771**	**0.909336**	**1.001273**	**1.045815**	**1.073586**
	(0.006799)	(0.008243)	(0.009418)	(0.009993)	(0.010562)
ΔF_{t-1}	0.00517	-0.00507	0.017243	0.030208	0.035034
ΔF_{t-2}	0.018423	0.010919	0.009382	0.011021	0.013445
ΔS_{t-1}	0.000805	0.004674	0.005452	0.012519	0.021384
ΔS_{t-2}	**-0.04216**	**-0.04563**	**-0.04562**	**-0.04486**	**-0.04374**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.116236**	**0.11517**	**0.11076**	**0.106773**	**0.104185**
GARCH	**0.88356**	**0.884967**	**0.890158**	**0.894626**	**0.897583**
Adjusted R-Squared	0.473899	0.5463	0.533187	0.513024	0.49242
Log-Likelihood	14067.54	14418.65	14341.25	14204.68	14072.88
ARCH-LM (5)	8.129499	4.712533	7.086755	8.426825	10.39599

Table A.3. WTI Test Results (continued)

WTI ECM-GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.774559**	**0.909959**	**1.001557**	**1.045872**	**1.073283**
	(0.006745)	(0.008206)	(0.009441)	(0.010031)	(0.010576)
ΔF_{t-1}	-0.00311	-0.01158	0.012603	0.026771	0.032197
ΔF_{t-2}	0.010549	0.005296	0.005595	0.00812	0.010901
ΔS_{t-1}	0.007782	0.010024	0.009697	0.01583	0.024205
ΔS_{t-2}	**-0.03537**	**-0.04064**	**-0.0417**	**-0.04165**	**-0.04093**
e_{t-1}	**-0.01425**	**-0.0115**	**-0.00868**	**-0.00687**	**-0.00566**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.116814**	**0.115621**	**0.111364**	**0.107089**	**0.104078**
GARCH	**0.882275**	**0.88438**	**0.889477**	**0.894218**	**0.897611**
Adjusted R-Squared	0.479771	0.550248	0.536089	0.515367	0.494412
Log-Likelihood	14085.6	14432.37	14351.04	14212.27	14079
ARCH-LM (5)	7.850179	4.850799	7.248721	8.535928	10.40054

Table A.4. Brent Results

Brent Covariance					
	1-Month	3-Month	6-Month	9-Month	12-Month
Hedge Ratio	1.020602	1.101034	1.151488	1.180107	1.213179
R-Squared	0.515376	0.541371	0.533657	0.517	0.509235

Brent OLS					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.807396**	**0.942804**	**1.035912**	**1.075471**	**1.094932**
	(0.011582)	(0.012561)	(0.014194)	(0.015609)	(0.01674)
Adjusted R-Squared	0.493672	0.530595	0.516621	0.487836	0.461882
Log-Likelihood	13081.46	13270.16	13197.05	13052.9	12929.72
ARCH-LM (5)	**615.1766**	**609.1136**	**598.0085**	**591.4396**	**572.5104**

Brent ECM					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.809972**	**0.943125**	**1.03715**	**1.079769**	**1.101618**
	(0.01148)	(0.012485)	(0.014134)	(0.015552)	(0.016702)
ΔF_{t-1}	**0.039346**	0.026278	**0.040822**	**0.078718**	**0.087803**
ΔF_{t-2}	**0.061525**	**0.06633**	**0.082176**	**0.09751**	**0.099314**
ΔS_{t-1}	**-0.03437**	-0.01903	-0.01259	-0.01607	-0.0094
ΔS_{t-2}	**-0.06056**	**-0.05684**	**-0.06247**	**-0.0667**	**-0.06184**
e_{t-1}	**-0.03358**	**-0.02872**	**-0.02035**	**-0.01564**	**-0.013**
Adjusted R-Squared	0.505189	0.539113	0.523715	0.495586	0.469529
Log-Likelihood	13135.4	13312.32	13230.45	13087.52	12962.05
ARCH-LM (5)	**626.4285**	**610.4858**	**588.6348**	**581.5674**	**563.2034**

Table A.4. Brent Results (continued)

Brent ARCH(1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.837967**	**0.958736**	**1.05154**	**1.099233**	**1.118719**
	(0.006886)	(0.007193)	(0.008823)	(0.00963)	(0.011016)
ΔF_{t-1}	**0.070715**	**0.051675**	**0.034735**	**0.10329**	**0.113622**
ΔF_{t-2}	**0.043026**	**0.042103**	**0.044875**	**0.057477**	**0.056206**
ΔS_{t-1}	**-0.05166**	**-0.03513**	-0.00122	**-0.03126**	**-0.03491**
ΔS_{t-2}	**-0.04809**	**-0.04416**	**-0.0436**	**-0.04543**	**-0.05005**
C	**0.000157**	**0.000139**	**0.00015**	**0.000167**	**0.000189**
ARCH	**0.548487**	**0.597036**	**0.559254**	**0.523995**	**0.460872**
Adjusted R-Squared	0.496365	0.532457	0.518385	0.491152	0.465409
Log-Likelihood	13717.16	13957.14	13831.24	13620.96	13427.19
ARCH-LM (5)	**133.4095**	**153.7241**	**144.8967**	**91.40228**	**76.52871**

Brent GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.841531**	**0.94254**	**1.012978**	**1.048781**	**1.068052**
	(0.007528)	(0.007835)	(0.008591)	(0.009217)	(0.009734)
ΔF_{t-1}	**0.060515**	**0.037615**	**0.035972**	**0.048928**	**0.049858**
ΔF_{t-2}	**0.046931**	**0.045038**	**0.04617**	**0.049607**	**0.057101**
ΔS_{t-1}	**-0.05131**	**-0.03225**	-0.02044	-0.01773	-0.00928
ΔS_{t-2}	**-0.05548**	**-0.05458**	**-0.05843**	**-0.05955**	**-0.0622**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.113761**	**0.133717**	**0.129694**	**0.119597**	**0.114029**
GARCH	**0.892489**	**0.876318**	**0.878958**	**0.887757**	**0.893641**
Adjusted R-Squared	0.4964	0.532692	0.518369	0.490508	0.464794
Log-Likelihood	14281.76	14625.75	14506.4	14324.23	14131.22
ARCH-LM (5)	**15.53628**	9.231074	9.849777	**11.46624**	**12.24918**

Table A.4. Brent Results (continued)

Brent ECM-GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.843623**	**0.943516**	**1.01384**	**1.049429**	**1.068313**
	(0.007537)	(0.007827)	(0.008629)	(0.009268)	(0.009768)
ΔF_{t-1}	**0.050446**	**0.031649**	**0.032687**	**0.046182**	**0.047337**
ΔF_{t-2}	**0.03915**	**0.040345**	**0.043423**	**0.047875**	**0.055742**
ΔS_{t-1}	**-0.04058**	-0.02515	-0.01568	-0.01356	-0.00552
ΔS_{t-2}	**-0.0459**	**-0.04789**	**-0.0536**	**-0.05569**	**-0.05909**
e_{t-1}	**-0.02215**	**-0.0169**	**-0.01232**	**-0.00996**	**-0.00834**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.112064**	**0.13355**	**0.129948**	**0.120418**	**0.114548**
GARCH	**0.894118**	**0.876687**	**0.878839**	**0.88703**	**0.893151**
Adjusted R-Squared	0.503041	0.537769	0.522251	0.493812	0.467741
Log-Likelihood	14303.97	14642.58	14519.4	14335.69	14141.01
ARCH-LM (5)	**16.29733**	9.555932	9.772597	**11.15019**	**11.91678**

Table A.5. Heating Oil Results

Heating Oil Covariance					
	1-Month	3-Month	6-Month	9-Month	12-Month
Hedge Ratio	**0.968411**	1.050415	1.082498	1.122214	1.150821
R-Squared	0.660258	0.665778	0.625482	0.606737	0.596076

Heating Oil OLS					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.896316**	**1.040844**	**1.123817**	**1.192209**	**1.22159**
	(0.008976)	(0.010453)	(0.012588)	(0.014115)	(0.015052)
Adjusted R-Squared	0.666786	0.66551	0.615268	0.588733	0.569251
Log-Likelihood	14124.12	14114.59	13765.86	13599.65	13484.32
ARCH-LM (5)	**365.9266**	**630.8454**	**668.7453**	**602.2236**	596.1056

Heating Oil ECM					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.904697**	**1.042901**	**1.125693**	**1.197936**	**1.232952**
	(0.008833)	(0.010336)	(0.012503)	(0.014042)	(0.014971)
ΔF_{t-1}	**0.071978**	**0.041295**	0.028775	**0.056384**	**0.090588**
ΔF_{t-2}	0.028853	**0.037135**	**0.065829**	**0.074055**	**0.084966**
ΔS_{t-1}	**-0.06053**	-0.01986	0.011794	0.018683	0.016704
ΔS_{t-2}	**-0.04731**	**-0.05247**	**-0.07114**	**-0.06263**	**-0.06414**
e_{t-1}	**-0.06003**	**-0.03809**	**-0.01751**	**-0.01307**	**-0.01202**
Adjusted R-Squared	0.679344	0.673476	0.621438	0.595509	0.578165
Log-Likelihood	14216.02	14170.84	13802.48	13637.45	13532.87
ARCH-LM (5)	**450.1174**	**635.8378**	**652.5502**	**582.3663**	**576.0552**

Table A.5. Heating Oil Results (continued)

Heating Oil ARCH(1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	**0.00**	**0.00**	**0.00**	0.00	**0.00**
ΔF_t (Hedge Ratio)	**0.968771**	**1.043666**	**1.114125**	**1.180833**	**1.228445**
	(0.003219)	(0.004115)	(0.005676)	(0.007042)	(0.007419)
ΔF_{t-1}	**0.316373**	**0.264492**	**0.192864**	**0.190994**	**0.240539**
ΔF_{t-2}	**0.109378**	**0.031033**	**-0.02445**	**-0.02676**	-0.01041
ΔS_{t-1}	**-0.31553**	**-0.24654**	**-0.14389**	**-0.10838**	**-0.13356**
ΔS_{t-2}	**-0.12722**	**-0.06713**	-0.00963	-0.00091	**-0.01291**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.996416**	**0.937363**	**0.803251**	**0.677655**	**0.701225**
Adjusted R-Squared	0.651171	0.652461	0.607576	0.584348	0.564047
Log-Likelihood	15186.84	14942.87	14523.6	14252.59	14153.44
ARCH-LM (5)	4.131121	8.288079	**26.84185**	**38.88366**	**80.91962**

Heating Oil GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.958475**	**1.01029**	**1.060608**	**1.108703**	**1.146875**
	(0.004404)	(0.005176)	(0.005901)	(0.007449)	(0.008011)
ΔF_{t-1}	**0.09416**	-0.00334	**-0.03617**	-0.02612	0.005286
ΔF_{t-2}	**0.068184**	0.012919	0.020108	**0.038522**	0.019658
ΔS_{t-1}	**-0.09314**	0.001912	**0.038214**	**0.047186**	**0.041396**
ΔS_{t-2}	**-0.08471**	**-0.04173**	**-0.0427**	**-0.05608**	**-0.04422**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.217681**	**0.171582**	**0.153799**	**0.115267**	**0.148638**
GARCH	**0.826054**	**0.851395**	**0.858844**	**0.894742**	**0.865586**
Adjusted R-Squared	0.668292	0.666145	0.61476	0.588161	0.570994
Log-Likelihood	16044.63	15845.33	15295.56	14949.54	14849.4
ARCH-LM (5)	0.55478	1.316538	3.246122	5.527034	5.602462

Table A.5. Heating Oil Results (continued)

Heating Oil ECM-GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	**0.00**	**0.00**	**0.00**	0.00	0.00
ΔF_t (Hedge Ratio)	**0.962405**	**1.012738**	**1.060739**	**1.108443**	**1.147432**
	(0.004307)	(0.005048)	(0.00585)	(0.007392)	(0.007938)
ΔF_{t-1}	**0.070294**	-0.012901	**-0.039858**	-0.028156	0.002902
ΔF_{t-2}	**0.047045**	0.002755	0.014583	0.030975	0.015117
ΔS_{t-1}	**-0.06881**	0.013105	**0.042408**	**0.051518**	**0.04534**
ΔS_{t-2}	**-0.06286**	**-0.02945**	**-0.0364**	**-0.04847**	**-0.0381**
e_{t-1}	**-0.0427**	**-0.02845**	**-0.01359**	**-0.01217**	**-0.01167**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.227266**	**0.171427**	**0.153439**	**0.116894**	**0.14831**
GARCH	**0.820485**	**0.851966**	**0.8604**	**0.893499**	**0.865901**
Adjusted R-Squared	0.675577	0.671375	0.617693	0.590831	0.573618
Log-Likelihood	16101.92	15875.79	15308.83	14968.56	14868.35
ARCH-LM (5)	0.633434	1.31117	3.49736	6.11643	6.010633

Table A.6. Gasoil Results

Gasoil Covariance					
	1-Month	3-Month	6-Month	9-Month	12-Month
Hedge Ratio	0.904697	1.011695	1.046672	1.073399	1.083539
R-Squared	0.309473	0.349796	0.331221	0.318181	0.309417

Gasoil OLS					
	1-Month	3-Month	6-Month	9-Month	11-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.665874**	**0.789358**	**0.856935**	**0.89733**	**0.905623**
	(0.0146)	(0.015907)	(0.018249)	(0.019899)	(0.02067)
Adjusted R-Squared	0.294405	0.33065	0.306679	0.289712	0.278001
Log-Likelihood	12254.48	12385.89	12298.21	12237.96	12197.2
ARCH-LM (5)	**576.0084**	**600.7937**	**595.242**	**588.9194**	**589.8425**

Gasoil ECM					
	1-Month	3-Month	6-Month	9-Month	11-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.767919**	**0.894715**	**0.952069**	**0.981485**	**0.984522**
	(0.014907)	(0.01628)	(0.018735)	(0.020416)	(0.021219)
ΔF_{t-1}	**0.129876**	**0.163981**	**0.165273**	**0.162322**	**0.165411**
ΔF_{t-2}	**0.065462**	**0.096638**	**0.10927**	**0.112723**	**0.111785**
ΔF_{t-3}	-0.0066	-0.007547	-	-	-
ΔF_{t-4}	0.020778	-0.004594	-	-	-
ΔS_{t-1}	**-0.21551**	**-0.236631**	**-0.213062**	**-0.187584**	**-0.17466**
ΔS_{t-2}	**-0.09719**	**-0.107207**	**-0.100929**	**-0.090108**	**-0.08603**
ΔS_{t-3}	0.012338	0.002216	-	-	-
ΔS_{t-4}	0.018723	0.022721	-	-	-
e_{t-1}	**-0.0739**	**-0.046295**	**-0.022908**	**-0.01611**	**-0.014**
Adjusted R-Squared	0.354147	0.383947	0.346867	0.321438	0.305996
Log-Likelihood	12467.82	12585.45	12443.89	12348.74	12292.69
ARCH-LM (5)	**563.0907**	**583.9525**	**588.6254**	**583.7984**	**583.5718**

Table A.6. Gasoil Results (continued)

Gasoil ARCH(1)					
	1-Month	3-Month	6-Month	9-Month	11-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.792512**	**0.943777**	**0.998653**	**1.021337**	**1.021661**
	(0.010636)	(0.011156)	(0.012665)	(0.013746)	(0.014983)
ΔF_{t-1}	**0.244467**	**0.3211**	**0.308588**	**0.294083**	**0.278555**
ΔF_{t-2}	**0.110025**	**0.134448**	**0.1266**	**0.11201**	**0.107318**
ΔS_{t-1}	**-0.32365**	**-0.385558**	**-0.331967**	**-0.273392**	**-0.24452**
ΔS_{t-2}	**-0.1379**	**-0.154478**	**-0.125729**	**-0.098111**	**-0.08916**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.322719**	**0.409265**	**0.387695**	**0.3513**	**0.326509**
Adjusted R-Squared	0.335417	0.36586	0.334187	0.312256	0.298552
Log-Likelihood	12717.49	12913.18	12759.8	12637.76	12568.39
ARCH-LM (5)	**70.82962**	**69.15171**	**106.3193**	**105.6653**	**99.48533**

Gasoil GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	11-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.793726**	**0.897573**	**0.93427**	**0.958125**	**0.957628**
	(0.012006)	(0.011855)	(0.013074)	(0.014647)	(0.015371)
ΔF_{t-1}	**0.246236**	**0.285332**	**0.265256**	**0.24901**	**0.246423**
ΔF_{t-2}	**0.100303**	**0.111489**	**0.102455**	**0.102126**	**0.102951**
ΔS_{t-1}	**-0.3227**	**-0.344773**	**-0.296776**	**-0.255145**	**-0.23509**
ΔS_{t-2}	**-0.1527**	**-0.153151**	**-0.127724**	**-0.112538**	**-0.10681**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.076969**	**0.088193**	**0.088405**	**0.088113**	**0.085348**
GARCH	**0.921816**	**0.910998**	**0.910247**	**0.910531**	**0.913159**
Adjusted R-Squared	0.335859	0.370445	0.337284	0.313894	0.299226
Log-Likelihood	13182.77	13364.62	13205.9	13096.57	13025.18
ARCH-LM (5)	**14.60327**	**18.66705**	**16.24063**	**17.09515**	**19.66765**

Table A.6. Gasoil Results (continued)

Gasoil ECM-GARCH(1,1)					
	1-Month	3-Month	6-Month	9-Month	11-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t (Hedge Ratio)	**0.806167**	**0.904239**	**0.9373**	**0.961119**	**0.960493**
	(0.012145)	(0.01174)	(0.013013)	(0.014624)	(0.015332)
ΔF_{t-1}	**0.213462**	**0.265737**	**0.257787**	**0.245573**	**0.243631**
ΔF_{t-2}	**0.085161**	**0.104441**	**0.100691**	**0.102238**	**0.103559**
ΔS_{t-1}	**-0.28062**	**-0.317569**	**-0.2852**	**-0.247612**	**-0.22835**
ΔS_{t-2}	**-0.12587**	**-0.136308**	**-0.120224**	**-0.107619**	**-0.10233**
e_{t-1}	**-0.06817**	**-0.046435**	**-0.01999**	**-0.013626**	**-0.01238**
C	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
ARCH	**0.077702**	**0.09032**	**0.089886**	**0.089633**	**0.086704**
GARCH	**0.921414**	**0.909278**	**0.908959**	**0.909099**	**0.911895**
Adjusted R-Squared	0.350236	0.379485	0.342621	0.317988	0.302969
Log-Likelihood	13228.48	13396.64	13220.23	13107.76	13036.01
ARCH-LM (5)	**15.26556**	**19.80802**	**16.94522**	**17.30927**	**19.72193**

Table A.7. 95% VaR Numeric Results

Percentage of Fuel use Hedged	Commodity: WTI	Brent	Heating Oil	Gasoil
0%	$(300,789.40)	$(300,789.40)	$(300,768.30)	$(300,789.40)
10%	$(277,893.20)	$(272,805.90)	$(259,891.50)	$(290,807.60)
20%	$(261,387.00)	$(248,685.60)	$(220,116.50)	$(280,911.80)
30%	$(243,160.10)	$(225,682.00)	$(186,171.60)	$(270,783.20)
40%	$(231,046.50)	$(208,084.70)	$(160,577.40)	$(261,921.40)
50%	$(225,009.80)	$(192,881.20)	$(149,137.00)	$(254,405.50)
60%	$(221,380.80)	$(188,356.00)	$(159,878.50)	$(247,616.50)
70%	$(221,428.30)	$(187,056.50)	$(189,279.70)	$(244,174.00)
80%	$(225,861.30)	$(189,302.90)	$(231,450.50)	$(241,604.50)
90%	$(234,228.50)	$(199,415.70)	$(279,605.10)	$(240,175.60)
100%	$(245,130.40)	$(214,362.40)	$(329,847.90)	$(238,556.60)

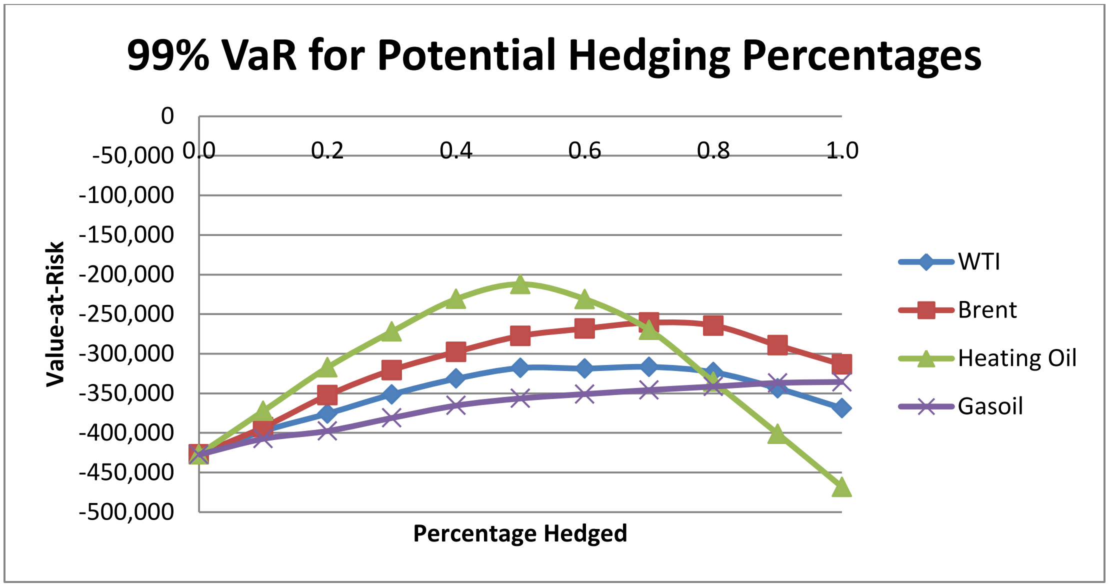

Figure A.1. 99% VaR Results Graph

Table A.8. 99% VaR Numeric Results

Percentage of Fuel use Hedged	Commodity			
	WTI	Brent	Heating Oil	Gasoil
0%	$(427,080.36)	$(427,260.23)	$(426,982.36)	$(427,442.08)
10%	$(397,720.33)	$(392,844.21)	$(372,271.31)	$(407,443.64)
20%	$(375,604.03)	$(352,424.32)	$(317,203.81)	$(397,559.83)
30%	$(351,388.79)	$(320,622.61)	$(271,941.74)	$(381,070.02)
40%	$(331,502.47)	$(297,651.84)	$(230,898.93)	$(365,439.72)
50%	$(317,963.12)	$(277,504.35)	$(212,111.16)	$(356,439.27)
60%	$(318,647.77)	$(268,294.20)	$(230,971.78)	$(350,956.49)
70%	$(316,604.47)	$(260,700.25)	$(269,822.69)	$(345,879.28)
80%	$(323,423.38)	$(264,450.75)	$(335,358.31)	$(341,420.39)
90%	$(343,769.87)	$(289,452.77)	$(401,116.11)	$(336,840.06)
100%	$(368,734.88)	$(313,614.90)	$(468,336.08)	$(335,591.02)