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Hedging jet fuel price risk: The case of U.S. passenger airlines

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ARTICLE INFO

Article history:

Received 2 July 2014

Received in revised form

12 January 2015

Accepted 17 February 2015

Available online 27 February 2015

Keywords:

Jet fuel

Airlines

Fuel price risk

Fuel hedging

ABSTRACT

Jet fuel accounts for a large portion of passenger airlines' operating costs, and airlines' earnings are susceptible to swings in the price of jet fuel. This study uses daily data over the past two decades to determine the minimum variance hedge ratio for airlines wishing to hedge jet fuel price risk with futures, while also establishing the best cross hedging asset. Airlines hedging with futures would create the most effective hedge by using heating oil futures contracts with a 3-month maturity. We also find that beyond the 3-month veil, increased time to maturity makes heating oil less effective as a cross hedge proxy for jet fuel. However, both in-sample analysis and Monte Carlo simulation results with daily data show that none of the 4 cross hedge proxies, including heating oil, can be considered highly effective.

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1. Introduction

The total number of travelers has more than doubled since deregulation of the U.S. airline industry in 1978. However, airlines are still having a difficult time staying profitable. Due to competition, the price premium that airlines are able to charge has fallen 20% over the past two decades (Borenstein, 2011). These have worked out as a tremendous advantage for passengers. However, it has not had the same favorable effect on airlines.

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 an input price increase. The combination of these factors means that for an airline to succeed it must manage costs more efficiently. 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 fuel costs have also become larger in both nominal and real terms.

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 risk management. Typically airlines use a cross hedge, where the hedging contracts 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 (Brent), heating oil and gasoil.

Nevertheless, the traditional benchmark used for jet fuel hedging, WTI, has started to follow jet fuel price 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. Recent shale revolution and increased unconventional oil production in North America strained the existing infrastructure at Cushing, resulting in a bottleneck that led to excess supply which resulted in the large price differential between WTI and Brent. Additionally, since the pipelines are at capacity, the truck and rail costs of transporting crude oil to the Gulf Coast also increased the price differential between the Gulf Coast and WTI. 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, 2013).

This study aims at finding risk minimizing hedge ratios for the different futures contracts used for cross hedging jet fuel. Airlines

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often feel that they should hedge, but admit that they are not sure of the best way to do so (Mercatus, 2012). 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 (Morrell and Swan, 2006; Halls, 2005), value creation from hedging (Carter et al., 2006), 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.

We examine four commodities (WTI, Brent, heating oil and gasoil) that are typically used by airlines for cross hedging jet fuel. We find heating oil to be the most suitable commodity for cross hedging, and contrary to an earlier finding by Adams and Gerner (2012), we find gasoil to be the least suitable of the four. This result, however, maybe sensitive to the price of jet fuel spot market location used for the analysis.

The paper is structured as follows: Section 2 provides a review of literature; respectively, Sections 3 and 4 present the models and the data used for our study; Sections 5 provides a discussion on the results, and Section 6 concludes.

2. Literature review

2.1. Industry background

In the decade after U.S. airlines deregulation in 1978, the 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).¹ 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, U.S. airlines have very low profit margins. This means that any sort of external shock to their already narrow profit margins could result in a huge loss for the airlines. If jet fuel costs were constantly rising, then airlines could react appropriately; however because the price will change frequently 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 Airlines, 2013).

While 2008 is by no means an average representation of a typical year for jet fuel prices, it is an extreme 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 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 resorted to other alternatives, like the 2012 Delta Air Lines

purchase of an oil refinery (Delta Air Lines, 2013). The takeover of an oil refinery gives many benefits to Delta. First, it may 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 support 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.

2.2. Fuel hedging and the U.S. airline industry

Because of jet fuel price risks, 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. U.S. airlines often have a difficult time hedging. Airlines frequently 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 OTC derivative markets were implicated as a systemic risk during the U.S. financial crisis of 2008. To address the regulatory oversight of the huge risk exposures associated with the OTC markets, one of the requirements under the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, or the Dodd-Frank Act, is that most OTC derivatives be traded on exchange (Miller and Ruane, 2012). More airlines may begin to hedge on exchange traded contracts after the implementation of the Dodd-Frank requirement and when more exchange traded contracts become available. During most of the period of this study (1994–2014), there were no exchange traded jet fuel contracts. 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.²

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 Airlines, 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 prices 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.

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 Airlines, 2014; page 27). Thus airlines hedging strategies are not necessarily successful (Morrell and Swan, 2006; Mercatus, 2012), and fuel hedging has no statistically significant effect on airline

¹ 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 and Cox, 2008).

² Under the Dodd-Frank Act, traders must put down cash at the opening of a contract to cover potential losses, and subsequent deposits are required to cover the actual losses of a position (Miller and Ruane, 2012).

Table 1
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

operating costs (Lim and Hong, 2014).

However, even with the trouble that cross hedging can give an airline, most U.S. airlines still hedge, while a smaller number of airlines ceased to hedge in recent years. 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).

Besides US Airways, Allegiant Air remains unhedged despite having 48.7% of their operating costs being jet fuel (Allegiant Travel Company, 2013).³ 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).⁴ Different hedging strategies (including unhedged) have led to airlines paying different prices for jet fuel. Table 1 shows the average prices paid for fuel by selected U.S. airlines.

If an airline decides to hedge, all strategies must meet a certain requirement to be considered hedging. In the U.S., 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 hedge accounting, the instrument must be highly correlated and effective at offsetting changes in fair value or cash flows. While the rule does not make any numeric definition, the rule-of-thumb is a correlation coefficient of 0.90 or an adjusted R^2 of 0.80 or higher (Finnerty and Grant, 2002; CME Group, 2012).⁵ 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 hedge 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 for or do not use hedge accounting, the gains and losses from a hedge are declared as income.

Another problem with cross hedging is 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 does not necessarily add value to a company. On the other hand, Carter et al. (2006) found that the firm value of airlines could increase by as much as 10% due to a hedging program.⁶ Stulz (2004) argued that if investors wanted to a firm to hedge, then they, the investors, could do it themselves. He noted that any investor who would find a firm's hedging practices that important would be able to make their own hedge in their portfolio.

Thus, there is still no general consensus on whether airlines should even hedge. Morrell and Swan (2006) argue that a permanent hedging policy is not worth it for airlines. This is consistent with industry leaders who acknowledge that in the long run, hedging should not be expected to save money, but just smooth out cash flows. In light of increased crack spread and the difficulty to find a feasible strategy, some industry leaders are contemplating abandoning fuel hedging and passing fuel costs to consumers, a practice commonly used by freight carriers like UPS and FedEx.⁷ But going unhedged may be riskier. Airlines are reluctant to raise ticket prices given the current market structure, rivals' strategy to continue hedging, consumers' sensitivity and response to airfare changes and other non-fuel-related economic conditions are beyond the firms' control.

3. Methodology

The risk of a portfolio may be measured by the variance of returns to the portfolio. Johnson (1960) shows that the optimal hedge ratio for a portfolio may be derived from minimizing the variance of the portfolio returns.

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

$$R_t = \Delta S_t - h \Delta F_t, \tag{1}$$

where h is the static ratio of the number of futures contracts needed to hedge jet fuel; ΔS_t represents the change in spot price S_t or the first log difference, $S_{t+1} - S_t$ at time t ; ΔF_t represents the first log difference of the futures prices, $F_{t+1} - F_t$. The variance of R_t is

³ Allegiant's operations differ from other commercial airlines in a way that they also offer vacation travel packages with air travel.

⁴ American Airlines hedged 21% of its 2013 fuel requirements and 19% of its estimated 2014 requirements.

⁵ A hedge with an R^2 of 80% of higher (or a correlation of 90% or higher) is deemed highly effective.

⁶ Jin and Jorion (2006) study the value of hedging to oil and gas companies, while Carter et al. (2006) examine the value of hedging for airlines. The motivations for hedging output and input prices are different. Hence, this may explain the difference in the two sets of results.

⁷ <http://www.bloomberg.com/news/2011-01-31/united-delta-profit-at-risk-from-silent-killer-in-fuel-hedges.html>.

$$\text{Var}(R_t) = \text{Var}(\Delta S_t) + h^2 \text{Var}(\Delta F_t) - 2h \text{Cov}(\Delta S_t, \Delta F_t), \quad (2)$$

The minimum variance of R_t is obtained by taking the first derivative of equation (2) with respect to the hedge ratio and setting the derivative equal to 0:

$$\frac{d\text{Var}(R_t)}{dh} = 2h \text{Var}(\Delta F_t) - 2 \text{Cov}(\Delta S_t, \Delta F_t) = 0. \quad (3)$$

The terms in equation (3) can be rearranged such that

$$h^* = \frac{\text{Cov}(\Delta S_t, \Delta F_t)}{\text{Var}(\Delta F_t)}. \quad (4)$$

The parameter h^* in equation (4) is the minimum-variance hedge ratio (MVHR). It is the most widely used hedge ratio and is considered optimal for producing the lowest variability in portfolio returns (Chen et al., 2003). Since the correlation coefficient of ΔS_t and ΔF_t is

$$\rho = \frac{\text{Cov}(\Delta S_t, \Delta F_t)}{SD(\Delta S_t)SD(\Delta F_t)}, \quad (5)$$

where $SD(\Delta S_t)$ and $SD(\Delta F_t)$ are the standard deviations of ΔS_t and ΔF_t respectively, the optimal hedge ratio in equation (4) is equivalent to

$$h^* = \rho \frac{SD(\Delta S_t)}{SD(\Delta F_t)}. \quad (6)$$

This study considers the h^* estimated from different econometric models to determine the optimal hedge ratio.

3.1. Ordinary least squares (OLS)

The relationship between S_t and F_t can be modeled as:

$$S_t = \alpha_0 + \alpha_1 F_t + \varepsilon_t, \quad (7)$$

where ε_t is assumed to be homoskedastic, serially uncorrelated, and independently and identically distributed over time. However, these assumptions do not hold and are inappropriate for the time series price data used in this study. To obtain the MVHR in (4), however, one takes the first difference of S_t and F_t :

$$\Delta S_t = \alpha + \beta \Delta F_t + u_t. \quad (8)$$

Equation (8) can be estimated with the ordinary least squares (OLS) approach, and the OLS estimate of the slope coefficient in (8) is variance-minimizing and equivalent to the value of h^* (Ederington, 1979). Also, the first difference of the log prices will transform the data to a stationary process.

3.2. Error-correction model (ECM)

In spite of its simplicity and the ease to obtain the MVHR, one of the known potential problems of equation (8) is that the model ignores the long-term relationship between the jet fuel spot price series with the futures price series of another petroleum commodity. That is the spot and futures prices can move together closely in the long term even though individually the price series is not stationary (Granger, 1981). This is probable for petroleum commodity prices; the prices of these related commodities are likely to have a common trend (Adams and Gerner, 2012). Ignoring the long-term equilibrium relationship between the contemporaneous price variables will result in overdifferencing. Thus, we apply an error correction term to account for the equilibrium relationship

between the spot and futures prices. The error correction model (ECM) improves upon the OLS by correcting for the cointegration relationship between the two price variables; Ghosh (1993) shows that the ECM model produces better forecasts.

Thus, we specify the error correction term, ε_{t-1} , which is the lagged error term from equation (7). The ECM is given by:

$$\Delta S_t = \alpha + \beta_1 \Delta F_t + \beta_2 \varepsilon_{t-1} + \sum_{k=1}^K \omega_k \Delta F_{t-k} + \sum_{l=1}^L \delta_l \Delta S_{t-l} + u_t. \quad (9)$$

Equation (9) models 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, 2002). 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 it measures the amount of correction made (Brooks, 2002). Besides the error correction term, the improvement of equation (9) over (8) includes the addition of autoregressive terms for the two price variables, and the coefficients associated with lagged futures and spot price variables are represented by ω_k and δ_l , respectively.

3.3. ARCH and GARCH specifications

For the OLS and ECM models, there still exists heteroskedasticity in the error term. The heteroskedasticity in the error term means that the standard errors are likely to be incorrect. 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.

To account for this, Engle (1982) proposes the use of an autoregressive conditional heteroskedastic (ARCH) model in which the mean and the conditional variance are modeled together. The ARCH model is given by:

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

$$u_t \sim N(0, \sigma_t^2),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2. \quad (10)$$

The residuals of (10) are assumed to be distributed normal, with a zero mean and a variance that depends on the past values of the squared residuals. Since σ_t^2 in (10) depends on the squared error term at $t-1$, the variance follows an autoregressive process of order 1. It is possible to include p lags in the ARCH term.

The ARCH framework was extended by Bollerslev (1986) to allow the conditional variance to be an autoregressive moving average process by which the variance of the residuals depends on both the past values of the squared residuals and the lag terms of the variance itself. The generalized ARCH (GARCH) specification is:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i u_{t-i}^2 + \sum_{j=1}^q \gamma_j \sigma_{t-j}^2, \quad (11)$$

where $\sum_{i=1}^p \alpha_i u_{t-i}^2$ would be referred to as the ARCH term and

$\sum_{j=1}^q \gamma_j \sigma_{t-j}^2$ is the GARCH term. The generalized form in equation (11) is of order GARCH(p, q).

This GARCH approach is widely used in modeling volatility of financial time series. The GARCH model is more efficient and avoids over fitting the data (Brooks, 2002). The model that will be used in this study is of order GARCH(1, 1), meaning that the model has one ARCH term and one GARCH term:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2. \quad (12)$$

3.4. EC-GARCH

Since the spot and futures price variables are likely to have the same long-term stochastic trend and the residuals in the above-mentioned models are heteroskedastic, we consider a GARCH model with error correction. The EC-GARCH(1, 1) model is specified as:

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

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

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2. \quad (13)$$

The EC-GARCH model adds the benefits of accounting for conditional variance to the improved error corrected model. In other words, the EC-GARCH specification in (13) simultaneously account for the volatility in the time series process as well as the long-term relationship between S_t and F_t .

3.5. Measuring hedge effectiveness

For hedge accounting purposes under FAS 133, a U.S. airline must first identify the instrument used for hedging and develop strategies to evaluate hedge effectiveness. Specific criteria for hedge effectiveness must be documented upfront before a hedge, and the effectiveness must also be evaluated on an ongoing basis. There are four primary methods of testing hedge effectiveness (Finnerty and Grant, 2002), one of which is regression analysis, a method commonly used by U.S. airlines.

Traditionally the hedge effectiveness measure has been the adjusted R^2 of a regression model, and the slope coefficient is the optimal hedge ratio. However, the design of the regression model may be debatable (Juhl et al., 2012), and with the increase in the regressors and the complexity of the models, the use of measuring hedge effectiveness with adjusted R^2 no longer seems proper. Ghosh (1993) uses adjusted R^2 to determine which hedge ratio is a better estimate; Adams and Gerner (2012) use the log likelihood measure 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 an “ R^2 Analogue” (Juhl et al., 2012):

$$R^2 \text{ Analogue} = 1 - \frac{SSE^*}{SST^*}, \quad (14)$$

where SSE^* is the error sum of squares which measures the total variation in the time series ($\Delta S_t - \beta \Delta F_t$), where β is the optimal hedge ratio determined by the regression model; SST^* is the total

sum of squares which measures the total variation in 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.

The goal of a hedge is to reduce risk. While this study generates many different hedge ratios and potential portfolios that an airline could use to hedge, these ratios should be tested to ensure accuracy. 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.

4. 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.⁸

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 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 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, and No. 2 heating oil 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 1000 barrels of sweet crude delivery at the hub in Cushing, Oklahoma. The underlying physical asset for Brent is 1000 barrels delivered at the Sullom Voe, Scotland. The underlying physical asset of heating oil is 1000 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 is a common measure of U.S. airlines' exposure to jet fuel price risk. The time span of the daily data is from April 15, 1994 through February 27, 2014.

Due to the nature of time series, a number of tests should be conducted on the data to determine the appropriate model specification. The tests that have been conducted are the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the

⁸ Based on Refinery Yield from the U.S. Energy Information Administration (2014a).

Table 2
Cointegration test results.

Engle-Granger	
Contract	Tau-statistic
Brent 1-month	−9.0655 ^a
Brent 3-month	−9.6937 ^a
Brent 6-month	−7.2419 ^a
Brent 9-month	−6.0771 ^a
Brent 12-month	−5.4417 ^a
WTI 1-month	−7.3757 ^a
WTI 3-month	−8.1496 ^a
WTI 6-month	−6.8340 ^a
WTI 9-month	−5.8930 ^a
WTI 12-month	−5.2870 ^a
Heating oil 1-month	−12.9310 ^a
Heating oil 3-month	−10.5373 ^a
Heating oil 6-month	−6.4328 ^a
Heating oil 9-month	−5.4842 ^a
Heating oil 12-month	−5.1197 ^a
Gasoil 1-month	−12.0422 ^a
Gasoil 3-month	−9.2766 ^a
Gasoil 6-month	−6.5794 ^a
Gasoil 9-month	−5.5689 ^a
Gasoil 11-month	−5.2167 ^a

^a Significance at the 1% level according to MacKinnon (1996) p-values.

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). Because these tests depend on the number of lags included, a Schwartz Information Criterion (SIC) value is used to determine the optimal amount of lags.

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. The test results show that the price levels are non-stationary while the first log differences are stationary.⁹ Thus, equation (8) would be an appropriate model.

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. We use the Engle-Granger test for cointegration (Engle and Granger, 1987). The 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 ADF test used to check for stationarity in the error term. The results for Engle–Granger test, shown in Table 2, were that the non-stationarity in the error terms was rejected, meaning that the jet fuel spot price is cointegrated with the futures prices. Hence, the specification of error correction is justified.

⁹ Due to the length of the PP, ADF and KPSS test results for all the price levels and the respective first log differences, the results are not reported here. The detailed test results, however, are available from the authors upon request.

Table 3
OLS results^b of equation (8): $\Delta S_t = \alpha + \beta \Delta F_t + \varepsilon_t$

OLS regression of jet fuel spot price on WTI futures price					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t	0.7270 ^a (0.0108)	0.9228 ^a (0.0119)	1.0277 ^a (0.0136)	1.0839 ^a (0.0150)	1.1199 ^a (0.0162)
Adj R-squared	0.4754	0.5461	0.5328	0.5120	0.4908
Log-likelihood	12992.9	13353.99	13282.04	13173.59	13067.23
ARCH-LM [5]	31.6613 ^a	28.8252 ^a	25.3171 ^a	24.0066 ^a	21.1315 ^a

^a Significance at the 1% level.

^b Values in () are standard errors.

Table 4
ECM results^c on equation (9):
 $\Delta S_t = \alpha + \beta_1 \Delta F_t + \beta_2 \varepsilon_{t-1} + \sum_{k=1}^K \omega_k \Delta F_{t-k} + \sum_{l=1}^L \delta_l \Delta S_{t-l} + u_t$

ECM regression of jet fuel spot price on WTI futures price with AR terms					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t	0.7349 ^a (0.0108)	0.9256 ^a (0.0118)	1.0288 ^a (0.0136)	1.0860 ^a (0.0149)	1.1240 ^a (0.0161)
ΔF_{t-1}	0.0170	0.0160	0.0418 ^b	0.0665 ^a	0.0847 ^a
ΔF_{t-2}	0.0632 ^a	0.0660 ^a	0.0614 ^a	0.0639 ^a	0.0623 ^a
ΔF_{t-3}	0.0100	0.0144	—	—	—
ΔF_{t-4}	0.0420 ^a	0.0318	—	—	—
ΔS_{t-1}	−0.0193	−0.0145	−0.0091	−0.0061	−0.0016
ΔS_{t-2}	−0.0666 ^a	−0.0686 ^a	−0.0622 ^a	−0.0590 ^a	−0.0542 ^a
ΔS_{t-3}	0.0049	−0.006	—	—	—
ΔS_{t-4}	−0.0233	−0.0151	—	—	—
ε_{t-1}	0.0299 ^a	0.0268 ^a	0.0195 ^a	0.0147 ^a	0.0117 ^a
Adj R-squared	0.4843	0.5532	0.5389	0.5183	0.4974
Log-likelihood	13028.05	13385.07	13311.42	13202.06	13096.31
ARCH-LM [5]	654.7391 ^a	582.1442 ^a	575.4598 ^a	565.4451 ^a	567.1922 ^a

^a Significance at the 1% level.

^b Significance at the 5% level.

^c Values in () are standard errors.

5. Results

5.1. Hedge ratios

We first consider WTI as the underlying asset for jet fuel cross hedging based on equation (8). The OLS results for equation (8) are presented in Table 3 below.

The OLS model yields the MVHR as the coefficient on the change in log futures prices. The hedge ratio increases with contract month. For a one-month contract, the hedge ratio is 0.727; a 3-month contract has a higher hedge ratio of 0.923; the hedge ratios for the 6-, 9- and 12-month contracts are greater than 1.¹⁰ Additionally, all adjusted R²'s are well below the 80% conventional threshold for a hedge to be considered highly effective.

The ARCH-LM test results suggest that there is heteroskedasticity in the residuals, and equation (8) also does not account for the long run relationship between the spot and futures prices. Thus an ECM was used, and equation (9) was estimated. The ECM results are reported in Table 4.

The results from the ECM show a higher hedge ratio for each contract compared to the simple OLS estimated hedge ratios in

¹⁰ The hedge ratio is greater than 1, suggesting that the changes in futures prices are less volatile than the changes in the spot price of jet fuel.

Table 5
GARCH results^b:

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

$$u_t \sim N(0, \sigma_t^2),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2$$

GARCH(1, 1) for WTI futures contracts					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t	0.7728 ^a (0.0068)	0.9093 ^a (0.0082)	1.0013 ^a (0.0094)	1.0458 ^a (0.0100)	1.0736 ^a (0.0106)
ΔF_{t-1}	0.0052	−0.0051	0.0173	0.0302	0.0350
ΔF_{t-2}	0.0184	0.0109	0.0094	0.0110	0.0134
ΔS_{t-1}	0.0008	0.0047	0.0055	0.0125	0.0214
ΔS_{t-2}	−0.0422 ^a	−0.0456 ^a	−0.0456 ^a	−0.0449 ^a	−0.0437 ^a
C	0.00 ^a	0.00 ^a	0.00 ^a	0.00 ^a	0.00 ^a
ARCH	0.1162 ^a	0.1152 ^a	0.1108 ^a	0.1068 ^a	0.1042 ^a
GARCH	0.8836 ^a	0.8850 ^a	0.8902 ^a	0.8946 ^a	0.8976 ^a
Adj R-squared	0.4739	0.5463	0.5332	0.5130	0.4924
Log-likelihood	14067.54	14418.65	14341.25	14204.68	14072.88
ARCH-LM [5]	8.1295	4.7125	7.0868	8.4268	10.3960

^a Significance at the 1% level.
^b Values in () are standard errors.

Table 3. 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 R² and the log-likelihood values are both higher than those produced by the OLS, the presence of heteroskedasticity is still shown by the ARCH-LM test. We thus estimate the GARCH(1, 1) model with the GARCH term specified by equation (11), where $p = q = 1$.

The results from the GARCH(1, 1) in **Table 5** show that the hedge ratio for the 1-month contract is higher than the ones in **Tables 3 and 4**. But the hedge ratios for the 3-month and longer contracts are lower. The GARCH 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. The sum of the ARCH and GARCH parameters is roughly equal to 1, implying that the time series have highly persistent volatility, but even so, **Nelson (1990)** shows that the standard GARCH is still valid, since it is not a nonstationary process.

Both the ARCH and the GARCH terms are significant in **Table 5**, and the ARCH-LM test on the null hypothesis of homoskedasticity cannot be rejected, suggesting 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 spot-futures relationship. To accommodate both of these factors we estimated equation (13), and the results for the EC-GARCH model can be found in **Table 6**.

The EC-GARCH model has the highest log-likelihood value; there is no heteroskedasticity in the errors. However, the hedge ratio each contract is only marginally different from those found in **Table 5**.

In addition to WTI, we estimated the hedge ratio for each of the other three petroleum commodities discussed in **Section 4** and with varying contract durations using the methods presented in **Section 3**. For comparison purposes, the hedge ratios are jointly presented in **Table 7**.¹¹

These results show that, for 1- and 3-month contracts, the OLS model has a lower hedge ratio than the ECM and the EC-GARCH. This is expected since the hedge ratio produced by the OLS model minimizes the variance of the in-sample portfolio returns (**Kroner**

Table 6
EC-GARCH results^b:

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

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

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2.$$

EC-GARCH(1, 1) for WTI futures contracts					
	1-Month	3-Month	6-Month	9-Month	12-Month
Constant	0.00	0.00	0.00	0.00	0.00
ΔF_t	0.7746 ^a (0.0067)	0.9100 ^a (0.0082)	1.0016 ^a (0.0094)	1.0459 ^a (0.0100)	1.0733 ^a (0.0106)
ΔF_{t-1}	−0.0031	−0.0116	0.0126	0.0268	0.0322
ΔF_{t-2}	0.0105	0.0053	0.0056	0.0081	0.0109
ΔS_{t-1}	0.0078	0.0100	0.0097	0.0158	0.0242
ΔS_{t-2}	−0.0354 ^a	−0.0406 ^a	−0.0417 ^a	−0.0417 ^a	−0.0409 ^a
ε_{t-1}	−0.0143 ^a	−0.0115 ^a	−0.0087 ^a	−0.0069 ^a	−0.0057 ^a
C	0.00 ^a	0.00 ^a	0.00 ^a	0.00 ^a	0.00 ^a
ARCH	0.1168 ^a	0.1156 ^a	0.1114 ^a	0.1071 ^a	0.1041 ^a
GARCH	0.8828 ^a	0.8844 ^a	0.8895 ^a	0.8942 ^a	0.8976 ^a
Adj R-squared	0.4798	0.5502	0.5361	0.5154	0.4944
Log-likelihood	14085.6	14432.37	14351.04	14212.27	14,079
ARCH-LM [5]	7.8502	4.8508	7.2487	8.5359	10.4005

^a Significance at the 1% and 5% levels, respectively.
^b Values in () are standard errors.

and **Sultan, 1993**), and as time till maturity increases so does the hedge ratio; this is consistent with an earlier finding by **Ripple and Moosa (2007)** who point out that as futures contracts approach maturity, they tend to be more sensitive to information on market conditions, therefore contracts with distant maturity are less volatile than those that are closer-to-maturity.

WTI and gasoil appear to have the lowest hedge ratios especially for 1-month contracts. Additionally, with the exception of gasoil, the hedge ratios for WTI and Brent exceed 1 for contracts with a maturity 6 months or beyond; heating oil futures with 3 months or longer maturities also have hedge ratios greater than 1. **Cheng and Xiong (2014)** assert that it is “problematic” to differentiate hedgers from speculators since, as do speculators, hedgers may “engage in non-output related trading” based on their belief on market information or their knowledge of local market conditions. The actual effectiveness of the hedge ratio generated, however, is not clear by any of the values presented in the tables so far. This led to the use of a hedge effectiveness measure to determine the desirability of a commodity for jet fuel cross hedging.

5.2. Hedge effectiveness

Adams and Gerner (2012) use the log-likelihood value to measure how well the model explains the relationship between the spot and futures prices. Thus, the higher the log-likelihood value, the better the model. They conclude that the better the model, the better the hedge effectiveness. Since for every asset, the log-likelihood of the EC-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 **Fig. 1** show that based upon log-likelihood value the best asset to hedge jet fuel is heating oil and the shorter the contract duration the better. The second best asset is Brent, followed by WTI and gasoil. The hedge effectiveness of Brent, WTI and gasoil, based on model's log-likelihood, is highest with the 3-month contracts. Contrary to **Adams and Gerner (2012)**, who find gasoil to be the best cross hedging instrument among all the commodities, we find that gasoil has the lowest log-likelihood value for all contract maturities, meaning it is the least effective of the four commodities in question. One plausible reason for such a

¹¹ Regression results are available from the authors upon request.

Table 7
Estimated hedge ratios.

WTI						Brent					
Contract maturity in months						Contract maturity in months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS	0.7270	0.9228	1.0277	1.0839	1.1199	OLS	0.8074	0.9428	1.0359	1.0755	1.0949
ECM	0.7349	0.9256	1.0288	1.0860	1.1240	ECM	0.8100	0.9431	1.0372	1.0798	1.1016
GARCH(1,1)	0.7728	0.9093	1.0013	1.0458	1.0736	GARCH(1,1)	0.8415	0.9425	1.0130	1.0488	1.0681
EC-GARCH(1,1)	0.7746	0.9100	1.0016	1.0459	1.0733	EC-GARCH(1,1)	0.8436	0.9435	1.0138	1.0494	1.0683

Heating oil						Gasoi					
Contract maturity in months						Contract maturity in months					
Model	1	3	6	9	12	Model	1	3	6	9	11
OLS	0.8963	1.0408	1.1238	1.1922	1.2216	OLS	0.6659	0.7894	0.8569	0.8973	0.9056
ECM	0.9047	1.0429	1.1257	1.1979	1.2330	ECM	0.7679	0.8947	0.9521	0.9815	0.9845
GARCH(1,1)	0.9585	1.0103	1.0606	1.1087	1.1469	GARCH(1,1)	0.7937	0.8976	0.9343	0.9581	0.9576
EC-GARCH(1,1)	0.9624	1.0127	1.0607	1.1084	1.1474	EC-GARCH(1,1)	0.8062	0.9042	0.9373	0.9611	0.9605

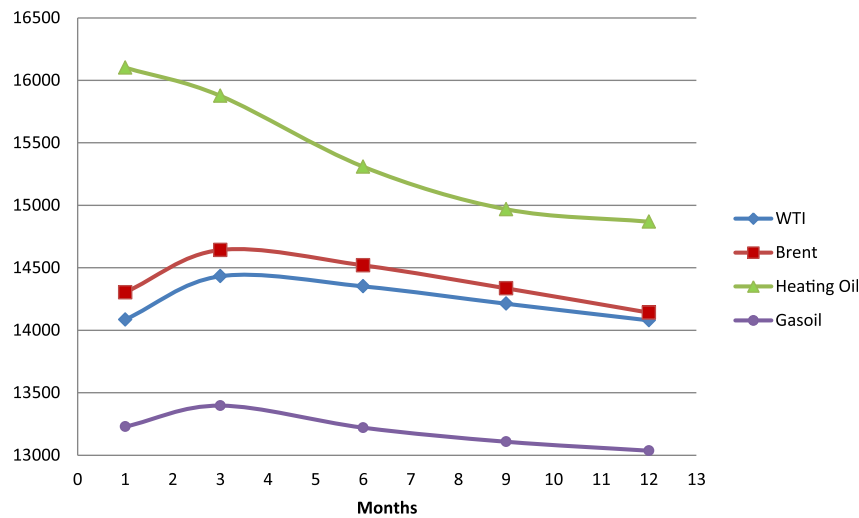


Fig. 1. Log-likelihood results for EC-GARCH models.

contrast in the findings is that [Adams and Gerner \(2012\)](#) use the weekly spot price of European jet fuel and the forward price of gasoil contracts both with a delivery within ARA. Our study, on the other hand, uses the U.S. Gulf Coast 54 jet fuel daily spot price because the Gulf Coast is the most active jet fuel market in the U.S. ([Argus, 2012](#)); the Gulf Coast spot price is a standard spot price benchmark for jet fuel recorded and reported by the [U.S. Energy Information Administration \(2014b\)](#); it is also the single, most commonly used spot price measure for the North American jet fuel spot market ([Airlines for America, 2014](#); [Federal Reserve Bank of St. Louis, 2014](#)).¹²

Next, as a cross check, we use the “ R^2 Analogue” proposed by [Juhl et al \(2012\)](#) to measure hedge effectiveness. 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. In other words, the measure yields the percentage of reduction in the total variations of portfolio returns. [Table 8](#) presents the hedge effectiveness.

The results in [Table 8](#) show that, as expected, gasoil yields the lowest hedge effectiveness, while heating oil is the most effective hedge among the four products. For example, a 1-month gasoil

futures contract is estimated to reduce the total variations in returns by less than 30%, compared to 67% for a 1-month contract for heating oil.

For WTI, Brent and gasoil, hedge effectiveness is highest with 3-month contracts, and the effectiveness reduces for contracts 6 months and longer. Heating oil is most effective with 1-month or 3-month contracts and becomes less effective with longer maturity. In spite of that, the lowest effectiveness of a 12-month heating oil contract is still higher than the highest effectiveness of a futures contract in WTI, Brent or gasoil.

As a robustness check, we estimated the hedge ratio and hedge effectiveness of each commodity and contract using weekly data for the same study period. We constructed the weekly price series using Wednesday-to-Wednesday's closing prices. If there is no trading on Wednesday due to a public holiday, then the closing price on Tuesday is used. The resulting sample size is 1032 weekly observations from April 18, 1994 to February 24, 2014. We applied the weekly data to the OLS and EC-GARCH models and estimated the hedge ratio and effectiveness of each commodity. The results are reported in [Table 9](#).

The results in the table show that generally the hedge ratios increase with contract maturity – a pattern consistent with the results in [Table 7](#). With weekly hedge horizon, the performance of gasoil improved considerably. Heating oil remains the most effective hedge compared to the other three commodities. Its effectiveness continues to be highest with 1-month and 3-month contracts.

¹² The other six spot markets in the U.S. are New York Harbor, Group 3 (in Oklahoma), Chicago, Los Angeles, San Francisco and Pacific Northwest.

Table 8
Results of Hedge Effectiveness based on Equation (14).

WTI						Brent					
Contract maturity in months						Contract maturity in months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS	0.4754	0.5462	0.5329	0.5121	0.4909	OLS	0.4938	0.5307	0.5167	0.4879	0.4620
ECM	0.4754	0.5462	0.5329	0.5121	0.4909	ECM	0.4938	0.5307	0.5167	0.4879	0.4620
GARCH(1,1)	0.4736	0.5461	0.5326	0.5115	0.4900	GARCH(1,1)	0.4929	0.5307	0.5165	0.4876	0.4617
EC-GARCH(1,1)	0.4734	0.5461	0.5326	0.5115	0.4900	EC-GARCH(1,1)	0.4928	0.5307	0.5165	0.4877	0.4618
Heating oil						Gasoil					
Contract maturity in months						Contract maturity in months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS	0.6669	0.6656	0.6153	0.5888	0.5693	OLS	0.2945	0.3308	0.3068	0.2899	0.2781
ECM	0.6668	0.6656	0.6153	0.5888	0.5693	ECM	0.2876	0.3249	0.3030	0.2873	0.2760
GARCH(1,1)	0.6636	0.6650	0.6134	0.5859	0.5672	GARCH(1,1)	0.2837	0.3246	0.3043	0.2885	0.2772
EC-GARCH(1,1)	0.6632	0.6651	0.6134	0.5859	0.5672	EC-GARCH(1,1)	0.2815	0.3238	0.3042	0.2884	0.2771

Table 9
Estimated Hedge Ratios and Hedge Effectiveness using Weekly Data.

WTI						Brent					
Contract maturity in months						Contract maturity in months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS						OLS					
Hedge Ratio	0.7544	0.9452	1.0326	1.1031	1.1512	Hedge Ratio	0.8433	0.9672	1.0658	1.1329	1.1671
H. Effectiveness	0.4849	0.5399	0.5303	0.5144	0.4941	H. Effectiveness	0.5335	0.5302	0.5424	0.5258	0.4998
EC-GARCH(1,1)						EC-GARCH(1,1)					
Hedge Ratio	0.7789	0.8990	0.9929	1.0447	1.0784	Hedge Ratio	0.8781	0.9585	1.0261	1.0737	1.1053
H. Effectiveness	0.4844	0.5403	0.5295	0.5130	0.4921	H. Effectiveness	0.5326	0.5561	0.5416	0.5243	0.4984
Heating oil						Gasoil					
Contract maturity in months						Contract maturity in months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS						OLS					
Hedge Ratio	0.9462	1.0611	1.1384	1.2324	1.3106	Hedge Ratio	0.8791	0.9918	1.0869	1.1514	0.9720
H. Effectiveness	0.7157	0.6869	0.6166	0.5812	0.5754	H. Effectiveness	0.5571	0.5617	0.5253	0.4891	0.4577
EC-GARCH(1,1)						EC-GARCH(1,1)					
Hedge Ratio	0.9800	1.0185	1.0628	1.1016	1.1570	Hedge Ratio	0.9269	0.9872	1.0336	1.0827	1.1227
H. Effectiveness	0.7148	0.6858	0.6138	0.5747	0.5675	H. Effectiveness	0.5554	0.5617	0.5241	0.4874	0.4720

5.3. Monte Carlo simulation

The comparison made of the R^2 analogue that is shown in Table 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 used Monte Carlo simulations to forecast and 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 results from the Monte Carlo simulation in Table 10 suggest that there is not one model that consistently estimates an MVHR that corresponds to the highest hedge effectiveness for each commodity. In Table 10 the boldfaced 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

Table 10
Monte Carlo simulation results of hedge effectiveness.

WTI						Brent					
Contract maturity in Months						Contract maturity in Months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS	0.5246	0.5337	0.5716	0.5628	0.5256	OLS	0.4865	0.5518	0.4613	0.4596	0.4466
ECM	0.5250	0.5336	0.5717	0.5630	0.5260	ECM	0.4864	0.5518	0.4612	0.4597	0.4467
GARCH(1,1)	0.5255	0.5338	0.5686	0.5586	0.5207	GARCH(1,1)	0.4847	0.5518	0.4625	0.4588	0.4459
EC-GARCH(1,1)	0.5255	0.5338	0.5686	0.5586	0.5207	EC-GARCH(1,1)	0.4845	0.5518	0.4625	0.4588	0.4459
Heating oil						Gasoil					
Contract maturity in Months						Contract maturity in Months					
Model	1	3	6	9	12	Model	1	3	6	9	12
OLS	0.6995	0.7045	0.6352	0.6242	0.5899	OLS	0.2594	0.2277	0.2178	0.1866	0.1904
ECM	0.7003	0.7047	0.6354	0.6244	0.5900	ECM	0.2464	0.2114	0.2054	0.1719	0.1804
GARCH(1,1)	0.7024	0.7012	0.6296	0.6182	0.5870	GARCH(1,1)	0.2410	0.2108	0.2083	0.1765	0.1843
EC-GARCH(1,1)	0.7024	0.7015	0.6296	0.6181	0.5870	EC-GARCH(1,1)	0.2380	0.2094	0.2078	0.1759	0.1839

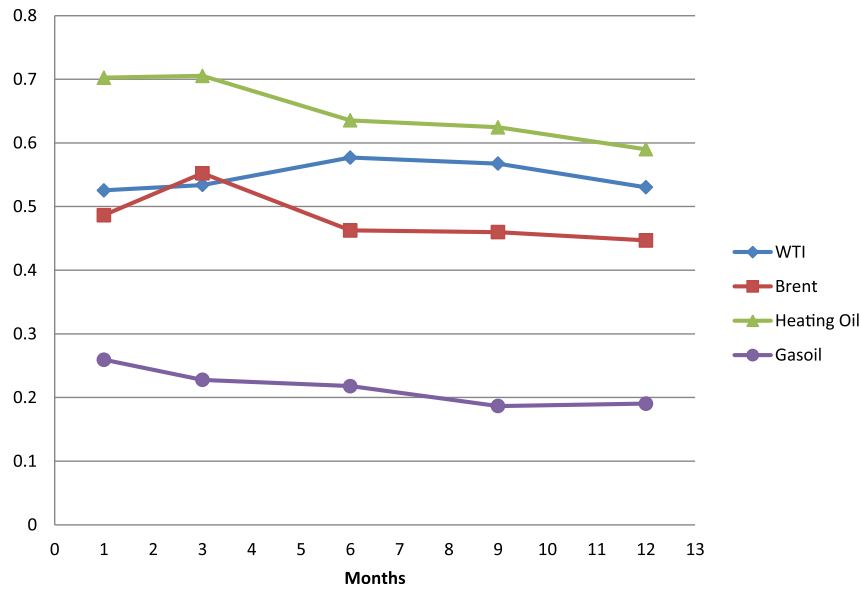


Fig. 2. Hedge effectiveness by commodity from the simulated results.

the OLS estimates from gasoil. For gasoil the OLS estimates for the hedge ratio were the optimal ratios for all contracts. Heating oil continues to be the most effective for jet fuel cross hedging. Contrary to the results in Table 8, the Monte Carlo results also suggest that WTI is the second best, followed by Brent.

We present the average effectiveness of all of the models for the four different commodities in Fig. 2. This is a graphical representation showing which commodity hedge is the most effective cross hedge, and which contract maturity is more desirable. As shown in Fig. 2, the best cross hedge commodity is heating oil for all maturities.

Equally noticeable from Fig. 2 is that gasoil is the least suitable cross hedging asset. Also important is that Brent and WTI were similar in effectiveness, but as maturity is further away, WTI becomes 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 better asset with which to hedge. However, based on the results shown in Fig. 2, the best asset use in cross hedging is heating oil.

6. 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. 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 study finds that airlines' 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. We also find that, with a daily hedge horizon, gasoil is inferior to the other three petroleum products and is least effective for jet fuel cross hedging regardless of the time to contract maturity, but its performance improved with a weekly hedge horizon. Additionally, airlines hedging with futures would create the most effective hedge by using 3-month maturity

contracts of heating oil, but the hedge effectiveness of heating oil diminishes with increased time to contract maturity.

However, based on our in-sample analysis and Monte Carlo simulation results, even with heating oil, the hedging performance is less than 67% for hedge effectiveness; the performance improves to about 71% with weekly hedge horizon. The results in this study may be sensitive to the hedge horizon. To gain a more holistic view of hedging performance and model usage, the duration of a hedge should be carefully examined in future research to associate data frequency with the intended hedge horizon.

Acknowledgment

The authors are grateful to the Upper Great Plains Transportation Institute for funding this research. We thank William Wilson, Alan Dying and two anonymous referees for their valuable comments and suggestions

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