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HOW FUEL PRICE SHOCKS AFFECT AIRLINE STOCK RETURNS: AN EMPIRICAL STUDY OF MAJOR US CARRIERS

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ABSTRACT

This study investigated how airline stock prices respond to fuel price shocks using the asymmetric Glosten-Jagannathan-Runkle GARCH (GJR-GARCH (1,1)) model. Six airlines were selected, based on their service regions: American Airlines, Delta Air Lines, and United Airlines are larger international carriers that use various types of aircraft in their fleets and provide services in major continents, whereas Southwest Airlines, JetBlue Airways, and US Airways emphasize domestic market services and primarily use single-aisle aircraft. West Texas Intermediate Crude Oil (WTI) prices were adopted as the index of fuel prices. Based on our empirical results, a fuel price shock triggered fluctuations in airline stock returns. Moreover, American Airlines, Delta Air Lines, United, Airlines and US Airways experienced statistically significant negative relationships between their stock returns and fuel price shocks. Also, fuel price shocks significantly impacted airline stock returns during periods in which fuel prices increased but did not correlate with them during those in which such prices fell

JEL: G11, G14

KEYWORDS: Fuel Shocks, GJR-GARCH, Airline Stock Return, Return Volatilities

INTRODUCTION

How changes in fuel price affect a company's stock returns has always been an important topic for company administrators and investors, especially in industries that consume significant amounts of fuel. For most airlines, fuel cost is usually the second highest outlay after labor costs. However, unlike labor costs, which are relatively stable and typically used to reduce a company's expenditures rapidly, fuel costs are inelastic and tend to fluctuate. Therefore, based on the annual fuel consumption of all US airlines of approximately 17-19 billion gallons, an increase in fuel price by 1 penny would incur an additional \$170-\$190 million dollars in fuel costs for the entire US airline industry. Although many studies have focused on the relationships between oil price shocks and stock market returns, few have examined the sensitivity of this industry to fuel costs. This study investigated the impacts of fuel price shocks on airline stock returns. We determined whether fuel shocks increase volatility in airline stock and analyzed the relationship between airline stock returns and fuel price shocks. Specifically, we applied the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH (1,1)) model to evaluate the asymmetrical impacts of fuel price shocks on airline stock returns.

We adopted the daily adjusted closing stock prices of six major airlines in the US and the daily closing prices of West Texas Intermediate Crude Oil (WTI). The six airlines that we selected were American Airlines (AA), Delta Air Lines (DL), United Airlines (UA), Southwest Airlines (SW), JetBlue Airways (JB), and US Airways (US), of which AA, DL, and UA are the largest legacy carriers in the US. AA headquarters are located in Fort Worth, Texas, next to its largest hub, Dallas/Fort Worth International Airport. Currently, AA operates the largest fleet in the world. DL has the broadest services throughout all continents except Antarctica. DL headquarters are in Atlanta, Georgia, which houses Hartsfield-Jackson Atlanta International Airport, the world's busiest airport, based on passenger traffic. UA is headquartered in Chicago, Illinois and operates the second-largest fleet in the world.

Unlike legacy carriers, which operate wide-body, double-aisle aircraft across major continents, SW, JB, and US are classified as low-cost carriers with single-aisle narrow-body aircraft. Although these companies are classified as low-cost carriers in terms of fleet size and passengers served, SW is ranked as one of the top four airlines, along with AA, DL, and UA. JB, founded in February 1999, is the youngest company on the list and is the only airline that is based in the New York metro area, which has the largest volume of passengers in the world. US operates primarily in secondary cities in the US at three major hubs: Charlotte, Philadelphia, and Phoenix.

Table 1 reports the annual fuel consumption of the six airlines and the entire US aviation industry. The total annual fuel consumption of the six airlines was approximately 50% to 60% of that of all US airlines, indicating that our sample was large enough to represent the US market. Among the six airlines, AA had the highest consumption from 2007 to 2009, followed by UA and DL. Due to their operational scopes, the three low-cost carriers had relatively small fuel consumption volumes, especially JB, the annual consumption of which was approximately 20% of that of AA. The annual fuel consumption of DL jumped from 1.9 billion gallons in 2009 to 3 billion gallons in 2010 due to its merger with Northwest Airways. DL inherited the routes of Northwest Airways and thus increased its operational markets. Since 2010, DL has become the largest company in terms of fuel consumption.

Table 1: Annual Fuel Consumption (in Thousand Gallons)

	Entire US	AA	DL	UA	SW	JB	US
2007	19,886,200	2,833,789	1,965,697	2,299,122	1,490,801	443,292	1,191,665
2008	18,872,400	2,694,476	1,965,749	2,182,438	1,514,362	452,968	1,142,235
2009	17,060,500	2,507,855	1,939,316	1,936,981	1,431,253	453,993	1,068,963
2010	17,298,400	2,483,731	3,093,665	1,939,081	1,439,278	486,417	1,072,970
2011	17,558,000	2,445,075	3,133,175	1,889,995	1,508,891	524,784	1,094,586

This table reports the annual oil consumption from 2007 to 2011 of the entire US airlines, and the six sample airlines including: American Airlines (AA), Delta Air Lines (DL), United Airlines (UA), Southwest Airlines (SW), JetBlue Airways (JB), and US Airways (US), Data source: Bureau of Transportation Statistics.

The data period that we selected comprised May 1, 2007 to December 31, 2011, because there were two peaks in fuel price within this period: $145.31 per barrel on July 3, 2008, which was the highest price of WTI in history, and$113.39 per barrel on April 29, 2011. To capture the impacts during price fluctuations, we also separated the data into four sub-periods. Our empirical results revealed that fuel price shocks tended to increase stock return volatilities during the data period. In the sub-data periods, volatility in stock prices increased significantly only during periods in which fuel prices rose, indicating that investors responded to fuel shocks asymmetrically. The remainder of this paper is organized as follows. Section 2 reviews the literature, Section 3 introduces the data and methods, Section 4 discusses the empirical results, and Section 5 makes our conclusions.

LITERATURE REVIEW

A significant amount of studies have focused on the relationships between oil price shocks and stock market returns. Park and Ratti (2008) studied the impacts of oil price on 13 European countries and the US, finding a positive relationship between oil price increases and stock returns. Ciner (2002) evaluated the dynamic links between oil price and the stock market over three decades and suggested that this association was stronger in the 1990s. Zhu, Li, and Yu (2011) applied panel threshold cointegration models to study the relationships between oil price shocks and stock markets in OECD and non-OECD countries from 1995 to 2009. Their findings suggest that a positive relationship exists between oil prices and stock markets, differing from traditional expectations. In contrast, Chang, McAleer, and Tansuchat (2010) studied the conditional corrections and volatility between two major crude oil prices—Brent and West Texas Intermediate—and four major stock indices—Dow Jones, NYSE, S&P 500, and FTSE 100—with a symmetrical DCCGARCH model. Their empirical results indicated that a negative relationship existed between stock markets and oil price changes, especially during the pre-1999 period. Also, Apergis and Miller (2009) concluded that the stock markets did not respond significantly to oil price shocks in developed countries. Several studies have suggested that the relationships between oil price shocks and stock market returns are asymmetric and time-varying. For example, Lyasiani, Mansur, and Odusami (2011) employed the GARCH (1,1) model to investigate how excess stock returns and return volatilities respond to changes in oil returns and oil return volatility in 13 US industries and found robust results, supporting that at the sector level, fuel price volatility is a significant factor of asset price risk. Vo (2011) focused on the volatility of oil futures and stock markets and suggested that the relationships between oil futures and stocks were time-varying and tended to shift when price volatilities changed.

Pinho and Madaleno (2016) used a two-regime multivariate Markov switching vector autoregressive model to examine the nonlinear causalities between oil prices and stock returns with data from 75 countries for November 1992 to October 2012, indicating an asymmetrical relationship between oil prices and stock returns. Bastianin, Conti, and Manera (2016) examined the effects of crude oil price shocks on stock market volatility with monthly data from G7 countries for February 1973 to January 2015, finding that if the shocks originated from the supply side, stock return volatilities were unaffected, whereas if they came from the demand side, volatilities were significantly impacted. Phan, Sharma, and Narayan (2015) analyzed the responses of stock markets to fuel price changes and noted that stock markets responded asymmetrically to them. Specifically, the stock prices of companies in the oil industry moved positively, regardless of whether the direction of fuel prices.

Some studies have applied non-parametric or semi-parametric approaches. Salma (2015) investigated the dependence between oil and stock markets from 2005 to 2012 in Gulf corporate countries with various copula models, indicating that the volatility in the oil market is affected by past innovations in the stock market. Aloui, Hammoudeh, and Nguyen (2013) analyzed the dependence between the stock markets of six Central and Eastern European (CEE) countries and Brent crude oil prices with time-varying copula models, suggesting that the movement of stock markets in these countries and the change in Brent crude oil prices are positively associated. Wu, Chung, and Chang (2012) employed dynamic copula-based GARCH models to examine the dependence between the US dollar index and crude oil prices, showing that the tail dependence structure between them was not significant. Moreover, the dependence between the change in crude oil price and that in the US dollar index was negative and decreased continuously after 2003. Although the relationships between fuel prices and stock returns have been well documented, mixed results have been reported, and few studies have focused on the airline industry. Because fuel cost is one of the most important elements of an airline's cost structure and because the stock prices of airlines are scrutinized by the financial market, this area must be specifically addressed.

DATA AND METHODS

The data in this research were the daily closing stock prices of six airlines—AA, DL, UA, SW, JB, and US—and the daily closing prices of WTI, traded on the Chicago Mercantile Exchange. The data range spanned from May 1, 2007 to December 31, 2011, because fuel prices reached their historical high points during this period. Moreover, this period also covered one of the largest financial crises in the US: the financial crisis of 2008. To better grasp how airlines stock prices respond to fuel shocks during fluctuations in fuel price, we split the entire dataset into four sub-sample periods: May 1, 2007 to July 15, 2008, during which fuel prices rose from the lower $60s per barrel in May 2007 to over $140 per barrel in July 2008; July 16, 2008 to December 23, 2008, when fuel prices slumped from $140 to $30.28 per barrel; December 24, 2008 to April 29, 2011, during which fuel prices rose to another peak at $113.39 per barrel;

and May 1, 2011 to December 31, 2011, when fuel prices dropped again. Therefore, the first and third sub-data periods experienced fuel price increases, whereas the second and fourth sub-periods saw declines. The beginning date, ending date, and total observations are also explained in Table 2.

Table 2: Sample Periods

	Beginning Date	Ending Date	Total Observations
Entire Data Period	May 1, 2007	December 31, 2011	1169
Sub Period One	May 1, 2007	July 15, 2008	300
Sub Period Two	July 16, 2008	December 23, 2008	112
Sub Period Three	December 24, 2008	April 29, 2011	588
Sub Period Four	May 1, 2011	December 31, 2011	169

This table summarized the beginning date, the ending date, and the total observation of the entire data period, and the four sub periods.

To evaluate the impacts of fuel shocks on stock returns, we converted the daily stock and WTI prices into continuously compounded changes, as follows:

$$R_{i,t,} = LN(\frac{P_{i,t,}}{P_{i,t-1,}}) \tag{1}$$

where $R_{i,t}$ represents the return/change of the airline or WTI price on day *t*, which is measured as the log-difference between the price on dates t and t-1. The summary statistics of the daily returns of each airline and fuel price are reported in Table 3.

Table 3: Summery Statistics

	Mean (%)	Std	Skewness	Kurtosis	JB Test (P Value Reported in the Parenthesis)
WTI	0.03824	0.0285	-0.1319	8.612	1535 (0.00)***
AA	-0.3711	0.0804	-9.895	233.8	2611,892 (0.00)***
DL	-0.0805	0.0475	0.0008	6.815	708 (0.00)***
UA	-0.0435	0.0617	0.0399	13.94	5,828 (0.00)***
SW	-0.0444	0.0267	-0.4073	8.044	1,270 (0.00)***
JB	-0.0583	0.0399	0.2206	6.606	642 (0.000)***
US	-0.1668	0.0618	0.2254	8.255	1,535 (0.000)***

*This table presents the summery statistics including mean, standard deviations, skewness, kurtosis, and the results of Jarque-Bera (JB) test. The p-value of the JB test is reported in the parenthesis and the asterisks are used to indicate the statistical significance as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

During the sample period, except for WTI returns, the means daily stock returns of the six airlines were all negative. AA had the lowest average return, because it struggled through bankruptcy during that period. The kurtosis of all samples was greater than 3, and the skewness of all samples deviated from 0, which indicated that the daily returns of the six airlines and WTI were not normally distributed. The high values of the Jarque-Bera test results also verified that the data deviated from a Gaussian distribution. Thus, the nature of the data distribution justified the application of the generalized autoregressive conditional heteroskedasticity (GARCH) models. This study used the Glosten-Jagannathan-Runkle GARCH (1,1) model by Glosten, Jagannathan, and Runkle (1993). The advantage of the GJR-GARCH model is that it provides a mechanism for model the asymmetry in the ARCH process, allowing us to examine the asymmetrical impacts of fuel price shocks on airline stock returns. According to Hsu and Huang (2010) and Hsu (2013), the model is defined as:

$$R_{m,t} = \emptyset R_{m,t-1} + \varepsilon_{m,t} \tag{2}$$

$$\varepsilon_{m,t} = Z_t\sqrt{h_t} \tag{3}$$

$$h_{m,t} = \alpha_0 + \alpha_1 \varepsilon_{m,t}^2 + \gamma \varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t \tag{4}$$

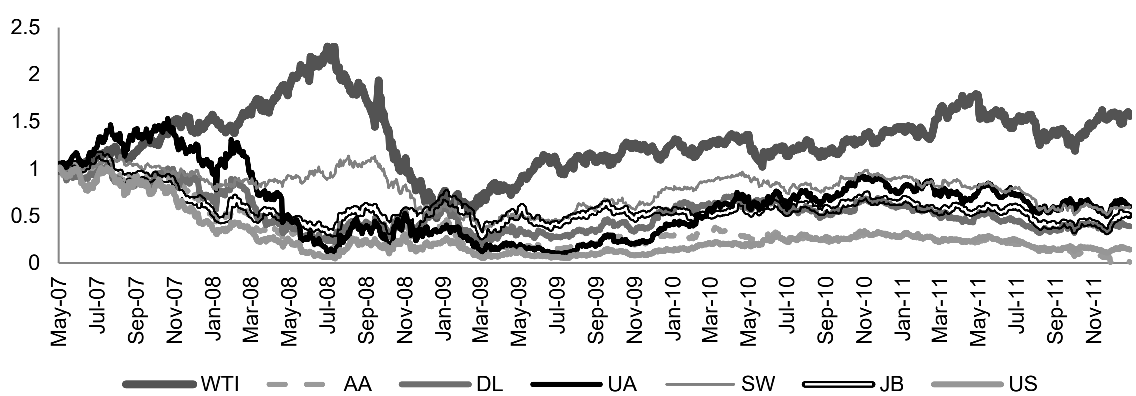
In this model, in equation (2), stock and WTI returns, $R_{m,t}$, follow the AR(1) process with a coefficient ϕ, multiplied by the return on the previous day $R_{m,t-1}$ plus the error term, $\varepsilon_{m,t}$. In equation (2), the error term, $\varepsilon_{m,t}$, contains two elements, h_t and Z_t, where h_t is a scaling factor and Z_t is a sequence that follows a standard normal distribution with mean 0 and variance 1. In equation (4), the residual variance is modeled with a constant α_0, the ARCH and GARCH coefficients α_1 and β_1, η, and dummy variables γ. By setting the dummy valuable $D^p_{t-1}=1$ when $\varepsilon_{m,t-1}<0$ and 0 otherwise, the coefficient γ was used to measure the asymmetrical response of volatility to shock. To investigate the impacts of fuel shocks on airline stock returns, we included a fuel price parameter, *fp,* in the model. Thus, η will be used to examine the relationship between the change in WTI returns and the change in airline stock returns, and γ will be used to evaluate whether fuel price shocks increased the volatilities of airline stock returns.

EMPIRICAL RESULTS

Trends in WTI and Airline Stock Prices

Figure 1 shows the trends in price. The prices were standardized to the base period of May 1, 2007. The WTI prices peaked twice during the data period. The first peak occurred on July 3, 2008, which was the highest price in WTI history, breaking the record of $120 during the energy crisis in 1980. The second peak occurred on April 29, 2011. Stock prices moved in opposite directions from that of WTI during the first peak, which can be explained as follows: when WTI prices were rising from 2007 to 2008, the economy was slowing. High fuel prices increased flight ticket prices, reduced demand for travel, and hurt the revenues of airlines, lowering their stock prices. During the second sub-period, when the financial crisis started in 2008, WTI and airline stock prices slumped. In the third sub-data period, airline and WTI prices climbed back, when the economy began to recover from the 2008 financial crisis. In the fourth sub-data period, when WTI prices began to decline, airline stock prices also fell, possibly because the entire aviation industry experienced a series of consolidations, signaling uncertainty to the market.

Figure 1: The Trends of the WTI and the Airlines Stock Prices



This figure shows the price trends of the WTI and the six airlines. To provide a better view for comparison, the prices were standardized to the base period of May 1, 2007.

Empirical Results of the GJR GARCH Model

The results of the GJR GARCH (1.1) model are reported in Tables 4-8. Table 4 reports the results for the entire sample data range. The negative value of η for all six airlines demonstrated that the changes in WTI and stock returns had negative relationships—a price shock in which WTI increases will lower airline stock returns and *vice versa*. However, only AA, DL, UA, and US reached at least 95% significance for this argument. The positive γ indicated that the change in fuel price increased the fluctuations in stock price returns. During the entire data period, except for AA, the other five airlines met at least 95% significance in supporting the claim that fuel shocks increased the volatility in their stock returns.

Table 4: Empirical Results of the Entire Data Period- 05/01/2007- 12/31/2011

	Parameter	Regression Coefficient	Standard Error	T Statistic
AA	η	-0.0113	0.0042	-2.693***
	γ	0.0226	0.0213	1.069
DL	η	-0.0080	0.0039	-2.029**
	γ	0.0767	0.0274	2.796***
UA	η	-0.0134	0.0048	-2.793***
	γ	0.0456	0.0204	2.237**
SW	η	-0.0023	0.0021	-1.102
	γ	0.0630	0.0258	2.440**
JB	η	-0.0059	0.0030	-1.943*
	γ	0.0906	0.0317	2.854***
US	η	-0.0103	0.0052	-1.966**
	γ	0.0609	0.0220	2.766***

*This table reports regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the entire data period. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with the asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 5 reports the empirical results of the first sub-period. During this period, the price of WTI rose to its historical highest point. As reported in Table 4, the negative value of η for all six airlines indicated that the returns between WTI and airline stocks had negative relationships. However, only AA, UA, and JB met the significance level of at least 95%. Moreover, there was 90% statistical significance with regard to the rise in DL and JB stock return volatility when the price of WTI increased.

Table 5: Empirical Results of the Sub Period One -5/1/2007 to 7/15/2008

	Parameter	Regression Coefficient	Standard Error	T Statistic
AA	η	-0.0165	0.0076	-2.170**
	γ	0.0770	0.0671	1.148
DL	η	-0.0131	0.0070	-1.865**
	γ	0.1596	0.0870	1.835**
UA	η	-0.0342	0.0080	-4.258***
	γ	0.0335	0.0686	0.4888
SW	η	-0.0014	0.0031	-0.4667
	γ	0.0736	0.0773	0.9523
JB	η	-0.0093	0.0043	-2.146**
	γ	0.1781	0.0971	1.833*
US	η	-0.0238	0.0094	-2.537**
	γ	0.0719	0.0587	1.225

*This table presents regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the first sub period from May 1, 2007 to July 15, 2008. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The significance of each regression coefficient is indicated with the asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 6 reports the empirical results during the second sub-sample period. During this period, the price of WTI dropped from its peak at approximately $143 per barrel to $30.28 per barrel within 6 months. However, γ and η did not reach statistical significance.

Table 6: Empirical Results of the Sub Period Two -7/16/2008 to 12/23/2008

	Parameter	Regression Coefficients	Standard Error	T Statistic
AA	η	-0.0101	0.0415	-0.2444
	γ	-0.0036	0.0966	-0.0369
DL	η	0.0003	0.0349	0.0079
	γ	-0.0815	0.3006	-0.2712
UA	η	-0.0090	0.0511	-0.1769
	γ	0.0499	0.1276	0.3906
SW	η	0.0159	0.0195	0.8151
	γ	0.1280	0.1477	0.8667
JB	η	-0.0060	0.0195	-0.3095
	γ	0.6584	0.4249	1.5494
US	η	0.0178	0.0514	0.3452
	γ	0.1241	0.1588	0.7818

This table shows regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1 \varepsilon_{m,t}^2 + \gamma \varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ *during the second sub period from July 16, 2008 to December 23, 2008. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 7 lists the empirical results of the third sub-sample period from December 24, 2008 to April 29, 2011. During this period, the price of WTI rose from the lower $30s per barrel to over $120 per barrel. For AA, DL, UA, SW, and JB, the climb in WTI price increased their stock return volatilities. However, only JB and DL had negative relationships between WTI returns and stock returns.

Table 7: Empirical Results of the Sub Period Three -12/24/2008 to 04/29/2011

	Parameter	Regression Coefficients	Standard Error	T Statistic
AA	η	-0.0031	0.0031	-0.9775
	γ	0.0284	0.0128	2.220**
DL	η	-0.0050	0.0029	-1.731*
	γ	0.0582	0.0235	2.481**
UA	η	-0.0039	0.0033	-1.181
	γ	0.0463	0.0216	2.140**
SW	η	-0.0037	0.0019	-1.946*
	γ	0.0467	0.0273	1.719**
JB	η	-0.0050	0.0025	-2.002**
	γ	0.0576	0.0285	2.021**
US	η	-0.0021	0.0038	-0.564
	γ	0.0351	0.0265	1.327

This table reveals regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1 \varepsilon_{m,t}^2 + \gamma \varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ *during the third sub period from December 24, 2008 to April 29, 2011. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 8 reports the empirical results of the fourth sub-sample period from May 2011 to December 2011. During this period, the price of WTI decreased again. Only UA and US reached 95% statistical significance in claiming a negative relationship between their stock returns and changes in the price of WTI .

Table 8: Empirical Results of the Sub Period Four -05/01/2011 to 12/31/2011

	Parameter	Regression Coefficients	Standard Error	T Statistic
AA	η	0.0075	0.0485	0.1551
	γ	0.5216	0.5435	0.9597
DL	η	-0.0407	0.0421	-0.9673
	γ	0.2952	0.2331	1.2660
UA	η	-0.0905	0.0370	-2.444**
	γ	0.0391	0.1926	0.2029
SW	η	-0.0134	0.0332	-0.4026
	γ	0.1267	0.1366	0.9277
JB	η	-0.0133	0.0449	-0.2970
	γ	0.0721	0.1434	0.5029
US	η	-0.1017	0.0495	-2.0528
	γ	0.2907	0.1811	1.6054

*This table reports regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the fourth sub period from May 1, 2011 to December 31, 2011. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

CONCLUSION

This paper examined the impacts of fuel price on the stock returns of six US-based airlines: AA, DL, UA, SW, JB, and US. We employed the GJR-GARCH (1,1) model to examine the asymmetrical impacts of fuel price shocks on airline stock returns. The empirical results indicated that during the entire data period, the stock returns for AA, DL, UA, and US had negative relationships with the changes in the price of WTI . Also, with the exception of AA, all airlines experienced greater volatility in their stock returns with fuel shocks.

Due to the nature of the two price peaks in WTI, we split our data into four sub-periods to analyze the stock return responses to fuel shocks during specific fluctuations in the price of WTI . During rises in WTI price, fuel shocks tended to increase airline stock return volatilities, and a negative relationship existed between changes in WTI price and airline stock returns. However, during periods of declines in WTI prices, no significant results were observed.

This analysis should be extended to major airlines worldwide, and the shocks in WTI and Brent should be compared. A greater understanding of the effects of fuel price shocks in WTI and Brent on stock returns for such airlines would help us determine whether the impacts of fuel shocks on airline stocks are global or regional, allowing practitioners and investors to make better investment decisions.

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