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Abstract: This paper investigates the nonlinearities in the behavior of jet fuel prices and air carrier yields as measured by revenue passenger miles(RPMs), where one RPM is defined as one passenger flown one mile in revenue traffic. It indicates that previous research might have overlooked the possibilities of nonlinear dynamics between these two series. Drawing on existing tests of nonlinearities and chaos, this paper first investigates the existence of chaotic behavior as the source of nonlinearities in the monthly prices of jet fuel and RPMs.

The findings show strong evidence that the two series exhibit nonlinear dependencies. Evidence is found, however, that this behavior may be inconsistent with chaotic structure. We propose and estimate bivariate GARCH(1,1) and bivariate EGARCH(1,1) models to ascertain the flow of information between jet fuel prices and revenue passenger miles. Estimation results of the bivariate GARCH models offer evidence that the shock transmission between the two series is mainly asymmetric, that is that positive and negative shocks impart degree of volatility differently. It is shown that the positive shocks to jet fuel prices show a substantially higher reaction from the revenue passenger miles. The conclusion is that, RPMs are quite responsive to upward volatility in prices of jet fuel, while falling jet fuel prices may not translate into efficiency gains.

JEL Classifications: L93, L90, L91

Keywords: Nonlinear dynamics, Chaos, EGARCH, Asymmetric shocks

1. Introduction

Given the airline industry's heavy dependence on fuel, air carrier analysts, carrier financial managers, financial markets and regulators have now become increasingly interested in the volatility of fuel prices and its impact on carrier performance. The International Air Transport Association (IATA, 2013) estimates the global airline industry's fuel costs were approximately \$207 billion in 2012, or 33% of operating expenses at \$110.0/barrel Brent crude. This is an increase of \$31 billion over 2011 and is almost 5 times the \$44 billion fuel expenses in 2003. The spot price of jet fuel in 2012 increased again to average just under \$130 a barrel. This was partly due to increase in the crack spread, i.e., the difference between crude oil and jet fuel to 16%. The crack spread is tending toward 20% as demand for jet fuel and other distillates increase. Hedging jet fuel costs is also becoming harder because of jet fuel cost divergence from West Texas Intermediate, its traditional benchmark.

A growing body of literature in the last decade has focused on the volatile oil and fuel prices and their effect on financial health and performance of air carriers. The main interest of researchers has been on the effects of these volatilities on air carrier performance, profitability, investment opportunities and hedging strategies that may enable carriers to cope with fuel price volatility.

Airlines recognize that given the extreme competitiveness of the industry, they are price takers, making it very difficult to pass higher fuel prices on to passengers by raising ticket prices. Therefore, carriers can attempt to prevent huge swings in operating expenses and reduced profitability by hedging fuel prices. Neidl and Chiprich (2001) found that in the second half of the year 2000, only profitable carriers were able to successfully hedge their fuel expenses. Carriers who didn't hedge suffered losses. In the fourth quarter of 2000, for example, US Airways, which had not implemented a fuel hedging strategy, suffered significant losses. It would have earned profits had it hedged its fuel.

Clubley (1999) notes that fuel price risk management strategies were employed by air carrier as early as 1989. Carriers can employ various traditional derivative instruments to hedge their fuel cost risks. Typically the instruments include forward contracts, futures contracts, options, collars, swaps, among others. Cartere et al. (2004), Clubley (1999), Cobbs et al. (2006) discuss the economic justifications and the hedging vehicles used by air carriers in detail.

Morell and Swan (2006) find that hedging instruments through exchange traded contracts have enabled major commercial airlines to hedge some of their future needs. Hedging protects firm profits against upward volatility in crude prices caused by political and economic instabilities and turmoil. Their findings show that regardless of the underlying reasons behind oil price volatility, hedging gains may improve profitability and help smooth out profit trends, reduce bankruptcy risks, and elevate stakeholder confidence in management.

Rao (2006) investigates hedging by examining heating oil futures contracts. The objective is to see whether this type of hedging can reduces the volatility profits of major airlines. Their findings show that after controlling for trend, seasonality, and shocks persistence, hedging may potentially reduce the volatility of an airline's profits. Results also suggest that both financially weak and strong carriers benefit from hedging their fuel cost risks in the long run, provided that they employ the appropriate futures contracts.

Carter et al. (2002) investigate the fuel hedging policies of US carriers during the 1994-2000 period. They find that airlines experience lower cash flows during the period of high fuel costs, as expected. However, higher jet fuel costs and air industry investment opportunities are positively correlated. Their results also provide some evidence that jet fuel hedging helps improve firm value.

Carter et al. (2006), using data from 1992–2003, inquire whether US airline jet fuel hedging added value for these companies They show that airline industry investment opportunities are positively correlated with jet fuel costs and higher fuel costs with lower cash flows, thus providing the carriers a positive value from hedging jet fuel. They also find that jet fuel hedging and airline firm value are positively correlated. Their regression estimates suggest that the "hedging premium" may fall between 5% and 10%. Their results show that most of the hedging premium is derived from the interaction of hedging with capital investment. This result bolsters the notion that jet fuel hedging benefits airlines through the reduction of underinvestment costs.

The focus of our paper differs from the above research. This paper investigates the effects of shocks to jet fuel prices on yields as measured by dollars per revenue passenger miles(RPM). One

RPM is one passenger flown one mile in revenue traffic. We examine the possibilities of a nonlinear dynamics between the two series. If there is a nonlinear relationship, then the volatility impact of jet fuel prices on carrier profitability and performance may be severe. This may explain some of the observations that those carriers without a jet fuel hedging strategy have seriously underperformed their potential and their competitors who have hedged in some manner.

Our paper is motivated by the following issues. First, transportation economists are interested in investigating jet fuel price volatility and air carrier performance. The research in the past decade has mainly focused on hedging practices of passenger air carriers and the economic justification for it. Second, economists have long been interested in volatility, nonlinearities, and chaotic behavior in price series of equities, commodities, and currencies, among others. For instance, the study of the chaotic behavior may shed some light on the performance of technical analysis in financial markets. Technical analysis has been used in forecasting other financial time series and may be successful in forecasting short-term fluctuations in the dollar if the series is nonlinear and/or chaotic (see for example, Blume, Easley, and O'Hara (1994), Bohan (1981), Brock, Lakonishok, and LeBaron (1992), Brush (1986), Clyde and Osler (1997), LeBaron (1991), Pruitt and White (1988, 1989), Taylor (1994), among others). Third, developments in the econometrics of nonlinearity over the last three decades offer researchers new tools for detecting relationships that are inherently nonlinear and may not be conducive to various methodologies that seek to impose linear modeling on nonlinear relationships. The recent studies using cointegration tests would fall in this category.

Typical linear models assume that the time series being studied are linearly related to underlying shocks that form the series. But if there are nonlinearities, the time series and past shocks are related through a nonlinear relationship. In these cases the time series may be nonlinear in mean or variance or both. Time series that are nonlinear in mean allow for nonzero higher moments. Those with nonlinearities in variance, under certain conditions, possess higher order moments with nonzero values. Various ARCH and GARCH models may be capable of explaining these nonlinearities.

While there have been advances in modeling deterministic nonlinear systems, their application in economics and finance has been limited for several reasons. First, unlike natural sciences, economic theory does not provide specific nonlinear functional forms in modeling the time series behavior. Second, controlled experiments are almost impossible in economics, thus preventing economists from deriving the parameters of deterministic non-linear systems underlying relationships among economic variables. Despite the above limitations, testing for nonlinearities and chaotic structures has made inroads in financial and economic research.

Drawing on existing tests of nonlinearities and chaos, we first investigate the existence of chaotic behavior as the source of nonlinearities in the two series. To accomplish this task, we estimate AR(1) and GARCH(1,1) models for each series. The filtered series, i.e., the model residuals are tested for chaos to see if there are any lingering nonlinearities originating from chaotic behavior in the series. If so, one would conclude that methods of investigation that are inherently seeking to establish liner relationship between the two series, one would fail to ferret out the underlying nonlinear relationships. These methods would include estimating correlation coefficient, linear regressions, and cointegration tests. If on the other hand, chaos is not the source of nonlinearities, then models that properly capture the underlying nonlinearities may be better-suited to explain the relationship between the variables.

Our findings show that jet fuel prices and revenue passenger mile series demonstrate nonlinearities. We also find evidence, however, that the series behavior may be inconsistent with chaotic structure. We identify a GARCH(1,1) process as the model that best explains the nonlinearities in the two time series. Therefore, we propose a bivariate GARCH(1,1) and EGARCH(1,1) models for the revenue passenger miles and the jet fuel price series. Estimation results of the bivariate GARCH models offer evidence that the shock transmission between the two series is mainly asymmetric; that is, that positive and negative shocks impart varying degree of volatility on the series under study. It is shown that the positive shocks to jet fuel prices show a substantially higher reaction on the revenue passenger miles.

This paper is organized as follows. Section 2 discusses the methodology of the paper. Section 3 proceeds to explain the sources of data and presents the summary statistics. Section 4 offers the main empirical findings. A brief summary and conclusion are presented in Section 5.

2. Methodology

We start by analyzing jet fuel prices and revenue passenger miles as the measure of air performance. Revenue passenger miles measure the number of revenue generating passengers times the number of miles traveled. Revenue passenger miles can be viewed as the measure of the quantity of output in the production of services by carriers. The ratio of revenue passenger miles to the_available seat miles is a measure of the overall passenger load factor. These measurements can further be used to define unit revenues and unit costs per revenue passenger mile. We are particularly concerned with detecting the sources of nonlinearities in each time series process. To rule in or out the existence of chaotic behavior, we apply the Brock, Dechert, and Scheinkman (1987) test (BDS) and Correlation Dimension tests of chaos to each series. We find that while nonlinearities are present, these nonlinearities are not consistent with chaotic patterns. We propose and estimate autoregressive models for the jet fuel and revenue series, along with bivariate GARCH(1,1) models of variances for the two series and show evidence that volatility spillovers occur across the two.

2.1 Testing for Chaos

The common tests of chaos are discussed in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi et al. (2004). We present them briefly to inform the reader. There are two tests that we employ here: (i) the Correlation Dimension of Grassberger and Procaccia (1983) and Takens (1984), (ii) the BDS statistic of Brock, Dechert, and Scheinkman (1987).

2.2 Correlation Dimensions

Assume a stationary time series x_t, t =1...T. Imbedding x_t in an m-dimensional space by forming M-histories starting at each date t: $x_t^2 = \{x_t, x_{t+1}\}$,.., $x_t^M = \{x_t, x_{t+1}, {}_{t+2},......,x_{t+M-1}\}$ and by forming the stack of these scalars, we can examine the dynamics of the created system. If the true system is n-dimensional, provided M ≥ 2n+1, the M-histories can help recreate the dynamics of the underlying system, if they exist (Takens (1984)). For a given embedding dimension M and a distance ε, the correlation integral is given by

$$C^M(\varepsilon) = \lim_{T\to\infty} (1/T^2)\{\text{the number of } (i,j) \text{ for which } \left\| x_i^M - x_j^M \right\| \le \varepsilon\} \quad (1)$$

where $\|\cdot\|$ is the distance induced by the norm. For small values of ε, $C^M(\varepsilon) \sim \varepsilon^D$, where D is the dimension of the system (see Grassberger and Procaccia (1983)). The Correlation Dimension in embedding dimension M is given by

$$D^M = \lim_{\varepsilon\to 0}\{\ln C^M(\varepsilon)/\ln\varepsilon\} \qquad (2)$$

and the Correlation Dimension is given by

$$D = \lim_{M\to\infty} \ln D^M \qquad (3)$$

We estimate the statistic

$$SC^M = \frac{\{\ln C^M(\varepsilon_i) - \ln C^M(\varepsilon_{i-1})\}}{\{\ln(\varepsilon_i) - \ln(\varepsilon_{i-1})\}} \qquad (4)$$

for various levels of M (e.g., Brock and Sayers (1988)). The SC^M statistic is a local estimate of the slope of the C^M versus the ε function. Following Frank and Stengos (1989), we take the average of the three highest values of SC^M for each embedding dimension.

2.3 BDS Statistics

Brock, Dechert and Scheinkman (1987) compute the correlation integral to obtain a statistical test that is robust in detecting various types of nonlinearity as well as deterministic chaos. BDS show that if x_t is (i.i.d) with a nondegenerate distribution,

$$C^M(\varepsilon) \to C^l(\varepsilon)^M, \quad as \quad T \to \infty \qquad (5)$$

for fixed M and ε. Employing this property, BDS show that the statistic

$$W^M(\varepsilon) = \sqrt{T}\,\{[C^M(\varepsilon) - C^l(\varepsilon)^M]/\sigma^M(\varepsilon)\} \qquad (6)$$

where σ^M, the standard deviation of [·], in the limit demonstrates a standard normal distribution under the null hypothesis of IID. W^M is termed the BDS statistic. A significant W^M for a stationary series purged of linear dependence would indicate nonlinearity. The presence of chaotic structure is rejected if it can be shown that the nonlinear structure is derived from a known non-deterministic system.

3. Data and Summary Statistics

We utilize monthly average jet fuel prices (JF) provided by (Bureau of Transportation Statistics of the US Department of Transportation) and the yield as measured by revenue passenger miles (RPM) spanning January 2000-May, 2010 (from Air Transport Association). Revenue passenger miles are a standard measure of air carrier firms' output. It could be thought of as a measure of efficiency in the sense that it relates the quantity of output given the number of planes available. The bilateral relationship between the two can be examined employing the VAR-GARCH(1,1). These models successfully isolate the effects of shocks to jet fuel price on the revenue passenger miles and any possible feedback. Percentage changes in the jet fuel price levels and the RPMs are obtained by taking the ratio of log of the price and quantity as in $R_t = (\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the daily jet fuel prices.

Table 1 presents the diagnostics for the R_t series. The returns series are found to be stationary employing the Augmented Dickey Fuller (ADF) statistics. There are linear and nonlinear dependencies as indicated by the Q and Q^2 statistics, and Autoregressive Conditional Heteroskedasticity (ARCH) effects are suggested by the ARCH(6) chi-square statistic. Table 1 summarizes our findings as follows: (i) There are clear indications that nonlinear dynamics are generating the two series, (ii) these nonlinearities may be explained by ARCH effects. Whether these dynamics are chaotic in origin is the question that we turn to next.

Table 1 shows that jet fuel price (JF) and the revenue passenger mile (RPM) series exhibit significant linear and non-linear dependencies as shown by the Lung Box Q and Q^2 statistics. These dependencies continue to persist in the first differences of the series as well. The Lagrange multiplier tests show that the nonlinearities in jet fuel prices and revenue series may be due to the ARCH effects. ARCH effects also persist in level and first-differenced series. These findings suggest that to model the series in a bilateral framework, one needs to move beyond linear models, and that some variations of

GARCH models may be better suited to analyze the dynamics between the two series.

Table 1. Diagnostics

	Panel A: Levels		**Panel B: First Differences**	
	JF	RPM	JF	RPM
Mean	1.500	0.139	0.013	1.76e-05
Stand. Dev.	0.748	0.010	0.126	0.005
Skewness	0.713	0.139	-1.938	-0.087
Kurtosis	2.856	2.039	12.094	2.783
Jaques-Bera	10.699	2.039	505.025	0.402
ADF	-2.762	-3.871	-7.384[a]	-2.651
Ng-Perron	-14.08	-33.1229	-52.757	0.387
Q(12)	990.240[a]	437.172[a]	49.843[a]	83.766[a]
Q²(12)	725.160[a]	432.852[a]	63.973	78.040[a]
LM-ARCH (>6)	39.200[a]	19.160[a]	21.290[a]	28.480[a]

Notes: JF and RPM represent jet fuel prices and revenue passenger miles. Table 1 presents the percentage change diagnostics for the two monthly series. Percentage changes are given by $R_t=\ln(P_t/P_{t-1})\cdot 100$, where P_t represents monthly values of each variable. ADF represents the Augmented Dickey Fuller tests (Dickey and Fuller (1981)) for unit root. The Q(12) and Q²(12) statistics represent the Ljung-Box (Q) statistics for autocorrelation of the R_t and R_t^2 series respectively. The ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) and is χ^2 distributed with 6 degrees of freedom. [a], [b] and [c] represent significance levels of 0.01, 0.05 and 0.10, respectively.

Prior to modeling the dynamics between the two series jf and RPM, we further investigate the nature of nonlinearities in each series reported in Table 1. To accomplish this objective, we filter each series employing autoregressive order one and GARCH(1,1) models. If the residuals still exhibit nonlinearities, then the series may follow a low dimensional chaotic process. This will render most econometric models ineffective. However, if the AR(1) or GARCH(1,1) standardized residuals do not exhibit patterns consistent with low dimensional chaotic processes, then perhaps the relationship between the two series may be modeled in a bivariate GARCH context and the dynamics of information arrival or volatility spillovers may be investigated. The correlation dimension and BDS statistics are employed to see if the nonlinearities are consistent with chaos.

To capture the linear structure, we first estimate autoregressive models for the series under study, as follows:

$$R_t = \alpha + \sum_{i=1}^{p} \beta_i R_{t-i} + \varepsilon_t \qquad (7)$$

Where, R_t represents percentage changes in each series. The lag length for each series is selected based on the Akaike (1974) criterion. The residual term (ε_t) represents the index movements that are purged of linear relationships and seasonal influences. The GARCH(1,1) model allows for the time varying conditional variance given by equation (8) as follows.

$$\sigma_{i,t}^2 = \beta_i + \gamma_i \varepsilon^2_{i,t-1} + \varphi_i \sigma^2_{t-1} \quad i=1,2 \qquad (8)$$

where $\sigma^2_{i,t}$ is the conditional variance at time t, and ε^2_{t-1} represents the squared of lagged innovations at time t. The log-likelihood function for the maximum likelihood estimation under the Gaussian distribution of ε is given by

$$L(\theta) = -0.5^* \text{ (n-q)*log } (2\pi)\text{-}0.5^* \sum_{t=q+1}^{n} \log \sigma_t^2 - 0.5 * \sum_{t=p+1}^{n} \varepsilon_t^2 / \sigma_t^2$$

where, p and q are the number of lags of the squared innovations and unconditional variance of innovation, s θ is the vector of parameters to be estimated.

4. Empirical Findings

4.1 Correlation Dimension Estimates

Table 2 reports the Correlation Dimension (SC^M) estimates for jet fuel prices and the revenue series alongside that for the Logistic series that we developed.

The values of the correlation dimension for chaotic series and its AR(1) filtered version shown in the first two rows of the Table 2 do not show an explosive trend. For instance, SC^M estimates for the logistic map stay around one as the embedding dimension rises. Furthermore, the estimates for the logistic series are not sensitive to the AR transformation, consistent with chaotic behavior.

For the JF and RPM series, on the other hand, SC^M estimates show inconsistent behavior with chaotic structures. For instance, the SC^M does not settle. The estimates for the AR transformation do not change results much, but are mostly larger and do not settle with increasing of the embedding dimension. These initial indicators suggest that the series under consideration are not showing signs of chaos.

Table 2. Correlation Dimension Estimates Fuel Prices and RPM

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
JF AR(1)	1.952	3.155	4.345	4.887
RPM AR(1)	3.642	4.613	5.483	9.176
JF GARCH(1,1)	3.850	7.022	UD	UD
RPMGARCH(1,1)	3.788	5.686	6.796	5.363

Notes: JF AR(1), RPM AR(1), JF GARCH(1,1), represent RPM GARCH(1,1), model residuals FROM AR(1) and GARCH(1,1) models fitted to JF and RPM percentage change series. "UD" indicates undefined.

Table2 reports SC^M statistics for the Logistic series (w=3.750, n=2000), monthly percentage changes in jet fuel and revenue passenger miles series over four embedding dimensions: 5, 10, 15, and 20. AR(1) represents autoregressive order one residuals. GARCH(1,1) represents standardized residuals from a AR1- GARCH(1,1) model.

4.2 Results of BDS Test

Tables 3 and 4 report the BDS statistics (Brock, Dechert and Scheinkman (1987)) for the [AR(p)] series, and standardized residuals $\varepsilon / \sqrt{h}$ from the GARCH(1,1) models, respectively. The BDS statistics are evaluated against critical values obtained by bootstrapping the null distribution for each of the GARCH models. The critical values for the BDS statistics are reported in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi et al. (2004).

The BDS statistics reject the null of no nonlinearity in the [AR(1)] errors for the jet fuel price series. For both series, BDS statistics for the standardized residuals from the GARCH-type models are mostly insignificant at the 1 and 5 percent levels. On the whole, the BDS test results provide compelling evidence that the nonlinear dependencies in the jet fuel price and revenue passenger mile series may be arising from GARCH-type effects, rather than from a complex, chaotic structure. In the coming sections, we focus on developing and estimating variations of GARCH models that may best explain nonlinearities and the dynamics of the two series under study.

Table 3. BDS Statistics for AR(1) Residuals

ε/σ	M=2	M=3	M=4	M=5
JF AR(1)				
0.50	2.3998	4.0980 [a]	4.9804 [a]	6.6605 [a]
1.00	3.0962 [a]	4.2349 [a]	4.7866 [a]	5.3200 [a]
1.50	3.5331 [a]	3.9925 [a]	4.5682 [a]	5.0203 [a]
2.00	3.0424 [a]	2.7866 [b]	3.4459 [a]	3.7873 [a]
RPM AR(1)				
0.50	-0.8143	-1.5609	-2.4256	-4.2509 [a]
1.00	-0.8344	-0.1244	0.4076	1.1122
1.50	-1.9831	-0.7151	-0.4514	-0.5987
2.00	-1.8083	-0.5356	-0.5732	-0.9172

Notes: JF AR(1) and RPM AR(1), represent model residuals fitted to jet fuel and revenue passenger miles series. The figures are BDS statistics for the AR(p). [a], [b], and [c] represent the significance levels of .01, .05, and .10, respectively.

Table 4. BDS Statistics for GARCH(1,1) standardized residuals

ε/σ	M=2	M=3	M=4	M=5
JF GARCH(1,1)				
0.50	-0.3100	-1.1502	-0.5618	0.8861
1.00	-0.5669	-0.8221	-0.7767	-0.4129
1.50	-0.5130	-0.4978	-0.5571	-0.4124
2.00	-0.4092	-0.5994	-0.7319	-0.5485
RPM GARCH(1,1)				
0.50	1.0387	0.4721	0.7257	0.4044
1.00	0.1189	0.4401	0.7361	1.0312
1.50	-0.5410	-0.0476	0.1378	-0.1258
2.00	-0.7063	0.0908	-0.0382	-0.5027

Notes: JF GARCH(1,1) and RPM GARCH(1,1), represent standardized residuals of GARCH(1,1) models fitted to percentage change in jet fuel and revenue passenger miles series. The figures are BDS statistics for the standardized residuals from GARCH(1,1) models. The BDS statistics are evaluated against critical values obtained from Monte Carlo simulations. [a], [b], and [c] represent the significance levels of .01, .05, and .10, respectively.

4.3 Bivariate GARCH Models

To model the dynamic relationship between the jet fuel and revenue passenger mile variables, while simultaneously accounting for the nonlinearities stemming from GARCH effects, we estimate a VAR model in a bivariate GARCH context. Zellner and Palm (1974) and Zellner (1979) show that a VAR represents a flexible approximation to any wide range of simultaneous structural models and may be viewed as Taylor series approximation for nonlinear models as well. Thus, we propose the following VAR model for the remainder of our empirical investigation.

$$R_{it} = \alpha_i + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + u_{i,t} \qquad \text{i,j=1 or 2,}$$

where the variance is time-varying and similar to equation (8) above.

Many researchers have shown that various equity, fixed income, and commodity prices demonstrate volatility persistence (Kyle (1985)), and there is a great deal of evidence that many financial price series exhibit time varying volatility. Specific to debt securities, several researchers have argued that interest rate risk premia are time variant (for instance, Shiller (1979) and Singleton (1980)). Weiss (1984), Engle, Ng, and Rothschild (1990), and Engle, Lilien, and Robins (1987) find significant ARCH effects or serial correlation in variances in short term rates over several decades. In the present study, variance persistence or clustering may arise from market features unique to commodity prices, crude oil, and its distillates.

There is also reason to suspect that these variance effects are correlated across the two variables. For example, Engle, Ng, and Rothschild (1990) show that the underlying forces behind volatility for the shorter end of term structure are common across different rates - indicative of co-persistence of variance. Such co-persistence will have important implications for an empirical analysis of variance behavior. In this case, similar underlying economic forces influence jet fuel price and air carrier volatility.

While jet fuel prices may exhibit high variance persistence in their univariate representations, this persistence may be common across different and related series, revenue passenger miles, for instance, so that linear combinations of the variables show lesser volatility persistence. Ross (1989) argues that volatility in a time series may be viewed as information arrival. Thus, if information arrives first in one series, volatility spillover from that series to others may occur. Therefore, to study the dynamics of revenue passenger miles and jet fuel prices, an appropriate extension to the above VAR model will be employed to simultaneously allow for time varying volatility and volatility spillovers between jet fuel prices and revenue passenger miles in a dynamic context.

The statistics in Table 1 justify some of the above suspicions in the relationship between the two series. The Ljung-Box Q(12) and $Q^2(12)$ statistics indicate significant levels of serial correlation in the returns and the square of the returns. These statistics indicate linear and nonlinear dependencies in the two series under study. Test statistics for ARCH errors (Engle (1982)) further suggest serial correlation in the errors. On the other hand, there is less evidence of serial dependencies in the standardized residuals from fitting the returns to a GARCH(1,1) model suggested by Bollerslev (1986) and Baillie and Bollerslev (1990). The Q(12) statistics are substantially smaller and the $Q^2(12)$ statistics are smaller or insignificant. This is evidence that the GARCH model effectively captures the nonlinearities in the data. Moreover, the standardized residuals show a decline in kurtosis, further evidence of the GARCH model providing a superior fit to the data (Hsieh (1989)).

To be able to investigate the volatility spillovers and information arrival in the context of our paper, we propose the VAR model of equation (8) while simultaneously controlling for the likely variance and covariance persistence via the bivariate GARCH model. Similar models have been employed by Hamao, Masulis and Ng (1990), Chan, Chan and Karolyi (1991), and Chatrath and Song (1998), among others. The following equations achieve this goal.

$$\sigma^2{}_{R1,t} = \alpha_0 + \alpha_1\sigma^2{}_{R1,t-1} + \alpha_2\varepsilon^2_{R1,t-1} + \alpha_3\varepsilon^2{}_{R2,t-1} \quad (9)$$

$$\sigma^2{}_{R2,t} = \beta_0 + \beta_1\sigma^2{}_{R2,t-1} + \beta_2\varepsilon^2_{R2,t-1} + \beta_3\varepsilon^2_{R1,t-1} \quad (10)$$

and

$$\sigma_{R12,t} = \gamma_0 + \gamma_1\,\sigma_{R12,t\text{-}1} + \gamma_2\,\varepsilon_{R1,t\text{-}1}\varepsilon_{R2,t\text{-}1} \quad (11)$$

assuming

$$\begin{pmatrix} \varepsilon_{R1,t} \\ \varepsilon_{R2,t} \end{pmatrix} \Bigg\| \Omega_{t-1} \sim \text{Student t} \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{1,t}^2 & \sigma_{1,2,t} \\ \sigma_{1,2,t} & \sigma_{2,t}^2 \end{pmatrix}, \Theta \right)$$

where: $\sigma_{1,t}$ and $\sigma_{2,t}$ are the standard deviations of error terms $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, respectively, conditional on information set (Ω) available up to time t-1; $\sigma_{1,2,t}$ represents the conditional covariance given by an autoregressive linear function of the cross product in the past squared errors; $\varepsilon_{Ri,t}$ (i=1,2) are the randomly distributed regression errors; Θ is the inverse of the degrees of freedom in the Student t distribution, and the conditional correlation,

$$\rho_{1,2,t} = \sigma_{1,2,t}(\sigma_{1,t}\,\sigma_{2,t})^{-1/2} \quad \text{is allowed to vary over time.}$$

The parameters α_2 and $ß_2$ in (9) and (11) are the measures of volatility persistence in the jet fuel and the RPM series, respectively, with a large value indicating that the conditional variance remains elevated for extended periods of time following return shocks. The parameters α_3 and $ß_3$ are intended to capture the volatility spillovers between series. For instance, $\alpha_3>0$ and $ß_3=0$ would be consistent with the hypothesis that the volatility spills over from the jet fuel prices to the revenue passenger miles, and not *vice versa*. In this example, the bivariate GARCH model results would be interpreted as evidence that supports the hypothesis that shocks to the jet fuel market induce changes in the air carrier firm behavior.

In the following discussion we offer the estimation results of the bivaraite GARCH(1,1) models of equation (9-11). The focus of this segment of the empirical results is the volatility spillovers between the two series. Thus, we do not present the results of the estimation of the VAR systems.

The log of the likelihood function is given by

$$L(\boldsymbol{\Omega}) = -.05{*}\ln|\boldsymbol{\Lambda}_t| - 0.5\ \boldsymbol{\varepsilon}_t^{'}\boldsymbol{\Lambda}_t^{-1}\boldsymbol{\varepsilon}_t\,,$$

where $\boldsymbol{\Omega}$ is a vector of 20×1 model parameters to be estimated, $\boldsymbol{\varepsilon}_t^{'}=[\varepsilon_{1,t}, \varepsilon_{2,t}]$ is the vector of innovations at time t, $\boldsymbol{\Lambda}_t$ is the 2×2 time varying variance and covariance matrix of errors, with its diagonal elements given by equations (9) and (10) and the off diagonal covariances given by equation (11). The nonlinear optimization methodology, BHHH (Brendt et al., 1974) is employed to obtain the maximum likelihood estimator of the bivariate model parameters. The methodology is a variation of the Newton's method that simplifies some of the computations and falls in the category of quadratic-hill-climbing approach to nonlinear optimization. The direction and intensity of the volatility spillovers are analyzed by examining the size and the significance of the cross equation squared lagged residuals. The coefficients of interest in these results are α_3 and β_3.

Table 5 reports the estimation results of the system of equations (9), (10) and (11). The Bivariate GARCH(1,1) models appear to capture volatility in each series quite well. Many model coefficients are statistically significant at commonly expected levels of significance. The mean equations indicate that the jet fuel prices are sensitive to their own past values and shocks, while the RPM responds significantly to the lagged changes in the jet fuel prices. This observation may show that jet fuel price volatility leads and triggers changes in the RPM.

Table 5. Bivariate GARCH model with cross variable volatility spillovers between JF Prices and RPM

Mean Equation	**JF**	**RPM**
Intercept	0.702	-0.164
	(0.595)	(0.038)
Own Lagged	0.255[a]	-0.018
	(0.090)	(0.091)
Corss Lagged	0.111	0.097[b]
	(0.633)	(0.046)
Variance Equation	**JF**	**RPM**
Intercept	22.116[c]	10.942[c]
	(11.907)	(6.442)
Lagged Conditional Variance	0.437	0.246
	(0.352)	(0.535)
Lagged Own Shocks	0.134	-0.117
	(0.178)	(0.082)
Intermarket Lagged Shock	-0.390[a]	0.018[c]
	(0.067)	(0.010)
Conditional Covariance Equation		
Intercept	0.006	
	(0.034)	
Lagged Conditional Covariance	1.049[a]	
	(0.021)	
Product of Lagged Residuals	-0.024	
	(0.027)	
Diagnostics on Satnadrdized residuals		
Q(12), ε_t/σ	12.249	95.462[a]
Q(24), ε_t/σ	24.226	191.772[a]
$Q^2(12)$, ε_t^2/σ	5.184	31.006[a]
$Q^2(24)$, ε_t^2/σ	19.710	49.555[a]
Q(12), $\varepsilon_{it}\,\varepsilon_{it}/\sigma_i\,\sigma_j$	15.384[b]	
Q(24), $\varepsilon_{it}\,\varepsilon_{it}/\sigma_i\,\sigma_j$	36.525[a]	

Sign Bias t-Statistic	**Equation 1**	**Equation 2**
Negative shock bias	-2.431[a]	-2.211[a]
Size bias	2.456[a]	-2.543[a]
Joint sign and size bias (χ^2)	14.240[a]	12.673[a]
System Log Likelihood	-479.973	
H_0: inter-variable lagged shock effects are equal	χ^2 =1.667	

Notes: (1) Jet fuel (JF) and revenue passenger miles (RPM) percentage changes and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it} / \sqrt{\sigma_{it}}$) and their squared values;

(2) [a], [b], and [c] represent significance levels at .01, .05, and .10, respectively.

The conditional variance for both the jet fuel and the RPM are sensitive to the spillovers from the other variable rather than their own past values and shocks. This is evident from the statistical significance of the cross variable shocks. The main observation is that the positive shocks to RPM reduce the volatility of jet fuel prices. This finding may mean that with upside volatility in their revenue passenger miles (the measure of output), air carriers may be searching for methods to reduce their jet fuel expenses. This may be achieved through effective hedging or more efficient scheduling. On the other hand, shocks to jet fuel prices in one period leads to more volatility in revenue passenger miles, a plausible finding consistent with the findings of the equations. For instance, positive shocks to jet fuel prices generate higher costs for airlines. Higher costs may lead to higher fares, a reduction in special fares, or in rout eliminations. All of these outcomes could result in lower RPMs and uncertainty and volatility for the carriers. The covariance equation verifies that the two variables affect each other and the lagged covariation of the jet fuel price and the revenue passenger miles in any period has a persistent effect on the future period conditional covariation and, thus, conditional correlation coefficient.

The Q statistics show that the model is partially successful in explaining non- linear dependencies in the two series. While the nonlinear and linear dependencies in jet fuel price variations are almost completely being captured by the bivariate GARCH(1,1) model, the same is not true of the RPM series. The effects of shocks across the two series are statistically equal, as shown by the value of chi-squared statistic.

A further consideration in modeling the dynamics of jet fuel prices and the revenue passenger miles is the asymmetric reaction of each series to positive and negative shocks (innovations) generated in either variable. For instance, a relevant question in this context would be whether the carrier passenger miles react symmetrically or asymmetrically to positive shocks and negative shocks in jet fuel prices. It is conceivable that a positive shock to jet fuel prices may force carriers to take counter measures that reduce shocks to their RPMs. On the other hand, a negative shock to jet fuel prices may show a dramatic volatility in a positive direction for revenue passenger miles, as airlines take advantage of falling fuel prices and expand their operations by offering promotional fares.

To account for asymmetric shock response within and across variables, we re-estimate the bivariate EGARCH models that can provide evidence in support, or lack thereof of an asymmetric volatility response within and across variables. It should be noted that the asymmetric shock response across two variables maybe due to a whole host of reactions by airlines in their attempt to deal with shocks to each variable.

The bivariate EGARCH model is an extension of the univariate EGARCH model of Nelson (1991) which is designed to capture the volatility dynamics between pairs of variables in a bivariate framework. The bivariate VAR- EGARCH model allows us to explicitly test the asymmetric volatility spillovers between two series. Koutmos (1992, 1996), Cheung and Ng (1992), among others have documented this pattern of asymmetric volatility transmission across variables.

We formulate the bivariate VAR-EGARCH model as follows.

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + \varepsilon_{i,t} \qquad \text{i,j=1 or 2} \tag{12}$$

$$Ln(\sigma_{i,t}^2) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij} \varphi_j (z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) \quad \text{i,j=1 or 2} \tag{13}$$

$$\varphi_j (z_{j,t-1}) = (\left| z_{j,t-1} \right| - E(\left| z_{j,t-1} \right|) + \delta_j z_{j,t-1}) \qquad \text{i,j=1 or 2} \tag{14}$$

Where

$$z_{j,t} = (\left| u_{j,t} / \sigma_{j,t} \right| - \sqrt{2/\pi}) + \delta_j u_{jt} / \sigma_{j,t}$$

and

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \qquad \text{i,j=1 or 2} \qquad (15)$$

R_{it} is the percentage monthly change in series i and time t, $\sigma^2_{i,t}$, and $\sigma_{i,j,t}$ are the conditional variance and covariances in series i, and between series i and j at time t, respectively, ρ_{ij}, the conditional correlation coefficient between series i and j, $z_{i,t}= \varepsilon_{it}/\sigma^2_{i,t}$, is the standardized innovations of series i at time t.

Equations (12) through (15) comprise the bivariate VAR-EGARCH model to be estimated. Equation one shows a standard VAR model for returns of two equity series. Each return is modeled as a VAR of order one. Equation (13) is the natural logarithm of the conditional variance for each series. It is formulated as a function of past volatility in the series, as well as cross series standardized shocks. Volatility persistence is measure by γ. This coefficient is expected to be less than one in order for the unconditional variance to exist.

The $\varphi(z)$ is derived from the last equation, which shows that z_{jt} is a function of standardized innovations of the VAR equation. This function reflects the asymmetric effect of lagged standardized shocks on the conditional variance of returns. Specifically, its slope measures the asymmetric impact of the positive and negative standardized own and cross series shocks on the conditional return variance in each series. For instance, the slope of the function is $-1+\delta$ for the negative z_{jt}, while for positive values of z_{jt} the slope is $1+ \delta$.

The $\varphi(z)$ provides further information on the size and sign effects of the standardized innovations. For example, if the standardized shocks and cross series shocks are such that $|Z_{j,t-1}|-E(Z_{j,t-1})>0$, depending on the sign of β_{ij},, the conditional volatility may respond asymmetrically. This is known as the size effect. The sign effect of shocks is captured by $\delta_j Z_{j,t-1}$. Positive shocks raise the conditional volatility, while the negative shocks dampen them if $\delta_j>0$. Therefore, depending on the sigs of β_{ij} and δ_j, the sign and size effects may reinforce or offset each other. For instance if $\delta_j>0$ and $\beta_{ij} <0$, this would indicate that the positive shocks in series j would result in higher volatility in series i, than the negative shocks. The impact of asymmetric size effect may be measured by the $|-1+\delta_j|/(1+ \delta_j)$, which has been dubbed the leverage effect in equities context.

The volatility persistence is measured by γ_i in equation (13), and it is an indication of the limits of volatility in a series. Nelson (1991) shows that the value of $\gamma_i <1$ indicates that the unconditional volatility is finite and measurable, while $\gamma_i = 1$ signals a non-stationary and unconditional volatility is not well-defined. However, Hsieh (1989) shows that the exponential volatility specification is unlikely to produce non-finite unconditional variances.

The log likelihood function is given by

$$L(\theta) = -.05*(\text{ n*T}) \ln(2\pi)-0.5 \sum_{t=1}^{T} (\ln|\mathbf{\Lambda}_t| + \boldsymbol{\varepsilon}'_t \mathbf{\Lambda}_t^{-1} \boldsymbol{\varepsilon}_t)$$

where θ is a vector of the 16×1 model parameters to be estimated, n is the number of equations in the system, which is two, T is the number of sample observations, $\boldsymbol{\varepsilon}'_t =[\varepsilon_{1,t}, \varepsilon_{2,t}]$ is the vector of innovations at time t, $\boldsymbol{\Lambda}_t$ is the 2×2 time varying variance and covariance matrix, with its diagonal elements given by equation (13) and the off diagonal covariances given by equation (15).

We use a combination of the simplex method and Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm to maximize the likelihood function, $L(\theta)$. The BFGS method is a numerical optimization method that approximates Newton's method. It boils down to a hill-climbing optimization technique that uses the first and second derivatives to find the stationary point of a twice continuously differentiable function. As in any optimization problem, the first order necessary condition for optimality is that the gradient be zero. The Hessian matrix of second derivatives is approximated iteratively by gradient evaluations. The BFGS method converges if the function has a quadratic Taylor expansion near an optimum. These methods use the first and second derivatives.

Table 6 reports the estimation results of the equation (12)-(14) for the jf and RPM percentage changes. In both equations statistically significant $\delta_j > 0$ shows the presence of asymmetric volatility effects. Coupled with positive β_{12} and β_{21}, the empirical findings show that volatility transmission across the two series is asymmetric. Positive shocks to each variable result in elevated conditional volatility in the other and there is feedback in a similar manner. The statistically significant β_{12} and β_{21} also verify that the feedback runs in both directions. Thus, positive shocks to jet fuel prices lead to higher volatility in the output volume than negative innovations. The size effect as measured by $(1+\delta_j)/|-1+\delta_j|$, are 3.51 and 1.45, respectively, for jet fuel and RPM series, indicating that asymmetric shock effects of positive shocks (innovations) in the jet fuel series are far greater than those for RPM. This could imply that the revenue passenger miles are likely to fall significantly, at least in the short-run, as the air carriers attempt to pass the higher jet fuel costs on to consumers. The unconditional volatility in both cases are finite as indicated by γ_1 and $\gamma_2<1$.

Table 6. Bivariate asymmetric VAR- EGARCH model with volatility spillovers
JF prices and RPM

$$R_{it} = \alpha_{i,0} + \sum_{j=1}^{2} \alpha_{ij} R_{i,t-1} + \varepsilon_{i,t} \qquad \text{i,j=1 or 2}$$

$$\ln(\sigma_{i,t}^2) = \beta_{i,0} + \sum_{j=1}^{2} \beta_{ij} \varphi_j (z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) \qquad \text{i,j=1 or 2}$$

$$\varphi_j (z_{j,t-1}) = (\left| z_{j,t-1} \right| - E(\left| z_{j,t-1} \right|) + \delta_j z_{j,t-1}) \qquad \text{i,j=1 or 2, where}$$

$$z_{j,t} = (\left| u_{j,t} / \sigma_{j,t} \right| - \sqrt{2/\pi}) + \delta_j u_{jt} / \sigma_{j,t}$$

and

$$\sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t} \qquad \text{i,j=1 or 2}$$

Mean Equations	**JF**	**RPM**
Intercept α_{10}, α_{20}	-0.110[a]	1.600[a]
	(0.013)	(0.026)
Lagged Return JF α_{11} α_{21}	-0.018	0.022
	(0.051)	(0.039)
Lagged Return RPM α_{12}, α_{22}	-0.118[a]	0.266[a]
	(0.026)	(0.019)

Variance Equations	**JF**	**RPM**
Intercept β_{10}, β_{20}	0.140[a]	3.500[a]
	(0.004)	(0.030)
Asymmetric Effect β_{11}, β_{21}	0.268[a]	0.619[a]
	(0.009)	(0.030)
Asymmetric Effect β_{12}, β_{22}	0.114[a]	0.601[a]
	(0.006)	(0.087)
Lagged stand. Shock δ_1 δ_2	0.557[a]	0.182[a]
	(0.029)	(0.006)
Lagged Conditional Variance γ_1 γ_2	0.934[a]	0.041[a]
	(0.001)	(0.001)

Diagnostics on Standardized residuals		
Q (12), ε_t/σ	20.281[a]	26.023[a]
Q (24), ε_t/σ	23.691	41.194[a]

Q^2 (12), ε_t^2/σ	31.530[a]	1.171
Q^2 (24), ε_t^2/σ	38.379[a]	3.757
Q(12), $\varepsilon_{it}\,\varepsilon_{it}\,/\sigma_i\,\sigma_j$	5.147	
Q(24), $\varepsilon_{it}\,\varepsilon_{it}\,/\sigma_i\,\sigma_j$	23.746	

Sign Bias t-Statistic	Equation 1	Equation 2
Negative shock bias	1.306	-0.083
Size bias	0.460	-0.804
Joint sign and size bias (χ^2)	15.497[a]	2.734
System Log Likelihood	-7452.40	

Notes: Jet fuel (JF) and revenue passenger miles (RPM) percentage changes and conditional variance equations are estimated in a system assuming variance correlations are constant. Q and Q^2 are the Ljung-Box statistics of the autocorrelation in the standardized residuals ($\varepsilon_{it} / \sqrt{\sigma_{it}}$) and their squared values. The sign bias test shows whether positive and negative innovations affect future volatility differently from the model prediction (see Engle and Ng (1993)). [a], [b], and [c] , represent significance at .01, .05, and .10, respectively.

The sign and size bias tests for VAR-EGARCH model reinforces the statistical validity of the asymmetric model in the sense that the model has successfully accounted for asymmetric volatility effects of positive and negative past shocks (leverage effects) and the size bias in each series. As opposed to the symmetric GARCH(1,1) model, the estimation results for the VAR-EGARCH model sign and size bias tests produce statistically insignificant t statistics indicating the model adequacy. Note that the joint sign and size bias coefficient are statistically significant only in one case. This indicates that when the magnitude of the shock, as well as the direction of the shock, are both included in the regression testing asymmetry effect of shocks on volatility, the model does not explain asymmetric shocks effects for the jet fuel equation. This finding is somewhat perplexing since the size and direction of shocks individually appear to have been captured by the model, given the statistical insignificance of the t tests of sign and size bias.

To examine the robustness of the results, we split the monthly data into two parts, one covering the period of January 2000 through December 2005 and the other from January 2006 through May 2010. The estimation results for the two sub-periods and the total sample are qualitatively identical despite different coefficient estimates. To further verify the robustness of the estimates, we generated ten random samples of one hundred observations by boot strapping. Again, VAR-EGARCH estimates resulted in virtually identical conclusions indicating that the estimation results are robust.

To summarize the impact of negative and positive shock transmissions between variables, we use the estimated δ_i and β_{ji} coefficients. For example, a one unit positive shock to jet fuel (say variable i) affects the conditional volatility in RPM(variable j) by $(1+\delta_i)*(\beta j_i)$. Table 7 summarizes these effects for a one unit positive and negative shock from variable i on the percentage change in volatility of variable j. It shows that the one unit positive shock in jet fuel prices contribute to volatility of the RPM by a factor of 0.731. However, negative innovations in jet fuel prices have relatively smaller impact on the volatility in both series. This finding verifies that the volatility responses in the RPM series to negative jet fuel price e innovations are different from responses to positive ones. The innovations in the RPM series mainly elevate the volatility in this series, and they do not affect the jet fuel price volatility substantially. This is plausible as jet fuel prices may be affected by other economic and geopolitical variables rather the revenue passenger miles “produced” by the carriers.

Table 7. Impact of cross variable shocks on the percentage change in volatility

Shock Origin(*t*-1)	JF	RPM
JF (+)	0.417	0.731
JF(-)	0.118	0.506
RPM (+)	0.117	0.710
RPM (-)	0.050	0.492

The time varying correlation coefficients between the jet fuel prices and the revenue passenger miles, given by equation (15) is 0.23 and statistically significant. This is down from the simple correlation coefficient of 0.42. This finding is consistent with those of other researchers who show that accounting for the conditional heteroscedasticity could result in more accurate and lower pairwise correlation coefficients in the realm of asset returns. We are showing the same effect for the jet fuel price and the RPM variables.

5. Summary and Conclusions

This paper investigates volatility spillovers and nonlinearities in the behavior of jet fuel price per gallon and the yield for the air carrier industry as measured by revenue passenger miles or RPM. The main contribution of this paper is investigating volatility in the relationship between jet fuel prices and air carrier output as measured by the revenue passenger miles in the US while testing for nonlinearities and nonlinear relationships in a framework of information arrival.

The paper is motivated by three issues. First, transportation economists are interested in investigating jet fuel price volatility and air carrier performance. The research in the past decade has mainly focused on the hedging practices of passenger airlines. Second, the volatility in financial markets has generated interest in applying chaos theory to these markets including movements in the prices of commodities, crude oil and its distillates. The study of the chaotic behavior may shed some light on the underlying nonlinear relationships. Third, developments in the econometrics of nonlinearity in the last three decades offer researchers new tools for detecting relationships that are inherently nonlinear and may not be conducive to various methodologies that are seeking to impose linear modeling on nonlinear relationships.

Employing existing tests of nonlinearities and chaos, we first investigate the existence of chaotic behavior as the source of nonlinearities in the monthly prices of jet fuel and a measure of yield in the air carrier industry, i.e., revenue passenger miles. To accomplish this task, we estimate AR (1) and GARCH(1,1) models for each series. The residuals or standardized residuals are tested for chaos to see if there are any lingering nonlinearities originating from chaotic behavior in the series. Our findings show strong evidence that the two series exhibit nonlinear dependencies. However, we find evidence that the series behavior may be inconsistent with chaotic structure. We identify the GARCH(1,1) process as the model that best explains the nonlinearities in the two monthly series. Therefore, we propose and estimate bivariate VAR-GARCH(1,1) and bivariate VAR-EGARCH(1,1) models of the variances to ascertain the flow of information between jet fuel prices and the RPM variable. Estimation results of the bivariate EGARCH models offer evidence that the shock transmission between the two series is mainly asymmetric, that is that positive and negative shocks impart varying degree of volatility on the series under study. It is shown that the positive shocks to jet fuel prices show a substantially higher reaction on the revenue passenger miles. This finding lends support to findings of previous research, which shows that airline firms may benefit from hedging against jet fuel prices upward volatility and their performance and value may benefit from hedging activities in the long term.

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References

[1] Adrangi, B., Chatrath, A., Kamath, R., & Raffiee, K. (2004), "Nonlinearity and chaos in the stock market of Thailand", *International Journal of Business*, 9(2): 159-176.

[2] Adrangi, B., Chatrath, A., Dhanda, & Raffiee, K. (2001a), "Chaos in oil prices? Evidence from futures markets", *Energy Economics*, 23(4): 405-425.

[3] Adrangi, B., Chatrath, A., Kamath, R, & Raffiee, K. (2001b), "Demand for the U.S. air transport service: A chaos and nonlinearity investigation", *Transportation Research Part E*, 37(5): 337-353.

[4] Akaike, H. (1974), "A new look at statistical model identification", *IEEE Transactions on Automatic Control*, 19(6): 716-723.

[5] Blume, L., Easley, D., and O'Hara, M. (1994), "Market statistics and technical analysis: The role of volume", *Journal of Finance*, 49(1): 153-181.

[6] Brock, W.A., Dechert, W., & Scheinkman, J. (1987), "A test of independence based on the correlation dimension", Unpublished Manuscript, University of Wisconsin, Madison, University of Houston, and University of Chicago.

[7] Brock, W.A., and Sayers, C.L. (1988), "Is the business cycle characterized by deterministic chaos?" *Journal of Monetary Economics*, 22(1): 71-90.

[8] Brock, W.A.., Lakonishok, J., & LeBaron B. (1992), "Simple technical trading rules and the stochastic properties of stock returns", *Journal of Finance*, 47(5): 1731-1764.

[9] Brush, J. (1986), "Eight Relative strength methods compared", *Journal of Portfolio Management*, 13(1): 21-28.

[10] Carter D.A., Rogers, D.A., and Simkins, B. J. (2002), "Does Fuel Hedging Make Economic Sense? The Case of the US Airline Industry", American Finance Association, 2004.

[11] Carter, D., Rogers, D., and Simkins, B. (2004), "Fuel hedging in the airline industry: The case of Southwest Airlines", [On-line] Available at *http://papers.ssrn.com/sol3/papers.cfm* .

[12] Carter, D. A., Rogers, D. A., and Simkins, B. J. (2006), "Does hedging affect firm value? Evidence from the US airline industry", *Financial Management*, 35(1): 53-86.

[13] Chan, K., K.C. Chan, and G. A. Karolyi (1991), "Intraday Volatility in the Stock Index and Stock Index Futures Markets", *Review of Financial Studies*, 4(4): 657-684.

[14] Chatrath, A., and F. Song (1998), "Information and the Volatility in futures and Spot Markets: The Case of the Japanese Yen", *Journal of Futures Markets*, 18(2): 201-223.

[15] Clubley, Sally (1999), "An Early Take-off", *Risk Magazine*, 12(5): 7-7.

[16] Clyde, W.C., and Osler, C.L. (1997), "Charting: Chaos theory in disguise?" *Journal of Futures Markets*, 17(5): 489-514.

[17] Cobbs, R., and Wolf, A. (2004), "Jet fuel hedging strategies: Options available for airlines and a survey of industry practices", *Unpublished manuscript*, [On-line]Available at *http://www.kellogg.northwestern.edu/research/fimrc/papers/jetfuel.pdf* .

[18] Dickey, D.A. and Fuller, W.A. (1981), "Likelihood ratio statistics for autoregressive time series with a unit root", *Econometrica*, 49(4): 1057-1072.

[19] Engle, R.F. (1982), "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation", *Econometrica*, 50(4): 987-1007.

[20] Engle, R. F., Lilien, D.M., and R.P. Robins (1987), "Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model", *Econometrica*, 55(2): 391-407.

[21] Engle, R. F., Ng, V.K., and M. Rothschild (1990), "Asset Pricing with a Factor ARCH Co-variance Structure: Empirical Estimates for Treasury Bills", *Journal of Econometrics*, 45(1/2):

213-238.

[22] Engle, R.F., and V.K. Ng (1993), "Measuring and Testing the Impact of News on Volatility", *Journal of Finance*, 48(5): 1749-1778.

[23] Frank, M. & Stengos, T. (1989), "Measuring the strangeness of gold and silver rates of Return", *Review of Economic Studies*, 56(4): 553-567.

[24] Grassberger, P. and Procaccia, I. (1983), "Measuring the strangeness of strange attractors", *Physica D*, 9(1-2): 189-208.

[25] Hamao, Y., Masulis, R.W., and V. Ng (1990), "Correlations in Price Changes and Volatility across International Stock Markets", *Review of Financial Studies*, 3(2): 281-308.

[26] Hsieh, D.A. (1989), "Testing for Nonlinear Dependence in Daily Foreign Exchange Rates", *Journal of Business*, 62(3): 339-368.

[27] International Air Transportation Association (IATA) (2013), "Annual Review, 2013", [On-line] Available at *www.ita.org/Pages/annual-review.aspx* .

[28] Kyle, A.S. (1985), "Continuous Auctions and Insider Trading", *Econometrica*, 53(6): 1315-1335.

[29] Pruitt, S.W. and White R.E. (1988), "The CRISMA trading system: Who says technical analysis can't beat the market?" *Journal of Portfolio Management*, 14(3): 55-58.

[30] Morrell, P., W. Swan (2006), "Airline Jet Fuel Hedging: Theory and Practice", *Transport Reviews*, 26(6): 713-730.

[31] Neidl, Raymond E. and Erik C. Chiprich (2001), "Major U.S. Carriers 2000 Results and 2001 Outlook", *Global Research*, Ing-Barings.

[32] Rao, V.K. (1999), "Fuel price risk management using futures", *Journal of Air Transport Management*, 5(1): 39-44.

[33] Takens, F. (1984), "On the numerical determination of the dimension of an attractor in dynamical systems and bifurcations", *Lecture Notes in Mathematics*, Berlin: Springer-Verlag Publishing.

[34] Taylor, S. J. (1994), "Trading futures using a channels rule: A study of the predictive power of technical analysis with currency examples", *Journal of Futures Markets*, 14(2): 215-235.

[35] Weiss, A. (1984), "ARMA Models with ARCH Errors", *Journal of Time Series Analysis*", 5(2): 129-143.

[36] Zellner A. (1979), "Statistical Analysis of Econometric Models", *Journal of the American Statistical Association*, 74(367): 628-643.

[37] Zellner A. and F. Palm (1974), "Time Series Analysis and Simultaneous Equation Econometric Models", *Journal of Econometrics*, 2(1): 17-54.