Asymmetric behavior of volatility in gasoline prices across different regions of the United States

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ABSTRACT

Volatility in gas prices is affecting all economies globally but the effects are much more pronounced here in the United States. This is true because, with only 5 percent of the world population, the US accounts for 20 percent of the global energy consumption. In fact, the US consumes more gasoline than South America, Europe, Africa and Asia combined according to EIA (Energy Information Administration.) This paper attempts to focus on fluctuations in gas prices across different regions of the US and the effects of exogenous shocks on their volatility by using time series data. The paper uses a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and its variant to measure the persistence of shocks to volatility and the asymmetric effects of these shocks. The results show evidence of high persistence of shocks to volatility and signs of an asymmetric behavior in volatility across regions which imply that gas prices may react differently to good news relative to bad news. The study sheds some light on understanding of the behavior of gas prices in the US better, with major implications for investors in the commodity markets.

Keywords: Volatility Persistence, Time Series, GARCH

INTRODUCTION

The stochastic behavior of time series has attracted the attention of many researchers in the past few decades. This is especially true for stock indexes, oil prices, commodity prices, and foreign exchange rates. Recent volatility in gas (gasoline) prices has been the focus of the financial press and the electronic media around the world. The United States, being the largest consumer of gasoline in the world, has bigger concerns than any other single nation. Latest analysis of gas prices in the recent past clearly reflects that the volatility of gas prices has been more significant now than ever before. These fluctuations have motivated analysts and researchers to study these phenomena in much greater depth. While volatility of gas prices is an important economic issue for most developed and developing countries, in general, as the world's largest consumer, it draws much attention and is of great concern to the public in the United States, in particular.

This paper focuses on frequent variations in gasoline prices for the four major regions of the US and how any external shocks may lead to a long lasting impact on them. Using weekly data for premium gasoline prices given in US dollars per gallon for the last ten years, this paper attempts to examine how these prices may respond differently to good or bad shocks. The results disclose high persistence of shocks to volatility and some signs of asymmetric behavior in volatility. These findings provide a better understanding of the energy markets and the behavior of gasoline prices in the different regions of the US. The paper is organized as follows: The next section discusses the literature review. Research methodology and data are addressed in subsequent sections, in that order. The last section discusses the empirical results and is followed by a section for concluding remarks.

LITERATURE REVIEW

A relatively large volume of literature mainly focused on volatility in financial markets, especially the volatility in equity or foreign exchange markets has appeared in the last few years. Some noteworthy mentions are Engle et al. (1990), Engle and Susmel (1993), Lee et al. (1995), Ewing (2002), Brooks and Persand (2003), Malik et al. (2005), Hassan and Malik (2007), Ederington & Guan (2010), and Hassan (2011.) Engle's (1982) Autoregressive Conditional Heteroscedasticity (ARCH) model, which was later generalized by Bollerslev (1986) and became known as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model tends to work better for modeling high frequency time series data as suggested by most researchers. A paper by Harris and Sollis (2003) and Engle (2002) explain the usefulness of ARCH and GARCH models in suggesting that ARCH models are very suitable for studying volatility of time series data. Most of the research in the recent years has been focused on oil and natural gas prices and very little attention, if any, has been given to the volatility of gasoline prices especially in the US. Fan et al. (2008) study the risk spillover between the West Texas Intermediate (WTI) and Brent crude oil spot markets using a variant of GARCH and find that the technique using the GARCH model proves more effective than historical simulation with ARMA forecasts (HSAF) model. Bettendorf, Geest, and Kuper (2009) analyze Dutch gasoline prices using an Exponential GARCH model and find evidence of asymmetric behavior in the volatility of gasoline prices as positive shocks to volatility result in a greater impact than negative shocks. Kilian (2010) explains the significance of the relationship between global crude oil prices and the US gasoline prices using a structured VAR model. Ma et al. (2011) discuss the relationship between grocery shopping behavior and gasoline prices and conclude that gasoline prices have a stronger impact on grocery shopping behavior than any other economic variable. Regnard and Zakoïan (2011) have studied the natural gas spot prices volatility using a GARCH model and explain that there are volatility regime shifts in these prices due to a change in temperature, hence giving another evidence of the use of a GARCH model for studying time series data. Nevertheless, not enough research has been done to test the volatility of US gasoline prices. This paper attempts to examine this issue by testing for persistence in shocks to volatility and the potential for any asymmetric behavior in gasoline prices.

METHODOLOGY

ARCH and GARCH models have been considered the best for modeling volatility of time series.[1] Non-linear GARCH models were introduced to capture the effect of good and bad news separately. One of the popular explanations for the use of ARCH and GARCH models is that volatility in high-frequency time-series data is time-varying, i.e., time periods of high volatility have a tendency to cluster and hence ARCH and GARCH models and their variants seem to work better for these types of data. As mentioned earlier, many researchers have used the ARCH and GARCH models to study high-frequency time series as they usually provide a better fit compared to some other models. The data used in this paper shows that time periods of high volatility seem to cluster with time periods of high volatility and vice versa which justifies the use of GARCH models. The paper utilizes a univariate GARCH model to study the persistence of volatility in gasoline prices return volatility and an Exponential GARCH (EGARCH) model to study the asymmetric behavior of the return series as a response to any exogenous shocks[2]. The two models are described as follows:

GARCH (1,1) model

The GARCH (1,1) can be written as:

$$Y_t = \mu + \varepsilon_t, \quad \varepsilon_t \,|\, I_{t-1} \sim N(0,h_t) \qquad (1)$$

$$h_t = \omega + \alpha\,\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (2)$$

The first equation is the mean equation whereas the second equation is the conditional variance equation from the univariate GARCH model. The term (1,1) in GARCH (1,1) refers to a first-order autoregressive GARCH term and a first-order moving ARCH term. Volatility of the time series is given by Y_t whereas h_t is the forecast variance in time period t based upon time period t-1. The residual term is given by ε_t where N is the conditional normal density with mean and variance within parenthesis. The information set available at time t-1 is given by I_{t-1}. The ω in the variance equation is the mean, the conditional variance from the previous period is given by h_{t-1} and ε_{t-1}^2 is the news from the previous period. The ARCH term in the variance equation is given by α which captures information about previous period observed volatility and β is the GARCH term which describes the previous period forecasted variance. Engle and Bollerslev

[1] Please refer to Engle (2002) for a detailed survey.
[2] Please refer to Hamilton (2003) for a discussion on oil shocks.

(1986) explained that the sum of the coefficients α and β in equation (2) measures the persistence of volatility for a shock (news). The shocks to volatility will be more persistent as the sum of α and β gets closer to 1, meaning the conditional variance will take a long time to get back to its steady state. If α plus β equals 1 then it becomes an *integrated* GARCH (IGARCH) process meaning a permanent effect of shocks on the variance of a series. The sum of α and β is expected to be close to 1 meaning high persistence of shocks. The AR (1) (autoregressive process of order one) specification for mean equation is used as the series shows significant autocorrelation detected by the Ljung-Box Q-statistic.

EGARCH (1,1) model

Typically for most time series, downward movements are followed by greater volatility as opposed to upward movements of comparable size, which can be explained in terms of the asymmetric impact of news on volatility. Exponential GARCH (EGARCH) model which was proposed by Nelson (1991) is a variant of GARCH and is designed to capture the asymmetries in the model. According to Engle and Ng (1993) the EGARCH model allows positive shocks (good news) to have a different impact on volatility than negative shocks (bad news.) The EGARCH model guarantees nonnegative forecasts of conditional variance[3]. The conditional variance is given as:

$$\text{Log}(\sigma_t^2) = \omega + \beta\log(\sigma_{t-1}^2) + \alpha(\varepsilon_{t-1}/\sigma_{t-1}) + \delta(\varepsilon_{t-1}/\sigma_{t-1}) \qquad (3)$$

Here, the term δ captures the asymmetric response so when the value of δ is zero, there is no significant difference in the effect of good news versus bad news. A non-zero value of δ signifies that good news has a different impact in contrast with bad news. The impact of bad news is measured by the difference between the values of α and δ and vice versa. Given a positive value of α, a negative value of δ will mean that the effect of bad news is greater than the effect of good news.

DATA

The data on US gasoline prices is published by the US Energy Information Administration. The paper uses weekly data for the four different regions of the US, namely East Coast, Midwest, Rocky Mountain, and West Coast, for a ten year time period starting January, 2002 and ending at January 2012 with a total of 523 usable observations[4]. The range of data is important because gasoline prices have shown more volatility over the past ten years than any other time in history. In the recent years, supply fears and political unrest in the Middle East has led to huge fluctuations in crude oil prices and hence causing fluctuations in gasoline prices since gasoline is a direct bi-product of oil.

Descriptive statistics of the gas price returns are given in table 1 which shows some evidence of skewness and kurtosis. A normally distributed random variable has zero skewness and kurtosis of three. The results here show that all of the series except for East Coast are

[3] Threshold ARCH (TARCH) is another variant of GARCH designed to capture asymmetries but does not guarantee nonnegative forecasts of the conditional variances.
[4] The number of observations is in conformity with earlier research.

negatively skewed and all of them have fat tails. The variables are non-normally distributed as shown by the probability values of the Jarque-Bera (1980) test statistic. The significant p-values for the Ljung-Box Q-statistic mean that autocorrelation exists in the residuals. The presence of unit root in the return series is confirmed by the results of the Augmented Dickey-Fuller (1979) and the Phillips-Perron (1988) tests which can be seen in table 2.

EMPIRICAL RESULTS

Table 3 shows the results for the GARCH (1,1) model and the sum of the ARCH and GARCH terms given by α and β respectively is close to 1 for all series which indicates that persistence of shocks to volatility is significantly high meaning that any news will have a long term effect on gas prices in all four regions of the US being discussed in this paper. The highest sum for α and β is for the rocky mountain and the west coast regions indicating a nearly permanent effect of shocks (news) to volatility. These results are consistent with the expectations laid out in this paper earlier.

The second part of table 3 shows results for the Exponential GARCH model. Here the estimated values of δ describe the asymmetric response of shocks to volatility of the series. A positive δ value implies a greater impact of positive shocks or good news whereas a negative δ value implies that negative shocks or bad news has a greater impact on the volatility of the series. The effect of positive or negative news will be the same as negative news when δ has a zero value. The value of δ is positive for all regions except for the rocky mountain region. Based on the p-values given in parenthesis, all results are statistically significant except for the value of δ (0.71) for the Midwest region. A positive and significant value of δ for the east coast and the west coast regions indicate that good news has a greater impact on the returns of gasoline prices. These results are consistent with some of the earlier research studies. However, for the rocky mountain region, a significant yet negative value of δ indicates that negative shocks or bad news have a greater impact on the return series which contradicts with what previous researchers have suggested.

CONCLUDING REMARKS

The paper attempts to study the persistence of exogenous shocks to volatility as well as how positive (good) or negative (bad) shocks or news may have an asymmetric effect on the volatility of return series of gasoline prices from the four different regions of the US. The results of the GARCH and Exponential GARCH models show that shocks to volatility is quite high for all series showing that any exogenous shocks may leave long term effects on the volatility of return series. The results of the Exponential GARCH model show that three out of four regions show asymmetric response to positive versus negative shocks. For the rocky mountain region, a bad news or a negative shock will have a greater impact on the returns of gasoline prices than any positive shocks or news. These results are important for investors in the futures and commodity markets. The results are also important for consumers as they shed some light as to why gasoline prices drop quickly as opposed to some other regions of the US. The paper will function as a doorstep to more research topics involving gasoline prices in the US. The authors hope to continue this research using data with different frequencies and employ other variants of the GARCH model to check the robustness of these results.

REFERENCES

Bettendorf, L., Geest, S. A. van der, and Kuper, G. H., 2009. "Do daily retail gasoline prices adjust asymmetrically?," *Journal of Applied Statistics*, vol. 36(4), pages 385-397

Bollerslev, T., 1986, Generalized Autoregressive Conditional Heteroscedasticity, *Journal of Econometrics* 31, 307-327.

Brooks, C., and Persand, G. 2003, Volatility Forecasting for Risk Management, *Journal of Forecasting* 22, 1-22.

Dickey, D., Fuller, W., 1979, Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association* 74, 427–431.

Ederington, Louis H. and Guan, Wei, 2010, How asymmetric is U.S. stock market volatility?, *Journal of Financial Markets*, 13, 225-248

Engle, R., 1982, Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of the U. K. Inflation, *Econometrica* 50, 987-1008.

Engle, R.F., and T. Bollerslev, 1986, Modeling the Persistence of Conditional Variances, *Econometric Reviews* 5: 1-50.

Engle, R., T. Ito and W. Lin, 1990, Meteor Showers or Heat Waves?: Heteroscedasticity Intra-Daily Volatility in the Foreign Exchange Markets, *Econometrica*, 58, 525-42.

Engle, R. F. and R. Susmel, 1993, Common Volatility in International Equity Markets, *Journal of Business and Economic Statistics* 11, 167-176.

Engle, R. F., and Ng, V. K., 1993, Measuring and Testing the Impact of News on Volatility, *Journal of Finance* 48, 1749-78.

Engle, R., 2002, New Frontiers for ARCH Models, *Journal of Applied Econometrics* 17, 425-446.

Ewing, B. T. 2002. The Transmission of Shocks among S&P Indexes, Applied Financial Economics 12, 285-290.

Fan, Ying, Yue-Jun Zhang, Hsien-Tang Tsai, and Yi-Ming Wei, 2008, Estimating 'Value at Risk' of crude oil price and its spillover effect using the GED-GARCH approach, *Energy Economics* 30, 3156-3171.

Hamilton, J. D., 2003, What is an Oil Shock?, *Journal of Econometrics* 113, 363-98.

Harris, R., Sollis, R., 2003, Applied Time Series Modelling and Forecasting. *John Wiley and Sons Limited, Chichester, England*.

Hassan, S. Aun and Malik, Farooq, 2007, Multivariate GARCH Model of Sector Volatility Transmission, Q*uarterly Review of Economics and Finance*, Vol. 47, No. 3, 470- 480.

Hassan, S. Aun, 2011, Modeling Asymmetric Volatility in Oil Prices, *Journal of Applied Business Research*, Vol. 27, No. 3, 71-78.

Jarque, C.M., Bera, A.K., 1980, Efficient tests for normality, homoskedasticity and serial independence of regression residuals, *Economics Letters* 6, 225–259.

Kilian, L., 2010, Explaining Fluctuations in Gasoline Prices: A Joint Model of the Global Crude Oil Market and the U.S. Retail Gasoline Market, *Energy Journal*, Vol. 31 Issue 2, 87-112.

Lee, K., Ni, S., and Ratti, R. A., 1995, Oil Shocks and the Macroeconomy: The Role of Price Variability, *Energy Journal* 16, 39-56.

Ma, Y., Ailawadi, K. L., Gauri, D. K., and Grewal, D., 2011, An Empirical Investigation of the Impact of Gasoline Prices on Grocery Shopping Behavior, *Journal of Marketing* Vol. 75, No. 2, pp. 18-35.

Malik, F., Ewing, B. T., and Payne, J. E., 2005, Measuring Volatility Persistence in the Presence of Sudden Changes in the Variance of Canadian Stock Returns, *Canadian Journal of Economics* 38, 1037-56.

Nelson, D. B., 1991, Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica* 59, 347-370

Phillips, P.C.B., Perron, P., 1988, Testing for a unit root in time series regression, *Biometrika* 75, 335–346.

Regnard, N., and Zakoïan, J-M., 2011 A conditionally heteroskedastic model with time-varying coefficients for daily gas spot prices, *Energy Economics*, Volume 33, Issue 6, November, 1240-1251.

Table 1
Descriptive Statistics for Return Series

	East Coast	**Midwest**	**Rocky Mountain**	**West Coast**
Mean	0.0021	0.0019	0.0018	0.0019
Median	0.0005	0.0035	0.0010	0.0009
Maximum	0.1928	0.1492	0.1317	0.0798
Minimum	-0.0944	-0.1244	-0.0992	-0.0792
Std. Dev.	0.0230	0.0294	0.0197	0.0176
Skewness	0.7789	-0.0880	-0.4430	-0.2404
Kurtosis	13.7238	4.8997	11.0508	6.5505
Jarque-Bera	2558.90 (0.00)	79.32 (0.00)	1429.55 (0.00)	279.74 (0.00)
Sum	1.0752	1.0139	0.9183	0.9687
Sum Sq. Dev.	0.2768	0.4512	0.2027	0.1613
Q(16)	275.97 (0.00)	105.42 (0.00)	868.63 (0.00)	757.90 (0.00)
Observations	523	523	523	523

Notes: The above statistics are for weekly gasoline returns. Q(16) is the Ljung-Box statistic for serial correlation. Jarque-Bera statistic is used to test whether or not the series resembles normal distribution. Actual probability values are in parentheses.

Table 2
Unit Root Tests

ADF	0.0000	0.0000	0.0000	0.0000
Lags	2	6	1	0
PP	0.0000	0.0000	0.0000	0.0000
Bandwidth	7	8	9	3

Notes: The lag length of the Augmented Dickey-Fuller (ADF) test was automatically selected through the Schwarz information criterion and the bandwidth for the Phillips-Perron (PP) was set using the Bartlett Kernel.

Table 3
GARCH (1,1)

	α	β	$\alpha + \beta$	TR^2	Q(16)
East Coast	0.20 (0.00)	0.72 (0.00)	0.92	0.03 (0.44)	18.88 (0.28)
Midwest	0.10 (0.04)	0.80 (0.00)	0.90	0.02 (0.64)	15.00 (0.53)
Rocky Mountain	0.25 (0.02)	0.74 (0.00)	0.99	0.01 (0.90)	21.66 (0.16)
West Coast	0.08 (0.02)	0.91 (0.00)	0.99	0.07 (0.10)	13.09 (0.67)

EGARCH (1,1)

	α	**δ**	**α + δ**	**TR^2**	**Q(16)**
East Coast	0.29 (0.03)	0.24 (0.00)	0.53	-0.00 (0.93)	22.42 (0.13)
Mid West	0.24 (0.01)	0.03 (0.71)	0.27	0.04 (0.31)	15.61 (0.48)
Rocky Mountain	0.68 (0.01)	-0.12 (0.01)	0.56	0.04 (0.34)	21.40 (0.16)
West Coast	0.26 (0.03)	0.21 (0.00)	0.47	0.01 (0.90)	17.41 (0.36)

Notes: The sum of α and β is close to 1 showing shocks to volatility of gasoline prices are highly persistent. TR^2 refers to the ARCH LM test for a null of no ARCH in the residuals. The Ljung-Box Q-statistics are given in the last column with 16 lags and tested for a null hypothesis of no autocorrelation.