Wild Oil Prices, but Resilient Natural Gas Markets!

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Abstracts

This paper investigates the association between volatility of crude oil and U.S. natural gas prices under two alternative models: Normal distribution and skewed-t distribution models. Despite evidence of significant kurtosis for both energy prices the paper shows the Normal distribution model outperform the skewed t-distribution model. It is also indicated in the paper despite evidence of low correlation between volatility of the two prices, the sensitivity of natural gas price to oil price change increased substantially when crude oil price surged above $40 per oil barrel. This implies that the association between volatility of the two prices is more complex than can be captured by constant relationship.

Keywords: GARCH, Volatility, Skewness, Kurtosis
JEL Codes: C22,C32, Q4

1-Introduction:

For many years in the past, natural gas and refined petroleum products viewed as close substitutes, as major users of natural gas substituted one product for the other depending on the price level of each. As a result, a common view held by some (Brown and Yucel, 2007) is that natural gas prices adjust to crude oil prices which in turn determined by world oil market conditions. Such stable relationship between oil prices and natural gas prices led in the past to the use of rules of thumb in energy industry that relate natural gas prices to those for crude oil. The simplest of these rules predict a constant relationship between the two prices[1]. However, as oil prices surged upward in past recent years the association between the two energy prices seemed more complex than can be explained by the simple relationship implied by the rules of thumb. As a result, in recent years the relationship between crude oil prices and natural gas prices became the focus of research work in the field of energy economic.

Serletis and Ricardo (2004) investigate the strength of shared trends and shared cycles between crude oil prices and Henry Hub natural gas prices using testing procedure suggested by Engle and Kozicki (1993), and Vahid and Engle (1993) to reject the null-hypothesis of common and codependent cycles. Similarly, Bachmeir and Griffin (2006) indicate that in recent years although natural gas prices have shown upward movements with crude oil prices, the natural gas prices seemed to lag well behind oil price movements. However, Villar and Joutz (2006), Asche and Sandsmark (2006) detect only long-term relationship between the two prices. In a different theoretical framework, Chen and Forsyth(2006), use stochastic regime switching models to confirm regime switching models explain better the dynamics of gas derivative prices. The findings of regime switching dynamic models support evidence of time-varying coefficient models rather than constant coefficient models implied by rules of thumb models.

To Investigate the relationship between natural gas price changes and crude oil price variability in this paper the Market Model, or what Sharpe (1963) originally called the diagonal model is employed. Unlike the error correction and cointegration approach adopted in the above mentioned research work,

[1] One simple rule determine natural gas prices as one tenth of crude oil prices, whereas another rule that takes the energy content of a barrel of oil, determine natural gas price as one sixth of crude oil price. For more details about these rules see Brown and Yucel (2006).

the Market Model approach has the benefit of measuring the range of variation of the sensitivity of natural gas prices to oil price changes.

Such information can play a key role when pricing derivatives on natural gas such as gas futures, options, gas storage facility contracts, and gas supply contracts as it allows assessment of upper and minimum levels of risk when holding such future contracts.

The remaining part of the paper is structured as follows. Section two includes basic statistical analysis. Section three illustrates the methodology of the research. Section four includes estimation results, and the final section concludes the study.

2. Summary Statistics:

Data employed in this study are weekly Henery Hub natural gas prices and West Texas intermediate crude oil prices as reported in the Wall Street Journal and recorded as daily series in the data base of the Center for Energy Studies of Luisiana State University. The sample period covers from January-2-1996 to August-30-2007, including 496 observations. Results in table (1) indicate the two energy prices yield positive mean returns. The high value kurtosis statistics indicate the stock price returns distribution is characterized by high peakness (fat tailedness) . The positive skewness results indicate a higher probability for energy prices increase.

The Jarque-Bera (JB) test statistic provides clear evidence to reject the null-hypothesis of normality for the unconditional distribution of the two price changes. The sample autocorrelation statistic indicated by Ljung-Box , Q statistic, show the Q(5) test statistic reject the null hypothesis of uncorrelated price changes for five lags. The high values for $Q^2(5)$ test statistic suggest that conditional homoskedasticity can be rejected for the two prices. To test the presence of hetroskidasticity more formally the LM test is employed. Results of LM statistics for ARCH(1) and ARCH(5) error terms confirm the significance of ARCH effects in the data.

Table (1): Summary statistics of log-differenced Energy prices.

	Gas	**Oil**
Mean	**0.004**	**0.01**
Skewness	**2.62**	**18.1**
Excess kurtosis	**30.1**	**377**
JB test **p-value**	**18808** **(0.00)**	**24850** **(0.00)**
Q(5) **p-value**	**11.8** **(0.04)**	**0.60** **(0.98)**
$Q^2(5)$ **p-value**	**40.7** **(0.00)**	**0.00** **(0.99)**
LM ARCH(1) **p-vlue**	**674** **(0.00)**	**98** **(0.00)**
LM ARCH(5) **p-value**	**837** **(0.00)**	**909** **(0.00)**

3- Methodology

3.1: Volatility modeling:

Although the simple GARCH specification is widely used in the empirical research of finance, there are substantial evidences that volatility of asset returns characterized by time varying asymmetry (Glosten, Jagannathan and Runkle (1993). As a result, to avoid misspecification of the conditional variance equation, a leverage term in the GARCH specification is included.

The GARCH-type specification introduced by Glosten, et al, (1993) allows a quadratic response of volatility to news with different coefficients for good and bad news, but maintains the assertion that the minimum volatility will result when there is no news[2].

To model the sensitivity of natural gas price change to crude oil price changes the following market model is employed:

$$\Delta G_t = \eta + \beta_t \Delta P_t + e_t \qquad (1)$$

$$\text{where} \quad e_t = \sigma_t z$$

$$z_t \overset{i.id}{\sim} f(\omega;0,1)$$

$$\text{and} \quad \sigma^2{}_t = \alpha_0 + \sum_{q=1}^{Q} \alpha_q e^2{}_{t-q} + \sum_{p=1}^{P} \delta_p \sigma^2{}_{t-p} + \varepsilon_t$$

where ΔP_t is the change in crude oil price, and ΔG_t is the change in natural gas price. η and β_t are a constant, and beta respectively.

e_t is a random error term specific to ΔG_t and is assumed to be uncorrelated with ΔP_t. And f(.) is the density function of the standardized residuals, z_t, where $E(z_t) = 0$, $v(z_t) = 1$, and ω is a vector of parameters reflecting skewness and kurtosis parameters. Equation (1) hypothesize that there is a systematic linear relationship between change in natural gas prices and crude oil price changes. The slope coefficient is often called the measure of volatility, sensitivity, or systematic risk. In this case it tells us that when crude oil price for a given period is 1% above its mean, the corresponding

[2] Any selection of an appropriate ARCH/GARCH model requires having a good idea of what empirical regularities the model should capture. Among documented other regularities in the literature are thick tails that characterize asset returns, and volatility clustering, which refers to the phenomena that large changes in volatility tend to be followed by large changes of either sign, and small changes to be followed by small changes.

change of natural gas price is β% higher than its mean return, and vice versa when oil price change is 1% below its mean.

In GARCH-type models the variance covariance matrix of change in the prices of oil price and natural gas are not constant over time. In this case beta defined as:

$$\beta_t^{GARCH} = \frac{\text{cov}(\Delta G_t, \Delta P_t)}{\text{var}(\Delta P_t)} \qquad (2)$$

so that equation (1) becomes,

$$\Delta G_t = \eta + \beta_t^{GARCH} \Delta P_t + e_t \qquad (3)$$

One approach to estimating β_t^{GARCH} is to estimate conditional covariance, $Cov(\Delta G_t, \Delta P_t)$ and conditional market variance $Var(\Delta P_t)$. Adopting asymmetric GARCH- type model the problem can be reduced to estimating the following specifications of variance and covariance equations:

$$\text{var}(\Delta G_t) \equiv \sigma^2{}_t = \omega + \sum_j [\alpha_j{}^+ I(e_{t-j} > 0) \,|\, e_{t-j} \,|^\lambda + \alpha_j{}^- (I-1)(e_{t-j} \le 0) \,|\, e_{t-j} \,|^\lambda]$$
$$+ \sum_{j=1} \delta_j \sigma^2{}_{t-j} \qquad (4)$$

where I denotes indicator function taking on the values of 1 when $e_{t-1} > 0$, and 0 otherwise. The threshold ARCH (TARCH) model of Zakoian (1993) corresponds to equation (4) with $\lambda = 1$, whereas GJR–GARCH –type specification treats equation (4) with $\lambda = 2$, to allow for quadratic response of volatility to news with different coefficients for good and bad news, while maintaining the possibility that minimum volatility occur when there is no news. Similarly, the variance of crude oil price from equation (4) hold.

The situation that $\alpha^{+} > 0,$ captures the asymmetric relationship between news (e_t) and volatility. For example, when $e_{t-j} > 0,$ then I=1 and the conditional variance becomes,

$$\sigma^2{}_t = \omega + \sum_{j,q} \alpha_i{}^{+} e^2{}_{t-j} + \sum_{j,p} \delta_j \sigma^2{}_{t-j}$$

and when $e_{t-j} < 0,$ then I=0 and the conditional variance becomes

$$\sigma^2{}_t = \omega + \sum_{j,q} \alpha_i{}^{-} e^2{}_{t-j} + \sum_{j,p} \delta_j \sigma^2{}_{t-j}$$

Therefore, the negative news result in a variance level different from that associated with positive news. This type of investors behavior imply risk aversion attitudes depend on the magnitude of risk investors expecting to face.

Since it can be verified from (4), that $E(R_i - E(R_i))^2 = E(e_i{}^2)$ then $v(R_i) = v(e_i), v(R_m) = v(e_m)$. Then the conditional covariance of the two prices can be computed by:

$$\text{cov}(\Delta G_t, \Delta P_t) = \rho \sqrt{\sigma^2{}_t \sigma^2{}_{p,t}} \qquad (5)$$

where ρ is the correlation coefficient between ΔG_t and ΔP_t.

3.2: Skewness effect:

It is well documented that even asymmetric GARCH models fail to fully account for skewness and leptkurtosis of high frequency financial time series when they are assumed to follow normal or symmetric student's t-distributions. This has led to the use of asymmetric non-normal distributions to better specify conditional higher moments. An important candidate in this respect is Hansen's (1994) distribution. Despite there are also other distributions that allow for skewness and excess kurtosis we choose Hansen's distribution due to its simplicity and its superiority in empirical performance (Patton, 2004).

Given the standardized errors $z_t = \frac{\varepsilon_t}{\sqrt{\sigma^2{}_t}}$, with mean zero and variance one, then Hansen's (1994) autoregressive conditional density model with skewed error terms specified as:

$$skt(z \backslash \phi, \theta) = \begin{cases} bc\left(1 + \frac{1}{\theta - 2}\left(\frac{bz + a}{1 - \phi}\right)^2\right)^{-(\theta+1)/2} & if\ \ z < -a/b \\ bc\left(1 + \frac{1}{\theta - 2}\left(\frac{bz + a}{1 + \phi}\right)^2\right)^{-(\theta+1)/2} & if\ \ z \geq -a/b \end{cases} \tag{6}$$

where Γ is a gamma function, and

$$a = 4\phi c\frac{\theta-2}{\theta-1}, \quad b = 1+3\phi^2 - a^2 \ , \quad c = \frac{\Gamma(\theta+1)/2}{\sqrt{\pi(\theta-2)}\Gamma(\theta/2)} \qquad (7)$$

Specification of conditional distribution of the standardized residuals, $Z_{t,}$ in equation (6) is determined by two parameters, Kurtosis (θ) and the skewness parameter (ϕ).The two parameters are restricted to $\theta > 2,$ and $-1 < \phi < 1$. When $\phi = 0,$ the skewed t-distribution tend to symmetric t-distribution, and when $\theta \to \infty$, tend to standardized normal distribution.

Hansen's skewed t-distribution is fat tailed, and skewed to the left (right) when ϕ is less (greater) than zero. Similar to the case of Student's t-distribution, when $\theta > 2,$ Hansen's skewed t-distribution is well defined and its second moment exist, while skewness exist if $\phi \neq 0$ and kurtosis is defined if $\theta > 4,$. The formulas for the third and fourth moments of Hansen's skewed distribution are given as:

$$E(Z^3) = (m_3 - 3am_2 + 2a^3)/b^3$$
$$E(Z^4) = (m_4 - 4am_3 + 6a^2 m_3 + 6a^2 m_2 - 3a^4)/b^4$$

where

$$m_2 = 1 + 3\phi^2$$
$$m_3 = 16c\phi(1+\phi^2)\frac{(\theta-2)^2}{(\theta-1)(\theta-3)} \qquad if \ \theta > 3$$
$$m_4 = 3\frac{\theta-2}{\theta-4}(1+10\phi^2+5\phi^4) \qquad if \ \theta > 4$$

(for proof see Hansen, 1994, and also Jondeau, and Rockinger 2000).

The log-likelihood function of the GJR-skt is defined as:

$$L(\Omega;\Psi_{t-1}) = \sum_{t=2}^{T} \ln[SKt(z \setminus \theta, \phi; \Psi_{t-1})]$$

The maximum likelihood estimator for Ω is the solution of maximizing the log likelihood function with respect to the unknown parameters.

3.3: Performance Evaluation:

To determine which model better describes volatility dynamic of the two prices, in this paper the predictive power of volatility forecast criteria is employed. To compute s-step ahead forecast for the conditional variance in equations (1) - (4), we need first to simplify equation (4) by assuming:

$$E(I(e_t > 0) = p(e_t > 0) = 0.5$$
$$E(I - 1)(e_t \leq 0) = p(e_t \leq 0) = 0.5$$
$$and$$
$$E(e^2 \setminus \Omega_t) = \sigma^2{}_t$$

Since ${e^2}_t$ and the indicator function $I_t(e_t)$ are uncorrelated, then s-step ahead forecast can be stated as:

$$\hat{\sigma}^2{}_{t+s\setminus t} = w + [(0.5\alpha^+ + 0.5\alpha^-) + \delta]\sigma^2{}_{t+s-1\setminus t} \qquad (8)$$

The parameters of the two models estimated using the sample data up to three days before the end of the sample date (Jan/13/2007). And then a forecast of one day ahead (Jan-14 observation) is computed. Using the estimated parameters and the one day-ahead forecast value of volatility a new forecast for volatility of Jan-15, is computed from equation (8) to obtain two days ahead forecast vaue. This procedure is repeated until we exhaust the actual realized values.

To test the predictive power of the two competing models (GJR-N, and GJR-skt) the Root Mean Squared Error (RMSE) employed, which is computed by comparing the forecast values F_{t+j} with the actually realized values, A_{t+j},

or $$RMSE(k) = \sqrt{\sum_{j=0}^{N_k - 1} \frac{[F_{t+j+k} - A_{t+j+k}]^2}{N_k}}$$

Where k=1,2,3 denotes the forecast step, N_k, is total number of k-steps ahead forecasts.

Diebold and Mariano (1995) (DM) test has been employed to compare the accuracy of forecasts. When comparing forecasts from two competing models; model A, and model B, it is important to verify that prediction of model A is significantly more accurate, in terms of a loss function, DM(d), than the prediction of model B. The Diebold and Mariano test aims to test the null hypothesis of equality of forecast accuracy against the alternative of different forecasts across models. The null hypothesis of the test can be written as:

$$d_t = E(h(e_t{}^A) - h(e_t{}^B)) = 0 \qquad (9)$$

where $h(e_t{}^i)$ refers to volatility forecast error of model i =A, B, when performing k-steps ahead forecast. The Diebold and Mariano test uses the autocorrelation-corrected sample mean of d_t in order to test significance of equation (9). If N observations available, the test statistic is:

$$DM = [\hat{w}(\bar{d})]^{-1/2}\,\bar{d}$$

$$where \quad \hat{w}(\bar{d}) = \frac{1}{N}\{\hat{\rho}_0 + 2\sum_{h=1}^{K-1}\hat{\rho}_h\}$$

and

$$\hat{\rho}_h = \frac{1}{N}\sum_{t=h+1}^{N}(d_t - \bar{d})(d_{t-h} - \bar{d})$$

Under the null hypothesis of equal forecast accuracy, DM is asymptotically normally distributed.

4: Results

The analysis in this paper investigate the association between conditional volatility of crude oil and natural gas prices assuming asymmetric GARCH, Normal distribution and skewed-t distribution models. Results reported in table (2) indicate as a result of crude oil price rise above $40 per oil barrel, the responsiveness of natural gas price to 1 per cent of oil price change increased from 0.3 per cent to 0.7 per cent. Also indicated in the same table, the range of variation (low and high) of such association between the two prices increased from (0.002 and 0.009) to (0.004 and 0.03). The correlation between volatility of the two prices is found very small.

Table (3) includes estimation of parameters of the equations (4), (6), and (7). The significance and the sizes of the asymmetry coefficients (α^-) and (α^+) for the normal distribution model indicate negative and positive news have equal effect on volatility of energy prices. Despite skewed t-distribution model indicate significance of the Kurtosis coefficient (θ) for the two price series, the insignificance of the conditional skewness parameter (ϕ) for the two energy prices combined with the log-likelihood values and the superior predictive performance of the normal distribution model as indicated by Diebold-Mariano test (table 4), strongly suggest the normal distribution model outperforms skewed t-distribution (GJR-skt) model, as it yield the lowest values of the RMSE loss functions compared to GJR-skt distribution specification. DM test statistic confirm that the predictive power of the two models are significantly different for all sectors; implying that GJR-N specification yield superior forecast performance for forward-looking beta values.

Table (2): Beta Coefficients.

sectors	GJR-GARCH (Low oil prices)	GJR-GARCH (full sample)
Mean (low/high)	0.003 (0.002/0.009)	0.007 (0.004/0.03)
Std. Deviation	0.001	0.02
Correlation (ρ)	0.001	0.004

Note: The main entries are mean values of Betas.
Low oil price is $40 or less per oil barrel .

Table (3):Conditional volatility parameter estimates

	Oil GARCH(1,1)		**Gas ARCH(1)**	
	GJR-t skew	**GJR-Normal**	**GJR-t skew**	**GJR-Normal**
ω	0.01	0.00	0.00	0.00
(p-value)	(0.00)	(0.03)	(0.68)	(0.41)
δ	0.15	0.001	0.00	-0.01
(p-value)	(0.00)	(0.93)	(0.91)	(0.00)
α^{+}	-0.01	1.01	0.24	0.99
(p-value)	(0.01)	(0.01)	(0.00)	(0.00)
α^{-}	-0.13	0.99	0.15	1.0
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
ϕ	0.46	-	0.07	-
(p-value)	(0.16)		(0.46)	
θ	3.91	-	3.99	-
(p-value)	(0.00)		(0.00)	
LnL	2300	17684	1904	5514

Conditional skewness and kurtosis parameters estimated using MLE and Quasi-Newton optimization algorism.

Table (4): RMSE Loss functions and Diebold & Mariano test.

	RMSE Loss Functions		D&M
	GJR-N	GJR-sk(t)	statistic
Full-sample	0.03	0.28	11.3
(p-value)			(0.00)
Low oil price	0.02	0.13	12.2
(p-value)			(0.00)

*The loss functions are based on three days ahead forecast errors. Root Mean Square Error (RMSE) and Diebold-Mariano (1995) test results in table (4) are based on the full sample period and on the low oil price period which is the period from January-2-1996 to July-14-2004, when crude oil price was below $40 per barrel.

Conclusion:

In pursuit for obtaining better specification of the relation between crude oil and natural gas prices, in this paper the focus on use of time-varying volatility models assuming normal and skewed t-distribution of error terms. An appropriate specification of time-varying volatility depends on what empirical regularities the model should capture. An important regularity that has been taken into account in the paper is the “leverage effect” phenomena which refers to the different response of volatility to bad news as compared to good news. To account for this type of asymmetric effect of news on volatility in this paper Glosten, Jagannathan, and Runkle (1993) specification of GARCH model is adopted. GJR-GARCH specification separates the effect of negative news on volatility from that of positive news. An important finding in this paper, unlikely to financial assets there is no evidence of leverage effect in energy markets. Also indicated in the paper, based on the predictive power performance of the two models, and log-likelihood values, the Normal distribution model outperforms the skewed t-distribution model in explaining dynamics of volatility.

The paper shows at low crude oil price levels (below $40 per oil barrel) the sensitivity of natural gas price volatility to 1 per cent of oil price changes is 0.3 per cent but as oil prices surged above $40 per oil barrel, such sensitivity increased to 0.7 per cent. This indicates the association between the two energy prices is more complex than can be explained by simple rules of thumb that predict constant relationship between the two prices.

Important implication of the finding in this paper is that estimation of the range of variation of the sensitivity of natural gas price to oil price changes allows better assessment of upper and minimum risk levels that can be utilized in pricing derivatives on natural gas such as gas futures and option contracts, and gas storage facility contracts.

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