Realized Volatility and Correlation in Energy Futures Markets

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ABSTRACT

Using high frequency returns, we examine realized volatility and correlation on the NYMEX light, sweet crude oil and Henry-Hub natural gas futures contracts. The unconditional distributions of daily returns and daily realized variances are non-Gaussian while the distributions of the standardized returns (normalized by the realized standard deviation) and the (logarithms of) realized standard deviations appear approximately Gaussian. The (logarithms of) standard deviations exhibit long-memory, but the realized correlation between the two futures does not, implying rather weak inter-market linkage in the long run. There is evidence of asymmetric volatility for natural gas but not crude oil futures. Finally, realized crude oil futures volatility responds with an increase in the weeks immediately before the OPEC events recommending price increases.

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INTRODUCTION

Financial market volatility plays a central role in the theory and practice of asset pricing, asset allocation and risk management. Indeed, there is an enormous literature on asset return volatility focusing on parametric GARCH models, stochastic volatility models and implied volatility from certain option pricing models. Recently, however, there has been much interest in obtaining improved daily volatility estimates by using high-frequency, intraday returns to construct daily "realized" volatility as the sum of intraday squared returns. Based on the theory of quadratic variation, it can be shown that the realized volatility estimator is a consistent estimator of the actual (but unobservable) volatility (Andersen, Bollerslev, Diebold and Labys, henceforth ABDL, 2001, 2003; Andersen, Bollerslev, Diebold and Ebens, henceforth ABDE, 2001). As such an estimator is model-free and does not depend upon any particular parametric assumptions, a number of subsequent studies have shown the superiority of such realized volatility over conditional volatility generated by various GARCH models and implied volatility from option data (e.g., Martens, 2002; Martens and Zein, 2004; Pong, Shackleton, Taylor, Xu, 2004; Koopman, Jungbacker and Hol, 2005).

In this paper, daily realized volatility and correlation of two important energy futures are constructed and examined using high-frequency, intraday returns. In particular, crude oil futures and natural gas futures contracts listed on the NYMEX are considered. Over the past decade, the NYMEX light, sweet (low-sulfur) crude oil futures contract has become the world's largest-volume futures contract trading on a physical commodity and is used as a principal international pricing benchmark. Also, since the NYMEX launched the world's first natural gas futures contract in April 1990, volume and open interest have grown rapidly, establishing the contract as the fastest growing instrument in the exchange history. Due to the two futures' high trading frequency, prices are available on a tick-by-tick basis which allows us to construct intraday returns.

The paper contributes to the literature in the following aspects. First, to our knowledge, this is the first study to thoroughly examine realized volatilities and correlations in energy markets. While many earlier studies have explored daily realized volatility in individual stocks and stock indexes (ABDE, 2001; Areal and Taylor, 2002; Martens, 2002; Thomakos and Wang, 2003; Martens and Zein, 2004; Chan and Fong, 2006; Illueca and Lafuente, 2006), bonds (Thomakos and Wang, 2003), currencies (ABDL, 2001, 2003; Martens and Zein, 2004; Pong, Shackleton, Taylor, Xu, 2004) and agricultural commodities (Chen, Daigler, and Parhizgari, 2006), unconditional distributions of realized energy futures volatilities and correlation have not yet been examined.[1]

Overall, the findings on distributional properties of daily returns, return volatilities, (log of) standard deviations, standardized returns of the two energy futures contracts are in line with earlier studies (e.g., ABDL 2001, 2003; ABDE, 2001; Areal and Taylor, 2002; Thomakos and Wang, 2003). Hence, much of the stylized facts of realized volatility can be extended to energy futures markets. Nevertheless, there are some important differences from earlier studies. Specifically, the realized correlation between crude oil and natural gas futures is found not to exhibit long memory. The finding extends Chen, Daigler, and Parhizgari (2006), who also found that the amount of volatility persistence differs across the type of futures contract, with agricultural commodity futures possessing less volatility persistence than stock index futures. The finding also sheds more light on the linkage between natural gas and crude oil market, as studied by Bachmeier and Griffin (2006). In addition, the finding on asymmetric volatility also differs from some earlier works using GARCH models (e.g., Switzer and El-Khoury, 2007), as this study finds that natural gas futures volatility reacts stronger to lagged negative returns than lagged positive returns, while it is not the case for oil futures.

Second, the potential OPEC impact on crude oil futures market volatility is investigated using the realized volatility and a more broadly defined news measurement (i.e., the World Oil Market and Oil Price Chronologies which is published by the Energy Information Administration of the U. S. Department of Energy). Thus far, the literature is ambiguous about whether OPEC has a significant impact on world oil markets particularly in more recent periods after the 1980s. For example, Wirl and Kujundzic (2004) and Horan, Peterson and Mahar (2004) found little or at best mixed evidence for the influence of OPEC meetings on the oil price and its volatility. Extending these earlier works, other OPEC-related event dates mentioned in the media beyond OPEC conferences (and Ministerial Monitoring Sub-committee meetings) are considered, and a new finding is documented that realized energy futures market volatility tend to go up before those OPEC meetings that recommend oil price increases.

The remainder of the paper is organized as follows. Section 2 describes the data and realized volatility measurement. Section 3 discusses the empirical results on various aspects of the realized energy futures volatility. Section 4 offers some concluding remarks.

REALIZED VOLATILITY AND CORRELATION MEASUREMENT

Data

This study uses high-frequency, intraday futures returns of NYMEX division light, sweet (low-sulfur) crude oil futures contracts and Henry-Hub natural gas futures contracts. Both futures have open outcry trading from 10:00 A.M. EST until 2:30 P.M. EST. They also have after hours trading via the NYMEX ACCESS internet-based trading platform beginning at 3:15 P.M. EST on Mondays through Thursdays and concluding at 9:00 A.M. EST the following day. In this paper, the data from the open outcry trading only are used. The data are time and sale transaction prices, not bid-ask quotes, recorded by exchange personnel who observe the pits and post the most recent price. The data set begins January 3, 1995 and ends December 30, 1999 for the Crude Oil futures contracts, a total of $T = 1235$ trading days; begins October 2, 1995 and ends September 30, 1999 for Natural Gas futures contracts, a total of $T = 977$ trading days.[2] In calculating the returns series, the nearby contracts are used to construct the continuous returns series for each futures contract.

Since the exchange does not record successive trades at the same price, the median length between price changes should be the upper bound for the median length of the times between trades. During the actual trading, market microstructure frictions, including price discreteness, infrequent trading and measurement errors, may affect the actual price records. In order to mitigate these effects while still sampling at a very high frequency, five-minute return horizons are used in the analysis, consistent with ABDE (2001).

Construction of Realized Futures Volatility and Correlation

The five-minute return series are constructed from the logarithmic differences between the prices recorded at or immediately before the corresponding five-minute marks. In practice, the selection of fixed-discrete-time return depends on the balance between the need of sampling at very high frequencies to approximate continuous-time models and the cost of market microstructure biases. Since tick-by-tick prices are generally available at unevenly spaced time points, it is well-known that the uneven spacing of the observed prices and inherent bid-ask spreads may induce negative autocorrelation in the fixed-discrete-time return series. Hence, the use of a fixed discrete time interval may allow dependence in the mean to systematically bias the volatility measures. Ultimately, the choice of fixed-interval return depends on market liquidity of the contract studied. Compared with the Dow Jones stocks which have a median inter-trade duration varying from 7 seconds for Merck & Co. Inc. to 54 seconds for United Technology Corps (ABDE, 2001, p. 49), the mean length of duration between price changes for Crude Oil futures contracts is 30.50 seconds; for natural gas contracts the mean length of duration is 74.64 seconds.[3] ABDE (2001) and Thomakos and Wang (2003) used five-minute return series to construct the realized daily volatility series. Recently, Bandi and Russell (2006) used optimal sampling to minimize the mean-squared-error in constructing daily realized volatility. By constructing the daily realized volatilities for the S&P100 stocks, they found the mean value of the optimal sampling intervals is around four minutes. Therefore, the choice of five-minute sampling interval is consistent with the literature.

In order to remove the serial correlation induced by the uneven spacing of the observed prices and the bid-ask spread, a MA(1) model is used to “filter” the (demeaned) five-minute return series. This procedure has been used by Thomakos and Wang (2003) and similar MA filters have also been used by ABDE (2001) and ABDL (2001). The estimated innovations are then used in place of the demeaned returns. The estimated moving-average coefficients are 0.0275 for crude oil contracts and 0.0658 for natural gas contracts.

Let the (2×1) vector of raw, five-minute returns be denoted by $\boldsymbol{r}_{t+i\Delta,\Delta}$ where t stands for the t^{th} day, i stands for i^{th} five-minute mark and $1/\Delta$ stands for the number of five-minute returns during a trading day. The filtered series are then given by:

$$\hat{\varepsilon}_{t+i\Delta,\Delta} = [I+\hat{\Theta}L]^{-1}(r_{t+i\Delta,\Delta} - \bar{r}_{\Delta}) \tag{1}$$

where $\hat{\Theta} = diag(\hat{\theta}_1, \hat{\theta}_2)$ is the (2×2) diagonal matrix of estimated MA coefficients and $\bar{r}_{\Delta}$ is the estimated sample mean vector over all observations $\boldsymbol{r}_{\Delta} = (\Delta/T)\sum_{t=1}^{T}\sum_{i=1}^{1/\Delta}\boldsymbol{r}_{t+i\Delta,\Delta}$.

The realized daily covariance matrix, denoted $\boldsymbol{C}_t$, for the two energy futures contracts is then computed as:

$$\boldsymbol{C}_t = \sum_{i=1}^{1/\Delta} \widehat{\boldsymbol{\varepsilon}}_{t+i\Delta,\Delta}\widehat{\boldsymbol{\varepsilon}}'_{t+i\Delta,\Delta} \tag{2}$$

where $t = 1, 2, ..., T$. T is 1235, 977 for the Crude Oil and Natural Gas contracts respectively. $1/\Delta = 54$. Note that only 977 days of observations when both oil futures and natural gas futures were traded are used to construct the daily realized covariances and correlations. The realized volatilities for the two futures contracts are given by the diagonal elements of the realized daily covariance matrix denoted by v_{tj}^2, $j = 1, 2$. The corresponding daily logarithmic standard deviations are denoted as $lv_{tj} = \ln v_{tj}$. The realized covariances are given by the off-diagonal elements of the daily covariance matrix. The daily covariances are constructed by summing the cross products of the five-minute returns within the day. Since there are more trading-day observations for the oil futures than the natural gas futures, only 977 days of observations are used for oil futures to match that of the natural gas futures to construct the daily realized covariances and correlations. Nevertheless, this has no consequence for the results as the study only uses intraday observations to construct daily realized volatilities, covariances and correlations.

With the above in mind, the realized daily correlation matrix is computed as:

$$\boldsymbol{R}_t = \boldsymbol{V}_t^{-1/2}\boldsymbol{C}_t\boldsymbol{V}_t^{-1/2} \tag{3}$$

where $\boldsymbol{V}_t = diag\left(v_{t1}^2, v_{t2}^2\right)$. By explicitly treating the volatilities and correlations as observable, we can now rely on conventional statistical procedures to characterize their distributional properties.

As a matter of definition, let $\boldsymbol{r}_t$ denote the vector of the daily unfiltered raw return series and $\bar{\boldsymbol{r}}$ denote the corresponding sample mean over all trading days. The vector of standardized daily returns is now given as:

$$\boldsymbol{z}_t = \boldsymbol{V}_t^{-1/2}\left(\boldsymbol{r}_t - \bar{\boldsymbol{r}}\right) \tag{4}$$

EMPIRICAL RESULTS

Unconditional Return and Volatility Distributions

Figures 1 and 2 plot the time series for the returns and the standardized returns (along with the realized variances and realized logarithmic standard deviations) for the Crude Oil futures and Natural Gas contract. The summary statistics in Table I show that the daily raw returns analyzed have fatter tails than the normal distribution. The Crude Oil futures returns are skewed to the right while Natural Gas returns are skewed to the left. The sample kurtosis coefficients for all daily returns are greater than three. The results are consistent with the existing literature which finds that the distribution of the daily returns in the asset markets is not normal.

Also presented in Table I are the summary statistics for the standardized returns. These are statistically unconditionally normally distributed for both futures contracts considered. The sample skewness for both contracts is close to zero, and the sample kurtosis is around 3. The close approximation to the normal densities contrasts sharply to the leptokurtic distributions for the standardized daily returns that are typically obtained when relying on an estimate of the one-day-ahead conditional variance from a parametric ARCH or stochastic volatility model. Instead, the summary statistics for these futures returns are consistent with those for the standardized returns found in the realized volatility literature.

Extending many earlier studies, the normality hypothesis is further formally tested in this study, using five statistics to test whether standardized futures returns are normally distributed. These are the Anderson-Darling (AD), Crámer-Von Mises (CVM), Jarque-Bera (JB), Kolmogorov-Smirnov (KS), and the QQ correlation coefficient based on the correlation coefficient between the theoretical quantiles of the standard normal distribution and the order statistics of the sample. Since the standardized returns were found to be serially uncorrelated, the usual critical values can be used when applying these tests. Based on the JB test in Table I, the normality hypothesis is rejected for the standardized returns for both futures contracts. The JB test statistics is 26.40 for Crude Oil and 269.65 for Natural Gas. None of the AD, CVM test statistics can reject the null hypothesis of normality for any of the futures' standardized returns. None of the KS test statistics can reject the normality hypothesis for the standardized returns. The QQ test statistic rejects the null hypothesis for the Natural Gas futures at the one percent level but not for Crude Oil futures. It is well known that all these test statistics will automatically become larger with a larger sample size, and given the sample size of this study it is more reasonable to use the critical values of the one percent level than the five percent level. Therefore, based on the results from virtually all of the tests, the standardized futures returns studied here are Gaussian to a very good approximation.

Table II provides the same set of summary statistics for the unconditional distribution of the realized daily volatilities and the realized logarithmic standard deviations. The realized volatilities, the sum of the five-minute return squared, have means of 0.002 and 0.005 respectively for the Crude Oil and Natural Gas futures contracts. The standard deviations given in the third row also indicate that the realized daily volatilities fluctuate across different futures markets. Furthermore, the distributions of the realized volatilities are skewed to the right, and are significantly leptokurtic relative to the normal distribution, as indicated in rows four and five of Table II.[4]

Also shown in Table II are the distributional characteristics for the realized logarithmic standard deviations of the two futures contracts. The values of the sample kurtosis coefficients of both contracts are reduced to about 3. In this case, the assumption of normality is clearly more appropriate. The same five statistics are employed in testing the normality hypothesis for the realized logarithmic standard deviations, as what has been done for the returns and standardized returns. As discussed below, the logarithmic standard deviations exhibit strong temporal correlation in the form of long-memory. It is possible that the presence of long-memory can have adverse effects on the performance of the normality test statistics. Thomakos and Wang (2003) did a simulation study to examine the extent of the adverse effects of long memory on the performance of the normality test statistics. The simulation results suggest that, when observations exhibit long-memory, the use of the JB test statistic for assessing normality cannot be entertained as an appropriate choice. In contrast, all the other four test statistics appear to be largely unaffected by the presence of long-memory and their use is thus recommended, at least when the sample sizes used for their construction are of the same (or larger) magnitude with the ones used in this study.

Not surprisingly, based on the statistics from the JB test in Table II, the normality hypothesis is rejected for the logarithmic standard deviations for Natural Gas futures contracts. None of the AD, CVM and KS test statistics rejects the normality hypothesis at any significance levels for the logarithmic standard deviations of the two futures contracts. Based on the QQ-test, the normality hypothesis can not be rejected for both contracts at any conventional significance levels.

The evidence on logarithmic standard deviations is consistent with ABDL (2001), ABDE (2001), Areal and Taylor (2002), and Thomakos and Wang (2003) that find that realized daily foreign exchange rate volatilities and realized daily stock returns volatilities constructed from intra-day high-frequency data are approximately log-normally distributed. Hence, the statistical evidence in Table I and II implies that the unconditional distribution for the daily energy futures returns can be well approximated by a continuous lognormal-normal mixture.

Finally, Table III presents the summary statistics and normality tests for daily realized covariance and correlation between Crude Oil and Natural Gas futures. The covariance is heavily leptokurtic and skewed to the right. The assumption of Gaussianity is strongly rejected by all test statistics. The correlation is lightly platykurtic and skewed to the left. The test statistics can not reject the hypothesis of Gaussianity for the correlations (except for the JB test at one percent level and QQ-test at ten percent level). In summary, our results suggest that the realized correlations are approximately normally distributed; however, the evidence is not as strong as the evidence on realized logarithmic standard deviations.

Long-Memory

The long-memory property of asset market volatility has been the subject of extensive research in the last decade. The literature on volatility modeling has documented that such temporal dependencies are highly persistent. The time series for the realized variances and realized logarithmic standard deviations in Figures 1 and 2 for the two futures indeed appear to be positively serially correlated, consistent with the well documented volatility clustering effect reported in the literature (e.g., ABDE, 2001; ABDL, 2001).

As shown in Table IV, based on the standard Ljung-Box portmanteau test for the joint significance of the autocorrelations up to first 20 lags of the logarithmic realized daily standard deviations, the null hypothesis of no serial correlation is overwhelmingly rejected for both futures contracts. For the McLeod-Li test statistics, the inference is qualitatively the same as that from the Ljung-Box test. Moreover, the autocorrelations start around 0.4 and decay slowly.

The low first-order autocorrelations, along with their slow decay, suggest that the logarithmic realized standard deviations do not contain a unit root but exhibit long-memory. A number of studies argue that the long-run persistence in financial market volatility may be modeled by fractional integrated ARCH or stochastic volatility models, see, for example, ABDE (2001). The fourth column of Table IV presents the estimates for the degree of fractional integration, or d , for the logarithmic standard deviations for the two futures contracts. These estimates are obtained using the Gaussian semiparametric estimator of Robinson (1995b).[5] The estimates for the degree of fractional order for the two contracts are 0.35 and 0.37 , and are all statistically significantly different from both 0 and 1. Importantly, parameter estimates d are more than two standard errors away from 0.5 implying that realized logarithmic standard deviations can be treated as covariance stationary and fractionally integrated.

Turning to the standardized returns series, they are also serially uncorrelated. The results in the fourth column of Table IV indicate that the estimates of the fractional order d are all negative (indicating short-memory or *antipersistence*). The two portmanteau tests for serial correlations have values less than the critical value of the $\chi^2_{20}(0.05)$ distribution, which is 31.41, except for the CL series whose Ljung-Box test value is 39.64. The McLeod-Li test does not indicate any significant correlation in the squares of the series. Therefore, there is strong evidence that all standardized returns series are serially uncorrelated.

Finally, the Ljung-Box statistics in Table IV for the joint significance of the first twenty autocorrelations show that the covariances and correlations between Crude Oil and Natural Gas futures are serially uncorrelated. The McLeod-Li statistics, however, give conflicting results. The estimate for the fractional order d for the correlations is -0.0096 . This result is also different from that of Thomakos and Wang (2003) that found the pairwise correlations among four financial futures (stock index, currency and bond futures) have long-memory.

In summary, the temporal characteristics of the realized logarithmic standard deviations and the standardized returns for the energy futures returns series are consistent with the findings from ABDE (2001) for Dow Jones index constituent stocks, ABDL (2001) for exchange rates and Thomakos and Wang (2003) for various financial futures. Realized logarithmic standard deviations can be adequately described by long-memory processes while the standardized returns series are serially uncorrelated. Realized correlations between Crude Oil and Natural Gas futures are also serially uncorrelated.

Asymmetric Volatility

Previous studies have documented asymmetric volatility, that is, the asymmetric relationship between equity volatility and returns: positive returns have a smaller impact on future volatility than have negative returns of the same absolute size. While asymmetric volatility has been examined extensively for stock returns, it has not been examined closely for futures returns, especially for commodity futures returns. Toward this end, the following equation is estimated using least squares:

$$(1-L)^{\hat{d}_{SP,j}} lv_{tj} = \alpha_j + \beta_j (1-L)^{\hat{d}_{SP,j}} lv_{t-1j} + \gamma_j r_{t-1,j} + \delta_j r_{t-1,j} I(r_{t-1,j} < 0) + u_{tj} \qquad (5)$$

where $I(\cdot)$ is the indicator function, j stands for one of the two futures contracts, lv_{tj} is the logarithmic realized standard deviation at time t, lv_{t-1j} is the lagged logarithmic standard deviation and $r_{t-1,j}$ is the lagged return. Our specification is consistent with the literature (e.g., Engle and Ng, 1993; Duffee, 1995).[6] The coefficient on the interacting term δ_j captures any asymmetries. If asymmetries are indeed present, we would expect δ_j to be negative and larger (in absolute magnitude) than the return coefficient γ_j .

Table V reports the regression estimates with their standard errors for both contracts. The γ_j coefficient from the Crude Oil and Natural Gas regressions are both positive and statistically significant. As for the asymmetry coefficient δ_j, the estimates are equal to and 0.0016 and -0.0301 for the Crude Oil and Natural Gas, respectively. The estimate for Natural Gas is with the right sign and statistically significant at the five percent level. Thus, the result on Natural Gas futures contract is consistent with the asymmetric volatility literature, indicating asymmetry in the influence of past negative and positive stock index returns on current futures market volatility. Conversely, the result on the Crude Oil futures contracts does not support the existence of asymmetric volatility.

The Impact of OPEC Conference meetings on Oil Price Volatility

In this section the crude oil futures volatility around OPEC meetings is to be studied. A significant amount of research has been done to assess the extent to which OPEC influences world oil markets. However, the results are ambiguous about whether OPEC has a significant impact on world oil markets. Deaves and Krinsky (1992) found that during the 1980s, the oil market reacted efficiently to the OPEC conferences that were associated with "good news" or bearish price outcomes. However, much research finds a much more diminished role of OPEC on the world oil market after 1985. Recently, Wirl and Kujundzic (2004) found very weak influence of OPEC conferences on the oil prices (Dubai light). Horan, Peterson and Mahar (2004) found that OPEC conferences coincide with little drop in volatility of crude oil futures options and the most pronounced decline in volatility is associated with meetings of the Ministerial Monitoring Committee.

Here, we first try to assess the impact of OPEC conference meetings on the daily volatility of crude oil futures. The appropriate ARFIMA model is estimated to filter daily volatility series. Taking different lag and lead values of the filtered daily volatility (fv_t^i) as dependent variable, a conference dummy c_t is introduced, which equals one if there is an OPEC meeting on that date and zero otherwise as the independent variable. During the sample period, there are 10 OPEC conference meetings and one Ministerial Monitoring Sub-Committee meeting. A second set of dummy variables are also used, based on the World Oil Market and Oil Price Chronologies which is published by Energy Information Administration of U. S. Department of Energy[7]. These dates include both OPEC events and other events that Chronologies deem important to crude oil prices. 68 dates are extracted that are recorded in Chronologies during the sample period. Let the dummy variable $d_t = 1$ if the day is listed in Chronologies and zero otherwise. The following two regressions were estimated:

$$fv_t^i * 1000 = \alpha + \beta c_t + u_t \tag{6}$$

$$fv_t^i * 1000 = \alpha + \beta d_t + u_t \tag{7}$$

The results (available on request) do not give any evidence on the importance of either OPEC meetings or significant events on price volatility. Certainly, the news of OPEC meetings and important events could have additional impact to show up in the data with much higher frequency than the daily volatility used in this study. But it is difficult to investigate this possibility, since there is no clear way to pin down the exact time within a day of the market's absorption of these events. On the other hand, the OPEC impact on the volatility might emerge well before the event dates for two reasons. First, there may be some information leakage about scheduled events. Second, more importantly, the literature (see Horan, Peterson and Mahar (2004) and the references therein) suggest that market volatility should respond prior to scheduled information releases from the OPEC conferences (and other important events), as such an effect on volatility is attributable to the creation and resolution of uncertainty about future market movements. It is of course likely that the uncertainty may be developed several days or even weeks well before the events.

Similar to Horan, Peterson and Mahar (2004), the impact of OPEC conference meetings on crude oil futures volatility is thus studied in the weekly horizon. Weekly averages of daily crude oil futures volatility are calculated and the following regression is run:

$$v_t^i * 1000 = \alpha + \beta d_{ut} + \gamma d_{nt} + \delta d_{dt} + u_t \quad (8)$$

where v_t^i is the lag or lead values of weekly volatility. $d_{ut} = 1$ if there is a meeting in the week recommending a price increase and zero otherwise. Analogously, $d_{nt} = 1$ only if there is a meeting in the week and it is ambiguous about price change, and $d_{dt} = 1$ only if there is a meeting in the week recommending a price decrease.[8] Dummy variables are constructed in this way so that asymmetrical impacts of the conference meetings can be allowed for. From Table VI, it can be seen that the dummy variable for recommendations of price increases shows strong evidence of positive impact of the OPEC events on weekly volatility before the conference but not after the conference. The conferences that do not recommend price increases tend to reduce price volatility before conferences and after. But this effect is statistically insignificant. In sum, weekly market volatility tends to go up before OPEC meetings that recommend price increase. For conferences that are ambiguous about price change or recommending price decrease, market volatility does not statistically respond to them.[9]

CONCLUSIONS

In this paper the statistical properties of daily realized volatilities for two of most heavily-traded energy futures contracts (crude oil and natural gas) are examined using intraday returns over a five-year period. It is documented that while the distributions of the raw returns for both futures contracts are highly non-Gaussian, the standardized return distributions (i.e., the raw returns normalized by the realized standard deviations) become statistically indistinguishable from the Gaussian distribution. The distributions of the logarithmic standard deviations for both futures contracts are also approximately Gaussian, while realized variances are both highly non-Gaussian. The results suggest that all of the volatility measures can be characterized by slowly mean-reverting fractionally integrated processes with a degree of integration, d , estimated between 0.25 and 0.45. The overall findings of this study are consistent with existing work on realized financial market volatility (ABDE, 2001; ABDL, 2001, 2003; Areal and Taylor, 2002; Thomakos and Wang, 2003). Hence, this study extends the current literature on realized volatility to energy markets.

Noteworthy, however, the realized correlation between crude oil and natural gas futures is also found not to have long memory. As observed in Bachmeier and Griffin (2006), the phenomenon that the oil price spike often coincides with abnormally high natural gas prices has prompted energy traders to ask whether there exists a long-run relationship between the two fuels with certain substitutability for each other. Such a long-run relationship, if any, might well be reflected by the long memory in their correlation. In this context, the finding also differs substantially from earlier works (e.g., ABDE, 2001; ABDL, 2001, 2003; Thomakos and Wang, 2003) which extensively document long memory in realized correlations within and between exchange rates, stock markets and bonds. Nevertheless, the finding is well in line with Bachmeier and Griffin (2006), who show that crude oil and natural gas markets are only very weakly integrated in the long run (using an error correction model), despite the contemporaneous spike in oil and natural gas prices during certain time periods. Also, asymmetric volatility is found to be statistically significant at the five percent significance level for natural gas futures but not for crude oil futures at any conventional significance level: natural gas volatility reacts stronger to lagged negative returns than lagged positive returns, while it may not be the case for crude oil futures. This result also differs from the finding of Switzer and El-Khoury (2007) on the crude oil futures based on the volatility as measured by the GARCH model.[10]

Further extending Wirl and Kujundzic (2004) and Horan, Peterson and Mahar (2004), realized crude oil futures volatility is documented to respond with an increase in the weeks immediately before the OPEC events recommending price increases. It is also particularly interesting to contrast this finding with Wirl and Kujundzic (2004), who argue that the impact of OPEC conferences on the world oil market is weak at best, and if at all then restricted to meetings recommending a price increase.

Finally, the findings of this study strongly suggest the appropriateness of using realized volatilities and correlations on the energy futures markets that are constructed from high frequency data in practical financial risk management. It is well known that risk management requires a fully specified multivariate model and unfortunately standard multivariate GARCH models are often too heavily parameterized to be useful in realistic large-scale problems. By contrast, realized volatilities and correlations are easy to construct and implement (as long as intraday data are available), which clearly hold great promise for practical risk management. It would be interesting in the future research to use such measures to explore many important issues, such as forecasting energy market volatility, and modeling and forecasting correlation between energy markets and particularly between energy markets and other financial markets.

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TABLE I
Unconditional Daily Returns Distributions

	Returns (r_t)		Std. Returns ($\frac{r_t - \bar{r}}{v_t}$)	
	CL	NG	CL	NG
N	1234	976	1234	976
Mean	0.0003	0.0004	0.0765	0.0283
Std. Dev.	0.0203	0.0339	1.6046	1.4854
Skewness	0.1543	-0.9372	0.0293	-0.5932
Kurtosis	5.6350	9.9621	3.7141	5.2854
AD	5.8056 [c]	7.9091 [c]	0.3108	1.6012
CVM	0.9543 [c]	1.2292 [c]	0.0297	0.2191
JB	361.8998 [c]	2114.0427 [c]	26.3954 [c]	269.6452 [c]
KS	1.7428 [c]	1.7579 [c]	0.4763	1.1619
QQ	0.9868 [c]	0.9659 [c]	0.9975 [a]	0.9883 [c]

Notes:
1. The sample covers the period from January 3, 1995 through December 31, 1999 for the Crude Oil (CL) futures contracts, October 2, 1995 through September 30, 1999 for the Natural Gas (NG) futures contracts.
2. N is the number of observations. All summary statistics are calculated from daily decimal (standardized) returns.
3. AD, CVM, JB, KS and QQ are values of the normality test statistics of the Anderson-Darling, Crámer-Von Mises, Jarque-Bera, Kolmogorov-Smirnov, and the QQ correlation coefficient between the sample and standard normal quantiles.
4. The critical values derived under independence are:
   AD test: 1.929 (10%), 2.502 (5%) and 3.907 (1%).
   CVM test: 0.341 (10%), 0.458 (5%) and 0.744 (1%).
   JB test: 4.605 (10%), 5.992 (5%) and 9.210 (1%).
   KS test: 1.218 (10%), 1.350 (5%) and 1.628 (1%).
   QQ test: 0.998 (10%), 0.995 (5%) and 0.993 (1%).
5. For the QQ test, reject the null hypothesis of normality if the Table value is less than 0.995 at the 5 percent level, 0.993 at the 1 percent level.
6. a, b, c indicate significance at the 10%, 5%, and 1% level respectively.

TABLE II
Unconditional Daily Volatility Distributions

	Volatilities (v_t^2)		Log Std. Deviations ($\log v_t$)	
	CL	NG	CL	NG
N	1234	976	1234	976
Mean	0.0002	0.0005	-4.5088	-3.9625
Std. Dev.	0.0002	0.0006	0.4257	0.4245
Skewness	3.3415	4.3334	0.0418	0.1723
Kurtosis	22.1424	32.4126	2.7406	3.1667
AD	80.6669 [c]	86.9612 [c]	0.54888	0.5225
CVM	14.2179 [c]	15.6171 [c]	0.0992	0.0609
JB	21137.0197 [c]	38235.4023 [c]	3.8177	5.9583 [b]
KS	6.2523 [c]	6.5245 [c]	0.6993	0.6234
QQ	0.8431 [c]	0.7847 [c]	0.9992	0.9985

Notes:
1. See Table I for the sample span and description of statistics.
2. a, b, c indicate significance at the 10%, 5%, and 1% level respectively.

TABLE III
Unconditional Daily Covariance and Correlation Distributions
between Crude Oil and Natural Gas Futures

	Covariance	Correlation
N	967	967
Mean	1.9E-5	0.0645
Std. Dev.	9.2E-5	0.2375
Skewness	0.2795	-0.1267
Kurtosis	7.4896	2.5391
AD	15.0714 [c]	0.9935
CVM	2.5922 [c]	0.1437
JB	824.7404 [c]	11.1460 [c]
KS	2.4468 [c]	0.9260
QQ	0.9652 [c]	0.9974 [a]

Notes:
1. See Table I for the sample span and description of statistics.
2. a, b, c indicate significance at the 10%, 5%, and 1% level respectively.

TABLE IV

Dynamic Dependence

	Q_{20}	Q_{20}^2	$\widehat{d}_{SP}$
		Returns (r_t)	
CL	49.1472	12312.7795	-0.0622 (0.0290)
NG	28.1745	3172.6165	-0.0398 (0.0319)
		Daily Std. Returns ($\frac{r_t - \bar{r}}{v_t}$)	
CL	39.6366	1.4210	-0.0566 (0.0290)
NG	18.8022	1.5641	-0.0277 (0.0319)
		Volatilities (v_t^2)	
CL	1365.7309	330361068.9446	0.2897 (0.0290)
NG	843.1068	26648900.9696	0.2895 (0.0319)
		Log Std. Deviations ($\log v_t$)	
CL	3453.4462	94.6566	0.3498 (0.0290)
NG	1710.9974	34.6220	0.3744 (0.0319)
Covariances	26.2939	415541626.9128	-0.0553 (0.0320)
Correlations	15.1473	58.7036	-0.0096 (0.0320)

Notes:

1. CL stands for the Crude Oil futures. NG stands for the Natural Gas futures.
2. Q_{20} is the Ljung-Box portmanteau test for autocorrelation using 20 lags. The 5% critical value of the $\chi_{20}^2(0.05)$ distribution is 31.41.
3. Q_{20}^2 is the McLeod-Li portmanteau test for autocorrelation in the squares of the series using 20 lags.
4. $\widehat{d}_{SP}$ is the estimate of the fractional order using the Gaussian semiparametric estimator of Robinson (1995b). Standard errors are in parentheses.

TABLE V

News Impact Functions for Log Std. Deviations

	Coefficient Estimates and Std. Errors			
	α_j	β_j	γ_j	δ_j
CL	-0.3663 ***	0.2548 **	0.0492 ***	0.0016
	0.0364	0.1279	0.0123	0.0150
NG	-0.3552 ***	0.1939	0.0906 ***	-0.0301 **
	0.0272	0.1336	0.0182	0.0148

Notes:
1. CL stands for the Crude Oil futures. NG stands for the Natural Gas futures.
2. Least Squares coefficient estimates for the regression
   $(1-L)^{d_j} lv_{tj} = \alpha_j + \beta_j \cdot (1-L)^{d_j} lv_{t-1,j} + \gamma_j r_{t-1,j} + \delta_j r_{t-1,j} I(r_{t-1,j} < 0) + u_{tj}$
   where $\widehat{d}_{jSP}$ is fixed at the estimate of the fractional order from Table IV, $I(\cdot)$ is the indicator function and $r_{t-1,j}$ is the lag of the standardized return of the j^{th} contract. Standard errors are in the parentheses. Newey-West heteroscedasticity and autocorrelation consistent standard errors are in parentheses (using 20 lags).
3. *** , ** and * indicate significance at the 1%, 5% and 10% level respectively.

TABLE VI

The Impact of OPEC on Weekly Crude Oil Volatility

	2 Weeks Before	1 Week Before	Conference Week	1 Week After
α	0.1914 (22.38)	0.1928 (22.40)	0.1922 (22.33)	0.1972 (22.65)
β	0.1843*** (3.05)	0.1634*** (2.68)	0.1442** (2.36)	-0.0545 (-0.88)
γ	-0.0544 (-1.00)	-0.0411 (-0.75)	0.0015 (0.03)	-0.0081 (-0.15)
δ	0.1292 (1.52)	-0.0380 (-0.44)	-0.0957 (-1.11)	-0.1266 (-1.46)
No. of Observations	207	208	209	208
Adjusted R-squared	0.0448	0.0238	0.018284	-0.000585

Notes:

1. Least Squares coefficient estimates for the regression $v_t^i * 1000 = \alpha + \beta d_{ut} + \gamma d_{nt} + \delta d_{dt} + u_t$. T-statistics are in the parentheses.
2. $d_{ut} = 1$ if there is an OPEC conference meeting in the week recommended a price increase and zero otherwise. $d_{nt} = 1$ if there is a meeting in the week and it is ambiguous about price change. $d_{dt} = 1$ if there is a meeting in the week recommended a price decrease
3. *** , ** and * indicate significance at the 1%, 5% and 10% level respectively.

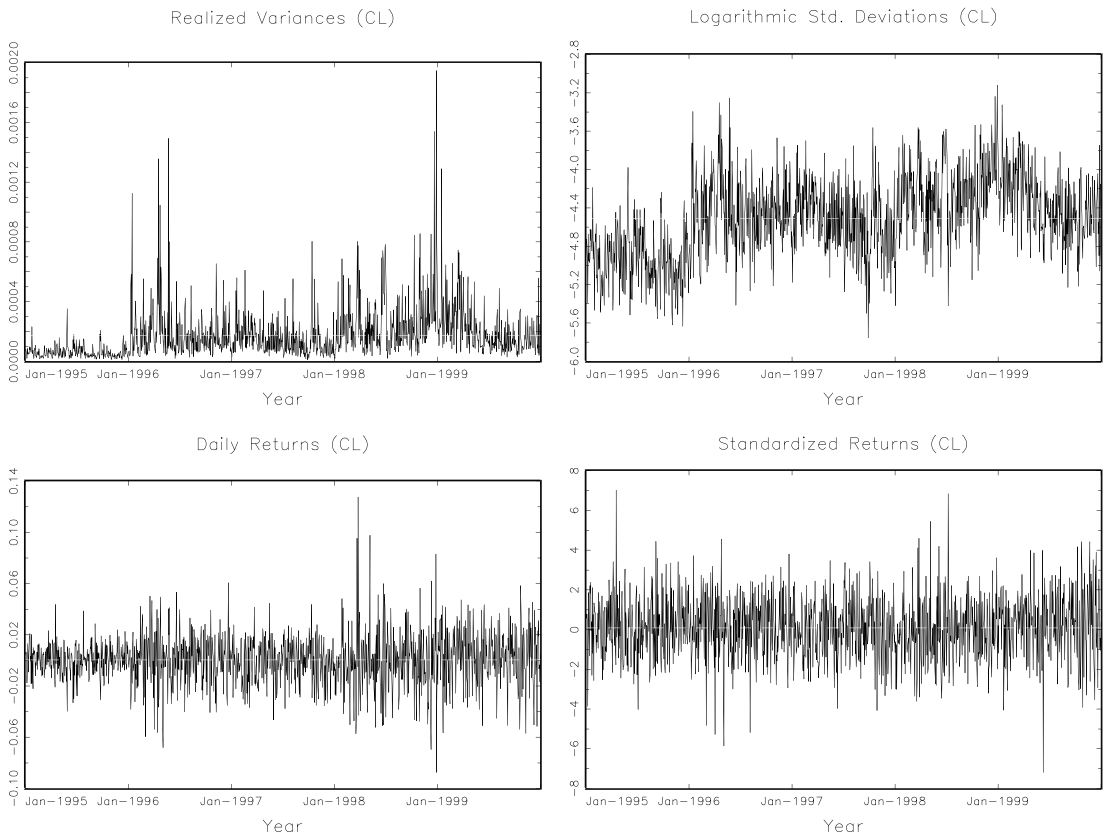

FIGURE 1

Time Series for Crude Oil (CL) Futures Series

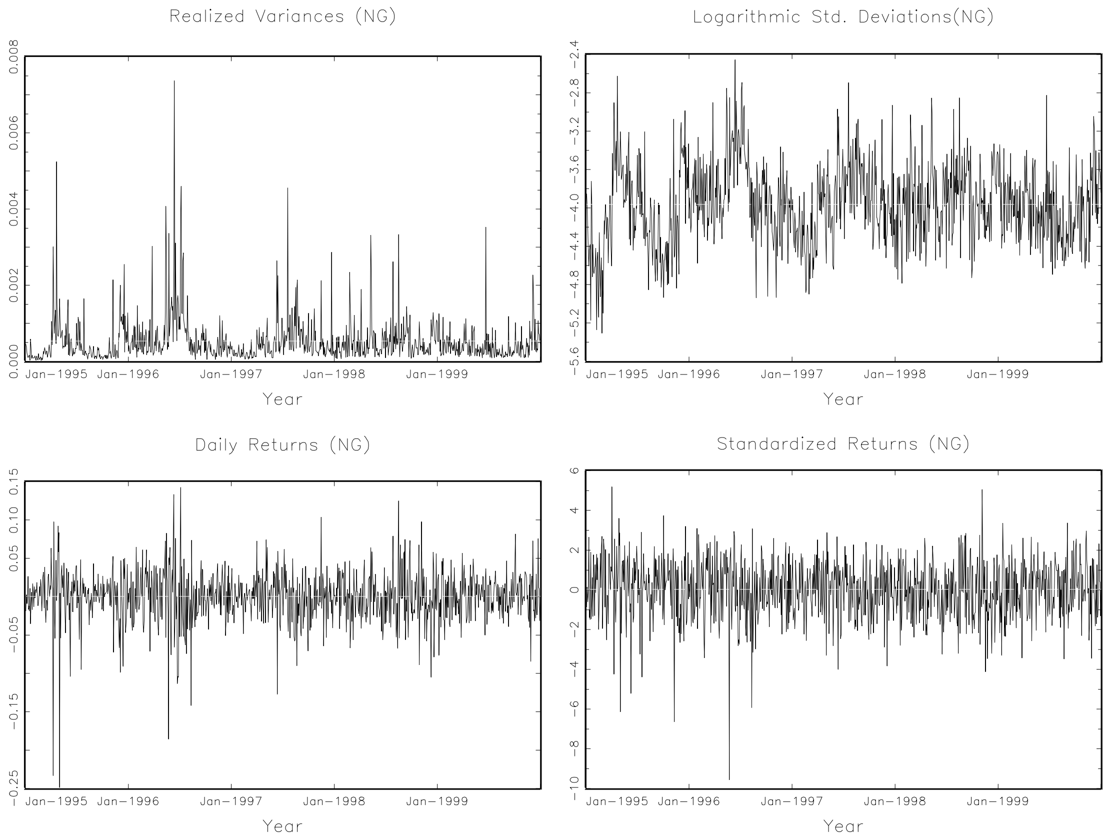

FIGURE 2

Time Series for Natural Gas (NG) Futures Series

FOOTNOTES

[1] Martens and Zein (2004) investigated the forecasting performance of realized crude oil futures volatility compared to implied volatility, but they did not address the issues as studied in this study.

[2] Because of the nature of the dataset, some business days have irregular records. We exclude these days in the construction of the returns series. There are 16 irregular days for Crude Oil futures and 10 days for Natural Gas futures.

[3] The average number of price changes per day from10:00 A.M. EST to 2:30 P.M. EST are 531 for the Crude Oil futures and 217 for the Natural Gas futures.

[4] The realized standard deviations exhibit the same properties as the realized variances. The square root transformation of the variances to standard deviations reduces both the skewness and kurtosis estimates significantly. However, the distributions of the realized standard deviations are still skewed to the right, and significantly leptokurtic.

[5] The estimator based on a log-periodogram regression (Robinson 1995a) is also used and the results are similar. However, the Gaussian semiparametric estimator preserves the consistency and asymptotic normality encountered in observable long memory series and it is more efficient than the estimator based on the log-periodogram regression under mild conditions (Arteche, 2004).

[6] The lagged filtered logarithmic standard deviations are included in the estimation as the filtered series still exhibit some serial correlation.

[7] The sources of the Chronologies include Associated Press, Bloomberg, Dow Jones, Energy Information Administration, Financial Times, Knight Ridder, Los Angeles Times, New York Times, Oil Daily, Reuters, USA Today, Wall Street Journal, Washington Post, and World Markets Research Center.

[8] The categorization of conferences is based on the official press releases which require some reading and judgment.

[9] We also conduct event studies on weekly realized volatilities following Bhattacharya et al. (2000). We use the non-parametric test on mean ranked realized volatilities as proposed in Corrado (1989). The test results suggest that volatilities jump one to two weeks before the OPEC conference week, but the jump is not statistically significant at conventional significance levels (with a p-value of approximately 0.15). Nevertheless, the application of the techinique may have low power in this case.

[10] Similar different inference on asymmetric volatility has been reported in ABDE (2001), which illustrates non-trivial differences in using realized volatility versus GARCH-based

volatility models (in some occasions). Also see Chen, Daigler, and Parhizgari (2006) and Illueca and Lafuente (2006) for recent illustration of this point.