Economics Bulletin

Volume 30, Issue 4

Crude Oil Volatility: Hedgers or Investors

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Abstract

We evaluate differential effects of the trading activity of two classes of traders: hedgers and general investors, on the volatility of the NYMEX crude oil futures returns. It appears that the rebalancing activity of oil hedgers has a significant and positive effect on the oil futures volatility. On the other hand, non-commercial players (investors) who take positions in the crude oil futures as well as stocks and bonds do not affect the crude oil volatility significantly by rebalancing their positions.

Citation: George Milunovich and Ronald Ripple, (2010) "Crude Oil Volatility: Hedgers or Investors", *Economics Bulletin*, Vol. 30 no.4 pp. 2877-2883.
Submitted: Aug 25 2010. **Published:** November 03, 2010.

1. Introduction

Given the continual debate[1] about the role of hedge funds and other types of market participants in the crude oil futures markets, it is of interest to be able to disentangle the influences of different classes of traders. The main obstacle to achieving this goal is the lack of publicly available data classified by the purpose of trading activity. Although the Commodity Futures Trading Commission (CFTC) provides open interest datasets categorized in the classes of commercial, non-commercial and non-reporting traders, this categorization is too broad to be useful in identifying the purpose of trading activity, e.g. hedging, investing or speculating. Some authors such as Haigh et al. (2007) and NYMEX (2005) resort to using proprietary datasets, which allow them to disaggregate open interest on a contract-by-contract basis between commercial and non-commercial traders. They both find a significant influence flowing from the trading activity of commercial players to oil volatility. In this paper we extend the literature by using a new approach to analyse differential effects of two trader classes: hedgers and investors, which does not require the use of proprietary datasets.

Our method assumes that the sole purpose of hedgers is to cover their underlying crude oil spot exposures, while investors treat crude oil futures as an investment instrument held in a portfolio of equities, bonds and oil. The hedgers and investors are assumed to form their optimal positions within a conditional mean-variance utility framework, vis á vis their respective assets, see for example Ferson, et al. (1987), and Bollerslev, et al. (1988). Given this model, we are able to construct proxies for the trading activity of the two types of market participants. The identification of the proxy variables relies on the assumption that the market participants maintain optimal portfolios by rebalancing their positions according to the evolution of the time-varying hedge ratio and optimal portfolio weights.

The implied causal linkage within this model is that the trading activity typically found to cause returns volatility, see for example Serletis (1992) and Herbert (1995), is itself caused by the rebalancing activities of the market participants. Our model posits that when hedgers and investors set out to incorporate a futures contract into a hedging or investment portfolio they begin with a benchmark holding position. We assume that the benchmarks are set according to the unconditional values for the hedge ratio and portfolio weights. Having established a benchmark, market participants monitor the market and rebalance to maintain an optimal position. A natural relationship to monitor is a deviation between the unconditional (benchmark) values and their time-varying conditional counterparts. In our model we focus on the squared deviation from the unconditional value, which may be interpreted as volatility. An advantage of doing this is that we avoid having to specify whether the hedgers and investors are long or short oil futures by using the *volatility* of the optimal hedge ratio and the *volatility* of the optimal portfolio weight as proxies for the trading activity, rather than the actual values themselves. Thus, when the volatility of the hedge ratio or the portfolio weight is high we expect the market participants to rebalance their positions more frequently irrespective of whether they are long or short, and vice versa.

We find that the volatility of the optimal hedge ratio, which motivates hedgers to rebalance, has a positive and significant effect on futures return volatility. On the other hand, we find no significant influence flowing from changes in the volatility of the optimal portfolio weight attributable to crude oil. Our results may be of interest to policy makers concerned with perceptions of excess trading activity in commodity futures markets by non-

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[1] See for example the testimony of James A. Overdahl, Chief Economist U. S. Commodity Futures Trading Commission (CFTC) before the U.S. Senate Banking sub-committee on Securities and Investment (2006), and the testimony of Walter L. Lukken, Commissioner Commodity Futures Trading Commission before the Committee on Agriculture, United States House of Representatives (2006).

hedgers, such as the U.S. Senate and House committees holding hearings on this issue. When hedgers are found to have a significant effect on volatility, and particularly if their effect is larger than that for non-hedgers, efforts to restrict the activities of investors (non-hedgers) may actually produce a detrimental effect on the markets by reducing market liquidity.

2. Data and Econometric Methodology

In our study we use four weekly time series including *i)* the Standard and Poor's 500 stock market index (S&P500), *ii)* Morgan Stanley Capital International (MSCI) US Government long-term bond index, *iii)* light sweet crude oil futures prices, and *iv)* West Texas Intermediate (WTI) crude oil spot prices. The crude oil price data are expressed in US dollars per barrel, and weekly returns are calculated as log differences of end-of-the-week[2] closing prices or values. The dataset covers January 1995 through December 2005 period and contains 562 weekly return observations. The S&P500 and MSCI bond index data are drawn from Datastream International, the futures prices are "near-month" contract prices sourced from the NYMEX, and the WTI spot prices are drawn from the U.S. Department of Energy, Energy Information Administration website. We construct the "near-month" futures series from the NYMEX raw daily data using a method for splicing the futures prices when a contract nears maturity established in Ripple and Moosa (2007).

Table 1 reports summary statistics on the four variables.

Table 1: Summary statistics - weekly returns (%).

	S&P 500	Bonds	Oil Futures	Oil Spot
Mean	0.18	0.13	0.22	0.22
Std. Dev.	2.34	0.67	4.77	5.25
Skewness	-0.36	-0.63	-0.69	-0.39
Kurtosis	5.91	4.20	5.42	4.96
J.B. p-value	0.00	0.00	0.00	0.00

The sample period is Jan 1995 – Dec 2005 and includes 562 weekly return observations.

Average weekly returns are about the same for the oil futures and spot prices, and are larger than the average return on the S&P 500 over the sample period. Long term government bonds, as expected, display the smallest average rate of return and lowest levels of risk, as measured by standard deviation. On the other hand, oil spot returns exhibit greatest returns and more than twice the amount of risk than the S&P 500. All four return series display considerable non-normality manifested in negative skewness and excess kurtosis as summarized by the Jarque-Bera *p*-value.

2.1 Econometric Method

Our empirical approach involves the following steps: *i)* de-mean the four return series and filter out autocorrelation using a vector autoregression (VAR) model, *ii)* estimate a time varying conditional covariance matrix for weekly returns on stocks, bonds, crude oil futures and spot crude oil. Next, *iii)* construct conditional optimal hedge ratios and portfolio weights, *iv)* calculate time-varying squared deviations of the conditional hedge ratio and portfolio weight from their unconditional counterparts, and *v)* use these deviations as *lagged*[3] explanatory variables for crude oil futures volatility. Our analysis is performed in a

[2] Weekly returns are based on closing prices/values for the last trading day of the week. If, for example, Friday is a holiday, Thursday closings are used, and so on.
[3] The difference in time periods described here resolves the endogeneity problem.

multivariate time-varying volatility framework of Dynamic Conditional Correlation (DCC) model described in Engle (2002).

The focus of this study is on the following augmented EGARCH (Nelsen, 1991) equation for the crude oil futures return volatility:

$$\ln\left(\sigma_{f,t}^2\right) = \omega + \alpha\left|\frac{u_{f,t-1}}{\sigma_{f,t-1}}\right| + \phi\ln\left(\sigma_{f,t-1}^2\right) + \beta\frac{u_{f,t-1}}{\sigma_{f,t-1}} + \gamma\left(h_{t-1} - \bar{H}\right)^2 + \delta\left(w_{f,t-1} - \bar{W}_f\right)^2. \quad (1)$$

The log of the conditional variance equation $\ln\left(\sigma_{f,t}^2\right)$ for the oil futures return is specified as an EGARCH process with two additional volatility spillovers terms $\left(h_{t-1} - \bar{H}\right)^2$ and $\left(w_{f,t-1} - \bar{W}_f\right)^2$. The variable $u_{f,t-1}/\sigma_{f,t-1}$ is the standardized oil futures return and controls for any asymmetric response in the conditional volatility.

The last two terms in Eq. (1) augment the standard EGARCH specification and may be interpreted as follows: $\left(h_{t-1} - \bar{H}\right)^2$ is the squared deviation of the conditional hedge ratio h_{t-1} from its unconditional value $\bar{H}$, and acts as a measure of the conditional hedge ratio volatility. A positive and statistically significant γ coefficient would indicate that the rebalancing of hedged positions in one period increases oil futures price volatility in the next period, and a negative value for γ would indicate the opposite. Similarly, the second volatility spillover term, $\left(w_{f,t-1} - \bar{W}_f\right)^2$, is a proxy for the volatility of the optimal portfolio crude oil futures weight, $w_{f,t-1}$. Statistical significance and sign of the coefficient δ are interpreted in the same manner as for γ. The time-varying optimal hedge ratio h_t and the portfolio weights w_t are calculated[4]

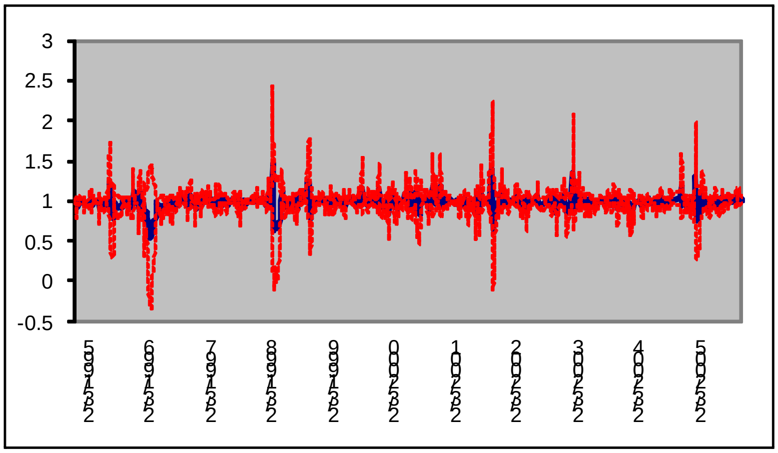
using standard mean-variance optimization formulas, and the estimates of the conditional covariance matrix given by DCC. We optimize the entire model including equation (1) in one step. Conceptually our approach resembles the standard volatility spillover studies such as Hamao, et al. (1990), Baillie and Bollerslev (1990), and Lin et al. (1994) but differs from them in that we analyze spillovers from two special variables, the optimal hedge ratio and the optimal portfolio weight.

3. Estimation Results

We present the estimated time-varying hedge ratio and portfolio weights in Figures 1 and 2.

[4] A single horizon mean-variance investor chooses the tangency portfolio that has the following vector of weights $w_t = \Sigma_t^{-1}\mu / i'\Sigma_t^{-1}\mu$, while the optimal hedge ratio is given by $h_t = \sigma_{f,s,t} / \sigma_{f,t}^2$. Here μ is a 4×1 vector of excess expected returns set equal to their historical averages, while i is a 4×1 vector of ones. The unconditional optimal portfolio weight and hedge ratio are calculated using the unconditional covariance matrix.

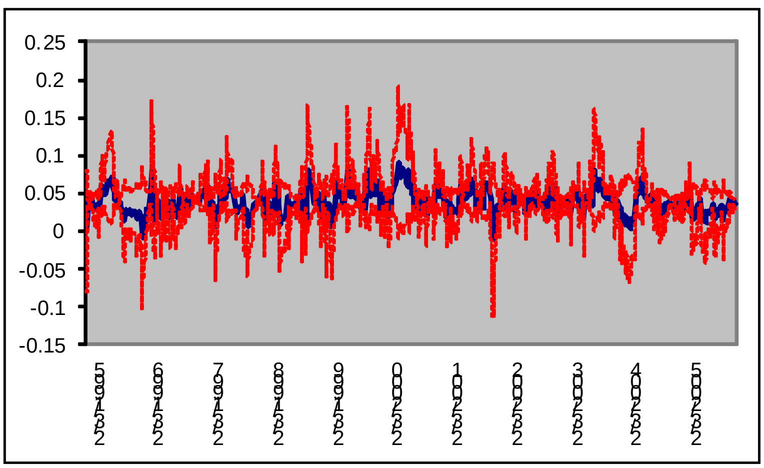
Figure 1: Estimated conditional crude oil futures hedge ratio.



Confidence interval bounds are calculated as $h_t \pm 2\sqrt{(h_t - \bar{H})^2}$.

The optimal hedge ratio oscillates near the value of 1.0, with occasional values exceeding unity. This result is due to the fact that spot oil returns exhibit a larger standard deviation than oil futures. In comparison, the optimal portfolio weights for crude oil are relatively small averaging less than 0.05. This implies that crude oil futures would amount to less than five percent of the optimal portfolio mix with equities and bonds.

Figure 2: Estimated conditional crude oil futures portfolio weight.



Confidence interval bounds are calculated as $w_{f,t} \pm 2\sqrt{(w_{f,t} - \bar{W}_f)^2}$.

The conditional hedge ratio and conditional portfolio weights presented above are used to compute squared deviations from their unconditional counterparts, that are used in our EGARCH equation (1) as lagged explanatory variables. The resulting coefficient estimates are reported in Table 2.

Table 2: Crude oil conditional volatility EGARCH (1,1,0) equation.

	Coefficient	t-statistic	p-value
ω	2.788	33.562	0.000
α	0.333	5.436	0.000
β	0.045	1.511	0.132
γ	4.884	4.837	0.000
δ	61.534	1.042	0.298

T-ratios and *p*-values are based on Bollerslev-Wooldridge (1992) robust standard errors.

The key results[5] from our study are reflected in the signs and significance of γ and δ parameters, the coefficients on the volatility of the hedge ratio and portfolio weight, respectively. The results show that volatility of the conditional hedge ratio has a positive and significant influence on the conditional volatility for crude oil futures returns. On the other hand, there is no statistically significant effect running from the volatility for the crude oil portfolio weight. This coefficient is, however, of positive sign as expected. The implication of these findings is that oil hedging activity increases the volatility of crude oil futures, while the trading activity in oil futures that results from portfolio rebalancing does not. Another observation to note is the lack of statistical significance (at 10%) found for β, which may be interpreted as evidence against the hypothesis of asymmetric responses of volatility to positive and negative news shocks.

4. Conclusion

We propose a new method to analyze the influence of different trader classes on the volatility of futures returns that categorizes traders based on the purpose of trading activity and not on an arbitrary description of the trading entity. The main advantage of our model is that it does not require the use of detailed proprietary open interest data, but instead is based on mean-variance portfolio optimizing techniques.

We apply our approach to the NYMEX crude oil futures market and evaluate differential effects of hedging versus investing in oil futures. Our model is implemented as a Dynamic Conditional Correlation specification with an augmented EGARCH variance structure. The augmentation, which captures differential influences of alternative trader classes, consists of proxy variables for the trading activity of two types of market participants: hedgers, who wish to eliminate their spot exposure, and investors, who treat oil as a general asset class and optimize a portfolio of stocks, bonds and oil.

We find that, if hedgers and investors optimize their respective hedging strategies and portfolios based on a mean-variance methodology and employ dynamic rebalancing to maintain optimality, hedgers have a positive effect on the volatility of crude oil futures, and investors' rebalancing activity does not. This result is particularly interesting because it runs counter to the typical expectation. Our method which is based on a completely different analytical approach to those of either Haigh, et al. (2007) or the NYMEX (2005) provides findings consistent with those obtained in these two earlier investigations.

[5] All DCC parameter estimates are of expected sign and relative magnitude and statistically significant. The full set of estimates are available upon request from the authors.

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