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HEDGERS, INVESTORS, AND FUTURES RETURN VOLATILITY: THE CASE OF NYMEX CRUDE OIL

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ABSTRACT

We present a new model to evaluate the volatility of futures returns. The model is a combination of Dynamic Conditional Correlation and an augmented EGARCH, which allows us to evaluate the differential effects of the trading activity of two classes of optimizing traders. We apply the model to the NYMEX crude oil futures contract, and we find that the rebalancing activity of hedgers has a significant and positive effect on returns volatility. However, we also find that the rebalancing activity attributable to crude oil futures for non-hedging investors has no significant effect.

JEL Classification: Q4, G11, G13

Keywords: portfolio choice, WTI oil volatility, optimal hedge ratio, dynamic conditional correlation

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I. Introduction

This paper presents a new model to evaluate the influence that different market participant classes may have on the volatility of futures returns. Our approach allows us to effectively partition the influence of futures trading activity into two broad classes of traders: hedgers and investors. We apply our model to crude oil futures and estimate the influence of the volatilities of optimal positions for hedgers and investors on the volatility of returns for crude oil futures. 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, and we find no significant influence flowing from changes in the volatility of the optimal portfolio weight attributable to crude oil.

Asset returns volatility is frequently modelled as a function of trading activity. The traditional measures of futures market trading activity, both trading volume and open interest, result from actions taken by all market participants, hedgers and non-hedgers alike. Our purpose in this paper is to evaluate the separate influences of hedgers and other market participants on crude oil futures volatility. However, data on trading activity attributable to alternative classes of traders is not readily available. Therefore, we construct a model to analyse the effects on futures volatility that are attributable to the trading activity of two trader classes following prescribed optimization strategies. To accomplish this, we construct proxies for trading activity that are based on hedge ratios, portfolio weights, and their volatilities.

In our model, both trader classes are assumed to form their optimal positions within a mean-variance utility maximization framework, vis á vis their respective assets. Our market participants maintain optimal positions by rebalancing according to the evolution of the time-varying covariance matrix of the assets they hold. When applied to crude oil futures, hedgers rebalance according to the relationships between the spot price of the underlying asset and the crude oil futures price, and investors

(non-hedgers) rebalance according to the relationships among equities, bonds, and crude oil futures. The posited causal linkage within this model is that the trading activity typically found to cause returns volatility is itself caused by the rebalancing activities of optimizing market participants.

The paper is motivated by our expectation that there should be an important influence on the volatility of futures returns coming from hedging participants that may be differentiated from that of non-hedging investors. For our application, observations of the crude oil futures market suggest that the influence of hedgers in the market may dominate the influence of non-hedgers (see Lukken 2006). Thus, the changes in their positions through rebalancing may be expected to significantly influence the market, including the volatility of returns on futures contracts. Moreover, typically less than one percent of the maximum open interest established in crude oil futures contracts goes to delivery (see Lukken 2006), so we may conclude that hedgers in this futures market are primarily concerned with price risk mitigation (not acquisition or disposal of future-dated supplies of the commodity at pre-determined prices) and that they will trade to rebalance accordingly.

In addition to the observation that hedgers hold the dominant position in the crude oil futures market, our expectation of their influence also derives from results presented in the Commodity Futures Trading Commission (CFTC) study of Managed Money Traders (Haigh *et al.* 2006). One of their results is that commercial traders change their positions more frequently than do non-commercial traders. This suggests that further analysis into the role of hedgers' contributions to futures returns volatility is warranted.

The second class of market traders we model are investors who hold portfolios containing crude oil futures, equities, and bonds. To the extent that so-called speculators in crude oil futures also hold other assets in addition to futures, they too may be covered by our trading class of investors who optimize their overall portfolios

and rebalance their asset weights accordingly. Together with hedgers, the rebalancing of investor portfolios will affect the trading activity associated with the crude oil futures market and thus the volatility of futures returns.

Our results may be of interest to policy makers concerned with perceptions of excess trading activity in commodity futures markets by non-hedgers, such as the U.S. Senate and House committees holding hearings on this issue. If 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 non-hedgers may actually damage the markets by artificially reducing market liquidity.

The paper progresses with a brief literature review. Section three presents our econometric methodology and provides a discussion of the model intuition and the distinction between previous work and ours. Section four reviews the data used, the method for constructing the futures price series, and the estimation results. Section five provides a summary conclusion.

II. Literature review

The study of the volatility of energy futures is a subset of analyses of futures volatility, generally, that have been examined in numerous academic papers as well as in government and regulatory papers. The earliest of these tested the Samuelson (1965) thesis that futures price volatility should increase as contract maturity nears. Serletis (1992) extended this to include trading volume, in addition to maturity, on a contract-by-contract basis for crude oil, gasoline, and heating oil contracts traded on the New York Mercantile Exchange (NYMEX). Herbert (1995) applied the same methodologies, employing a daily high-low price measure of volatility, to natural gas contracts, while using only near-month price observations. Both Serletis and Herbert find a significant and positive relationship between futures return volatility and trading volume.

Bessembinder and Seguin (1993) employ time series techniques to estimate the relationship between futures returns volatility and measures of trading volume and open interest. Their work does not include energy futures contracts; however, they do find a strong positive relationship between volatility and trading volume, but a negative relationship between volatility and open interest. Open interest is modelled as a measure of market depth, and greater market depth is expected to be associated with lower returns volatility.

Pindyck (2004) explores the time series characteristics of the volatility of both natural gas and crude oil futures prices. He concentrates on the inter-relationships between the two commodity price series, the existence of trends, the term of influence of shocks, and the influence of the collapse of ENRON. His analysis is carried out in an ARCH/GARCH framework without specific consideration of time to maturity or trading activity. As with the earlier research, Pindyck's analysis does not address questions of the potential for differential influence across trader classes.

The recent CFTC staff report and New York Mercantile Exchange (NYMEX) staff report shift the focus to the role played by commercial and non-commercial traders using the open interest measures they collect and maintain for regulatory and market oversight. Both Haigh *et al.* (2006) and NYMEX (2005) analyze the role of non-commercials employing data collected by the Commodity Futures Trading Commission and reported in their Commitment of Traders (COT) reports. These open interest data are subdivided into commercial, non-commercial, and non-reporting¹ market traders, and it is typically the non-commercial traders who are associated with speculation. There are flaws in concluding that these players represent the/a body of speculators; however, they do represent an observable group who for the most part do not have a commercial interest in the underlying commodity. As such, once one

¹ Non-reporting traders are small traders who do not maintain open interest positions of sufficient size to be required to submit reports. Their number is calculated as the residual of total open interest after accounting for reporting commercial and non-commercial traders. They usually account for about ten percent of the open interest.

acknowledges the lack of a direct mapping between non-commercial traders and speculators², these observations may be cautiously used as indicators of the activity of traders who would typically be classified as speculators; Haigh *et al.* (2006) employ a unique, proprietary³ open interest data set that disaggregates the open interest to a contract-by-contract basis between commercial and non-commercial traders. This allows them to arrive at a subset of non-commercial traders labelled as managed money traders, which may be deemed to represent hedge funds.

Haigh *et al.* (2006) and NYMEX (2005) both find a significant influence flowing from commercials to returns volatility. We extend the analysis of the role of hedgers via an alternative methodology based on trader position optimization and rebalancing.

III. Econometric methodology

Our analysis involves the following steps: (1) we estimate a time varying conditional covariance matrix for weekly returns on stocks, bonds, crude oil futures and spot crude oil, (2) we construct conditional optimal hedge ratios and portfolio weights, (3) we calculate measures for conditional hedge ratio and portfolio weight volatilities, and (4) we use these volatility measures as *lagged* explanatory variables for crude oil futures volatility. Thus, we investigate how hedging and investing with oil futures in one period affect the conditional volatility of crude oil returns in the next period. We perform our analysis in a time varying volatility framework described by a multivariate Dynamic Conditional Correlation (DCC) model of Engle (2002).

² There is no one-to-one mapping among the terms hedger/speculator, commercial/non-commercial, and hedger/investor. The CFTC specifically shifted their terminology away from hedger/speculator to commercial/non-commercial to try to better reflect the underlying activities of the participants and due to changes in trader reporting requirements.

³ The CFTC data that is readily available to the public is an aggregation of open interest across all traded contracts, which for crude oil at the time of this writing extends to December 2011.

The vector of returns $\mathbf{r}_t = [r_{1t} \ r_{2t} \ r_{3t} \ r_{4t}]'$ is derived from four weekly series: the S&P500, the MSCI US Government long-term bond index, NYMEX crude oil futures prices, and crude oil spot prices. The first step we take to model the variance equations is to de-mean the returns and filter out autocorrelation using the following vector autoregression (VAR) model:

$$\mathbf{r}_t = \mathbf{c} + \sum_{i=1}^3 \boldsymbol{\beta}_i \mathbf{r}_{t-i} + \mathbf{u}_t \quad (1)$$

where \mathbf{c} is a (4×1) vector of constants and $\boldsymbol{\beta}$'s are (4×4) parameter matrices. The lag length of 3 was chosen according to diagnostic specification tests and the AIC selection criterion.

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

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

The log of the conditional variance equation is therefore specified as an EGARCH (1, 0) process with two volatility spillover terms. We do not include a lagged volatility term based on results of Engle's (1982) LM test and visual examination of the

correlogram of the squared residuals \mathbf{u}_t . The term $\frac{u_{f,t-1}}{\sigma_{f,t-1}}$ controls for any asymmetric

response in the log of conditional volatility with respect to the sign of the volatility shocks. This may not be an issue for crude oil futures returns volatility, but it is a well documented finding in equities. Therefore, we want to control for and test for this effect when estimating the coefficients on hedge ratio and portfolio weight volatilities.

The additional terms in Eq. (2) are interpreted as follows: $(h_{t-1} - \bar{H})^2$ is the squared deviation of the conditional hedge ratio h_{t-1} from its unconditional value \bar{H} , and it is a measure of the conditional hedge ratio volatility. A positive and statistically significant γ coefficient indicates that the rebalancing of hedged positions in one period increases oil futures price volatility in the next period, and a negative value for γ indicates the opposite. Similarly, the second volatility spillover term $(w_{f,t-1} - \bar{W}_f)^2$ is a proxy for the volatility of the optimal portfolio crude oil futures weight $w_{f,t-1}$. The statistical significance and sign of its coefficient δ are interpreted in the same manner as for γ .

A. *Optimal hedge ratio and portfolio weights*

In order to construct the optimal hedge ratios h_t, \bar{H} and portfolio weights w_t, \bar{W} we assume (a) hedgers and investors use short-horizon mean-variance strategies; and (b) investors create portfolios from equities, government bonds, and crude oil futures relying on estimates of the conditional covariance matrix. Although mean-variance portfolios are not ideal for non-normally distributed returns, mean-variance modelling is a well-understood analytical tool that maps into the portfolio performance literature. Moreover, it is commonly applied in funds management practice, and can be simply adapted to changing levels of risk aversion. Therefore, we assume that our investors hold the tangency portfolio, as this portfolio is easily combined with the risk-free asset to form the best portfolio for given risk aversion. A single-horizon investor chooses the tangency portfolio which has the following vector of weights:

$$\mathbf{w}_t = \frac{\Sigma_t^{-1} \boldsymbol{\mu}}{\mathbf{i}' \Sigma_t^{-1} \boldsymbol{\mu}}. \quad (3)$$

In this equation for the conditional portfolio weights, $\boldsymbol{\mu}$ is a (4×1) vector of excess expected returns (over the risk free rate) and \mathbf{i} is a (4×1) vector of ones. Although issues with expected returns, such as large estimation errors, have been identified in a number of studies (e.g., Merton 1980), in this application we set the expected returns to their historical averages. Σ_t is the conditional covariance matrix of returns, which we explain in more detail below. The vector of unconditional portfolio weights is estimated in a similar way:

$$\bar{\mathbf{W}} = \frac{\Sigma^{-1} \boldsymbol{\mu}}{\mathbf{i}' \Sigma^{-1} \boldsymbol{\mu}} \quad (4)$$

where Σ is the unconditional covariance matrix.

Hedgers, on the other hand, are only concerned with minimizing risk associated with their spot position, and in our (mean-variance) framework they minimize their risk by buying or selling an optimal amount of futures contracts. The unconditional optimal hedge ratio⁴ is given by:

$$\bar{H} = \frac{\sigma_{f,s}}{\sigma_f^2}. \quad (5)$$

where $\sigma_{f,s}$ is the covariance between the futures and spot crude oil returns, and σ_f^2 is the variance of the futures returns. A time-varying version of the quantity is the conditional hedge ratio given by:⁵

$$h_t = \frac{\sigma_{f,s,t}}{\sigma_{f,t}^2}. \quad (6)$$

⁴ See Brooks, Henry and Persaud (2002) for details.

⁵ See Chen, Lee and Shrestha (2003) for a survey of the hedge ratio literature.

B. *The conditional covariance model*

We use Engle's (2002) Dynamic Conditional Correlation (DCC) specification to capture the conditional volatility and correlations dynamics among the four return variables. The DCC model assumes that the vector of innovations \mathbf{u}_t estimated by (1) can be decomposed as follows:

$$\mathbf{u}_t = \mathbf{D}_t \boldsymbol{\varepsilon}_t, \quad (7)$$

where \mathbf{D}_t is a diagonal (4×4) matrix of standard deviations and $\boldsymbol{\varepsilon}_t$ is a (4×1) vector of conditionally standardized innovations. Following Engle (2002), we further assume that the standardised innovations, conditional on the information set Ψ_{t-1} can be described as:

$$\boldsymbol{\varepsilon}_t | \Psi_{t-1} \sim (0, \mathbf{R}_t). \quad (8)$$

Here, the conditional correlation matrix \mathbf{R}_t of the standardized innovations $\boldsymbol{\varepsilon}_t$ is also the conditional correlation matrix of the return series \mathbf{r}_t . We can therefore specify the conditional covariance matrix for the returns vector \mathbf{r}_t as:

$$\begin{aligned} \text{Var}(\mathbf{r}_t | \Psi_{t-1}) &= \text{Var}_{t-1}(\mathbf{r}_t) = E_{t-1} \left[\mathbf{u}_t \mathbf{u}_t' \right] \\ &= E_{t-1} \left[\mathbf{D}_t \boldsymbol{\varepsilon}_t (\mathbf{D}_t \boldsymbol{\varepsilon}_t)' \right] \\ &= E_{t-1} \left[\mathbf{D}_t \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \mathbf{D}_t \right], \end{aligned} \quad (9)$$

and since \mathbf{D}_t is a function only of information at $t-1$, we may rewrite the conditional covariance matrix as:

$$\begin{aligned}
\boldsymbol{\Sigma}_t &\equiv \text{Var}_{t-1}(\mathbf{r}_t) \\
&= \mathbf{D}_t E_{t-1}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') \mathbf{D}_t \\
&= \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t
\end{aligned} \tag{10}$$

Finally, we specify the structure for the diagonal elements of \mathbf{D}_t :

$$\mathbf{D}_t = \begin{bmatrix} \sqrt{\sigma_{e,t}^2} & 0 & 0 & 0 \\ 0 & \sqrt{\sigma_{b,t}^2} & 0 & 0 \\ 0 & 0 & \sqrt{\sigma_{f,t}^2} & 0 \\ 0 & 0 & 0 & \sqrt{\sigma_{s,t}^2} \end{bmatrix}. \tag{11}$$

where e, b, f, and s denote equities, bonds, futures, and spot, respectively.

After having examined the correlograms of the squared innovations \mathbf{u}_t and performed Engle's (1982) ARCH-LM tests, we specify the conditional variances in the following way:

1. *Conditional variance for S&P500 return series: GARCH (1, 1)*

$$\sigma_{e,t}^2 = \sigma_e^2 (1 - \alpha_1 - \beta_1) + \alpha_1 u_{e,t-1}^2 + \beta_1 \sigma_{e,t-1}^2 \tag{12}$$

2. *Conditional variance for the MSCI US Government long-term bond index return series: GARCH (1, 1)*

$$\sigma_{b,t}^2 = \sigma_b^2 (1 - \alpha_2 - \beta_2) + \alpha_2 u_{b,t-1}^2 + \beta_2 \sigma_{b,t-1}^2 \tag{13}$$

3. *Conditional variance for crude oil futures return series: EGARCH (1, 1, 0)*

$$\sigma_{f,t}^2 = \exp(\ln(\sigma_{f,t})) \tag{14}$$

where $\ln(\sigma_{f,t})$ is given in Eq. (2).

4. Conditional variance for the crude oil spot return series: GARCH (1, 0)

$$\sigma_{s,t}^2 = \sigma_s^2 (1 - \alpha_4) + \alpha_4 u_{s,t-1}^2 \quad (15)$$

We model the oil futures return volatility in an EGARCH framework, rather than a vanilla GARCH (1, 1) model, because of the possibility of negative coefficients on the portfolio weight and hedge ratio volatility variables. The conditional correlation matrix \mathbf{R}_t is specified as follows:

$$\mathbf{R}_t = \text{diag}[\mathbf{Q}_t]^{-1} \mathbf{Q}_t \text{diag}[\mathbf{Q}_t]^{-1} \quad (16)$$

$$\mathbf{Q}_t = \bar{\mathbf{R}}(1 - \phi - \eta) + \phi \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}'_{t-1} + \eta \mathbf{Q}_{t-1}$$

where ϕ and η are scalar parameters, and \mathbf{Q}_t is a (4×4) matrix, which resembles a GARCH (1, 1) process in the standardized volatilities. Finally, we implement variance targeting with $\bar{\mathbf{R}}$ the unconditional in-sample correlation matrix. Combining conditional volatilities and conditional correlation elements produces the conditional covariance matrix $\boldsymbol{\Sigma}_t$ for the return vector \mathbf{r}_t .

Although Engle (2002) points out that the above model can be estimated in two steps, we take advantage of our relatively small number of variables and implement a one-stage estimation procedure in order to get more efficient estimates. We also calculate Bollerslev-Wooldridge (1992) standard errors that are robust to non-normality in the residuals.

To our knowledge, our spillover approach has not been applied before, and it differs from the standard volatility spillover tests (e.g., Hamao, Masulis and Ng, 1990; Baillie and Bollerslev, 1990; and Lin, Engle and Ito, 1994; among others). The distinguishing characteristic of our approach is that we analyse spillovers from the volatility of two special variables: the hedge ratio and the portfolio weight.

C. *Model intuition*

The approach taken in our paper differs from earlier works. We employ an underlying model that introduces a behavioural role for the variability of both the optimal hedge ratio and the optimal portfolio weight associated with crude oil futures contracts. This allows us to capture the influences that are brought to bear on the market price of the crude oil futures contract by both hedgers and investors.

We are arguing that the volatility of the futures returns on crude oil is a function of the lagged volatilities of the optimal hedge ratio and the optimal crude oil portfolio weight, which reflects trading activity. And, in turn, the optimal hedge ratio and the optimal portfolio weight are functions of the crude oil price volatility. To address this, we estimate the optimal hedge ratios and the optimal portfolio weights as they vary through time and the influence of measures of their lagged volatility on crude oil futures volatility. That is, we evaluate the impact on the volatility of futures returns at time t of a change in the optimal hedge ratio and optimal portfolio weight at time $t-1$.

Our model implies that when hedgers and investors set out to incorporate a futures contract into a hedging or investment portfolio strategy they will begin with some benchmark for the level of inclusion. Within our framework, the benchmarks are the optimal unconditional hedge ratio and the optimal unconditional portfolio weight for crude oil. Having established a benchmark, market participants will then monitor the market and rebalance to maintain an optimal position. A natural relationship to monitor is the deviation between the unconditional (benchmark) values and their time-varying conditional counterparts. When a re-estimated time varying optimal conditional hedge ratio deviates from the benchmark the hedger will have an incentive to rebalance the hedged position; similarly, this is the case for the investor with respect to the optimal portfolio weight. The rebalancing induces trading activity, and the more volatile is the deviation between the benchmark and the optimal

conditional measure the more we expect trading activity to increase and to influence the volatility of returns.

IV. Data and Estimation Results

A. *Data summary*

We estimate the DCC model using time series data on the S&P 500 stock market index, the MSCI long-term US Treasury bonds index, NYMEX light sweet crude oil futures, and 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-week⁶ closing prices or values. The dataset covers January 1995 through December 2005 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.

The construction of the “near-month” futures series from the NYMEX *raw* daily data requires establishing a decision rule for *splicing* the futures prices when a contract nears maturity. Different researchers and database providers employ different decision rules for constructing such series; consequently, it is useful to explain the procedure that we used to construct our dataset.

Our primary interest is to examine prices that reflect the focus of market activity; these will be the prices that most directly affect rebalancing decisions. As one futures contract nears maturity, the market focus shifts toward the next-near

⁶ 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.

contract. Moreover, as the maturing contract gets very near to the last trading day, the trading volume shrinks along with the open interest, and the price can become very volatile with the shrinking liquidity. Market focus is revealed to have shifted by observing increased trading volume and open interest in the next-to-near-month contract. The decision to be made is when to shift from near-month prices to the next-to-near-month prices.

We condition the timing for the transition to the next-near-month contract on observations of both the trading volume and the open interest. Denote the trading volume as V_i and the open interest as O_i , where $i = 1$ or 2 represents the near-month and next-near-month contracts, respectively. The decision rule then is to transition from the near-month price to the next-to-near-month price when $V_2 > V_1$ and $O_2 > O_1$. The satisfaction of both conditions is taken to indicate that the focus of the market has shifted from the near-month contract to the next-to-near month contract. This splicing methodology produces a price series that should be the focus of the market for rebalancing purposes.

Table 1 reports summary statistics on the four variables. 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 lowest average return with the smallest amount of risk, as measured by standard deviation. The standard deviations for oil returns are also the greatest of the four and about twice the size of the S&P's measure of risk. All four return series display considerable non-normality manifested in negative skewness and excess kurtosis.

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
Jarque-Bera	210.41	70.84	182.18	104.05
J.B. p-value	0.00	0.00	0.00	0.00

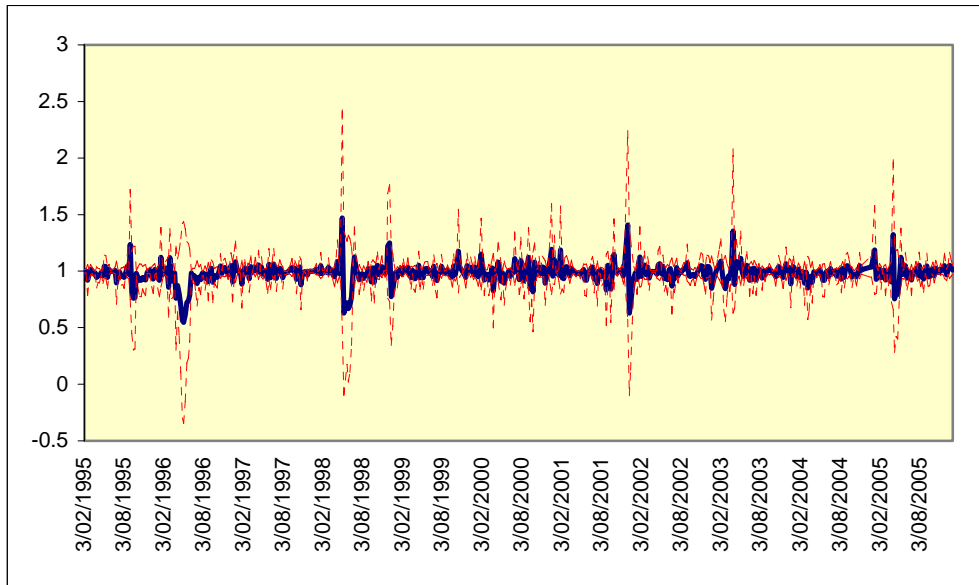
The sample period is Jan. 1995–Dec. 2005 and includes 562 weekly return observations.

B. Estimation results

Figures 1 and 2 show the estimated conditional optimal hedge ratios and the conditional optimal portfolio weights, respectively, for crude oil over the time period. The optimal hedge ratio oscillates near a value of 1.0, with occasional values exceeding 1.0. This result is due to the fact that the spot oil returns exhibit a larger standard deviation than that for the oil futures returns.⁷ The optimal portfolio weights for crude oil are relatively small by comparison with the hedge ratios. They average less than 0.05, implying that crude oil futures would constitute less than five percent of the portfolio mix with equities and bonds. These findings imply the role of crude oil futures held within a diversified portfolio may be expected to be relatively small when compared to the role of equities and bonds.

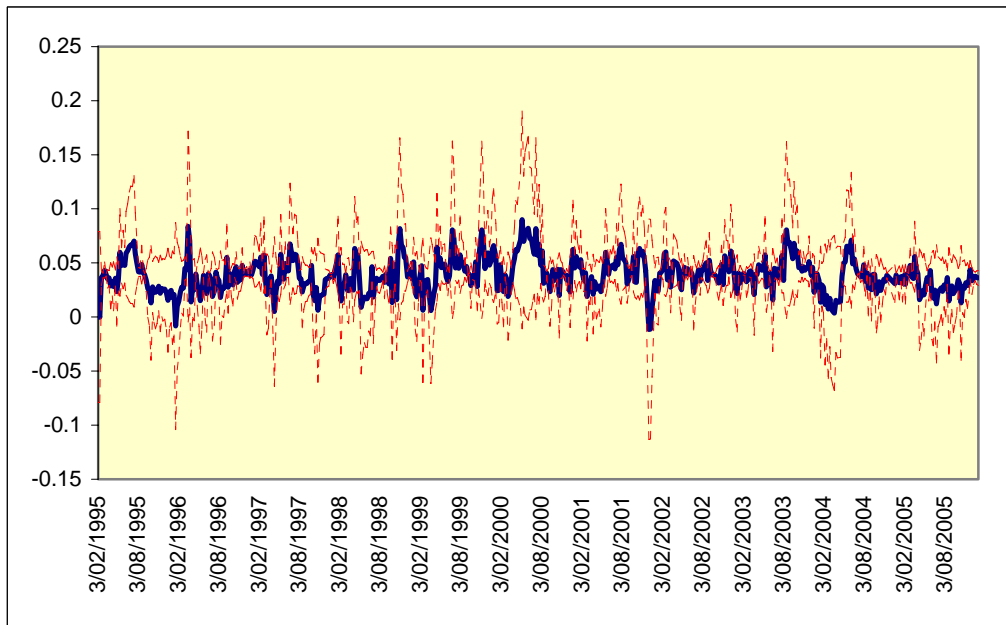
⁷ This condition is necessary but not sufficient for a hedge ratio greater than 1.0. See Ripple and Moosa (2005).

Figure 1. Estimated conditional crude oil futures hedge ratio.



Conditional confidence interval bounds are calculated as $h_t \pm 2\sqrt{(h_t - \bar{H})^2}$ where h_t, \bar{H} are defined in Eq. (5) and (6).

Figure 2. Estimated conditional crude oil futures portfolio weight.



Conditional confidence interval bounds are calculated as $w_{f,t} \pm 2\sqrt{(w_{f,t} - \bar{W}_f)^2}$ where $w_{f,t}, \bar{W}_f$ are the futures elements of the vectors defined in Eq. (3) and (4).

As detailed above, these conditional estimates enter our EGARCH estimation of the crude oil conditional volatility, and 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

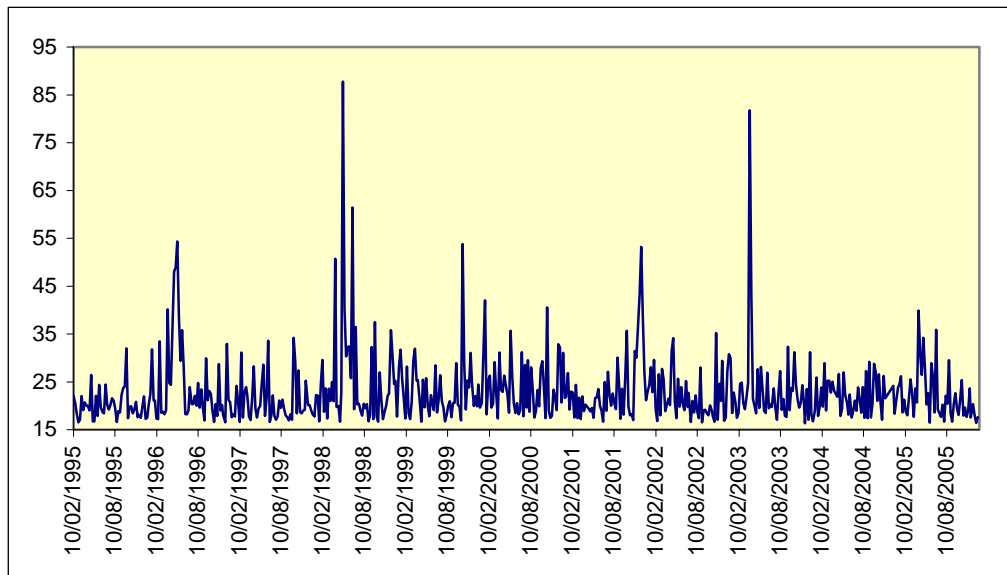
This table presents estimated coefficients for the conditional volatility defined in Eq. (2). T-ratios and p-values are based on Bollerslev-Wooldridge (1992) robust standard errors.

For our purposes the key results are reflected in the signs and significance of γ and δ , the coefficients on the measure of volatility of the hedge ratio and portfolio weight, respectively. The results show that the lagged volatility of the conditional hedge ratio relative to the unconditional 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 influence attributable to lagged volatility for the crude oil futures portfolio weight.

The lack of significance found for β may be evidence that the asymmetric responses observed in equities markets do not carry over into the futures markets, at least not the crude oil futures market. This implies that crude oil futures volatility does

not respond differently to either positive or negative shocks. Figure 3 reports the estimated conditional variance for crude oil futures returns.

Figure 3. NYMEX light sweet crude oil futures conditional variance.



Estimated conditional oil futures volatility as given by an EGARCH (1,1,0) model.

It is worth noting that the recent periods do not appear to be unusually volatile or uncharacteristic of the experience over the entire eleven-year period. This circumstance is contrary to general expectations and to recent commentary. Table 3 reports the DCC parameter estimates for the other three series.

Table 3: Remaining DCC parameter estimates.

	S&P 500	Bonds	Oil Spot
Variance Parameters			
α	0.149 (3.162)	0.076 (2.439)	0.180 (3.453)
β	0.822 (12.789)	0.811 (9.236)	N/A
Correlation Parameters			
ϕ		0.072 (3.192)	
η		0.768 (7.507)	

The Conditional Volatility (GARCH (1,1)) equations are specified as in Eqs. (12)-(15), and the Conditional Correlation Equation is given by Eq. (16). T-ratios are based on Bollerslev-Wooldridge (1992) robust standard errors.

The top portion of Table 3 reports the estimates for the variance equations of each of the returns series, while the lower portion reports estimates of the parameters of the correlation matrix. All coefficients are statistically significant at the 5 percent level.

The t-ratios presented in brackets are based on Bollerslev-Woodridge (1992) robust standard errors. The conditional correlation matrix parameters suggest that it is time varying, with a relatively large persistence parameter of 0.768.

Our results are derived from a completely different analytical approach than those of either Haigh, *et al.* (2006) or NYMEX (2005), but they are quite consistent. We find that, if hedgers and investors optimize their respective hedging strategies and portfolios based on a mean-variance expected utility maximization methodology and employ dynamic rebalancing to maintain optimality, hedgers are most likely to have a strong positive effect on the volatility of crude oil futures returns, and investors' rebalancing activities will not. This result is particularly interesting because it runs counter to the typical expectation.

V. Conclusion

In this paper, we present a new model that allows us to analyze the influence of different trader classes on the volatility of futures returns, and we apply this model to NYMEX crude oil futures. The model is a combination of a DCC and an augmented EGARCH structure, where the augmentation composes two elements that proxy the lagged volatility of the conditional optimal hedge ratio and the conditional optimal portfolio. The augmentation elements allow us to evaluate the influence of both hedgers and investors on the dynamics of the conditional volatility of oil futures returns.

Our principle result is that hedgers' trading activity, proxied by the volatility of the conditional hedge ratio, appears to have a positive and significant influence on the conditional volatility of crude oil futures returns. In addition, investors do not appear to exert any influence. This result is consistent with the findings of Haigh *et al.* (2006) who found that commercial traders tend to change their positions more frequently than do non-commercial traders.

We also find evidence that the volatility of crude oil futures returns is not asymmetrically sensitive to shocks of different signs.

Our results suggest that the focus on the role of speculators in the market may be misplaced, and that a more balanced analysis of the influences on the futures returns volatility is called for.

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