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The Efficiency of the Oil Futures Market and the Hedging Effectiveness of Symmetric vs. Asymmetric GARCH Models during Periods of Extreme Conditional Volatility

Mario El-Khoury

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ABSTRACT

The Efficiency of the Oil Futures Market and the Hedging Effectiveness of Symmetric vs. Asymmetric GARCH Models during Periods of Extreme Conditional Volatility

Mario El-Khoury

This paper investigates the efficiency of the NYMEX Division light sweet crude oil futures contract market during recent periods of extreme conditional volatility. Crude oil futures contract prices are found to be cointegrated with spot prices and unbiased predictors of future spot prices, including over the period prior the onset of the Iraqi war and until the formation of the new Iraqi government on April 2005. Both futures and spot prices exhibit asymmetric volatility characteristics. Hedging performance is improved when asymmetries are accounted for.

Keywords: oil futures; market efficiency; hedging.

JEL Codes: G13, G14.

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1. Introduction

Arbitrageurs, speculators, producers, and policymakers refer to the futures market for predicting future spot prices and minimizing their risk. A stress-test of any futures market is its ability to generate prices that are efficient, particularly during periods of extreme volatility/heightened uncertainty. Furthermore, during such periods, the choice of effective hedging procedures is of paramount importance for risk managers.

In recent years, oil markets have experienced sustained periods of extreme conditional volatility. Episodes of persistent market uncertainty are not unprecedented.[1] Historically, prolonged sharp increases in energy prices have led to inflation and adverse economic performance for oil importing countries. Similarly, sharp decreases create serious budgetary problems for oil exporting countries (see e.g. Abosedra and Baghestani, (2004)).

A number of studies have appeared that have addressed the efficiency of the oil futures market (e.g. Crowder and Hamed (1993), Moosa and Al-Loughani (1994), and Peroni and McNown (1998)). However, the literature to date does not provide any clear consensus. Moreover, no studies have appeared that

[1] As A. Greenspan noted: "In early twentieth century, pricing power was firmly in the hands of Americans, predominately J. D. Rockefeller and Standard Oil." Reportedly appalled by the volatility of crude oil prices in the early years of petroleum industry, Rockefeller endeavored with some success to control those prices. See A. Greenspan, Remarks to the National Italian American Foundation, Washington, D.C., October 15, 2004/

examine market behavior during periods of sustained extreme conditional volatility or of the effectiveness of alternative hedging models during such periods.

Our paper tests the efficiency of the oil futures during periods of extreme conditional volatility. Using Fama's (1984) regression approach with monthly data, a daily regression tests, as well as the Johansen (1998) cointegration techniques that are robust to varying error structures, we find that futures prices are unbiased predictors of future spot prices, consistent with the ***speculative efficiency hypothesis*** during the recent episodes of extreme volatility from the onset of the Iraqi war until the formation of the new Iraqi government.

Most applications of time-varying models of hedging have imposed symmetry in the responses of volatility to positive or negative shocks. In a recent study, Brooks, Henry, and Persand (2002) demonstrate that there are benefits to accounting for asymmetry in volatility in deriving optimal hedge ratios for equities with futures. The asymmetry that is typically found for equities associates negative price shocks with greater volatility increases than positive price shocks, due to leverage effects (e.g., Glosten, Jagannathan, and Runkle (1993) (GJR)). For oil, however, the asymmetry that we observe involves positive price shocks leading to greater volatility increases than negative shocks. To our knowledge, this is the first paper to incorporate asymmetries in volatility in the oil market to derive optimal hedge ratios for oil. Our results indicate that hedging performance is improved when such asymmetries are incorporated into the hedging procedures, based on out-of-sample estimates.

The paper proceeds as follows: In the second section, we provide a brief review of the literature. The third section describes the data. The efficiency tests and hedging analyses are provided in section four. The paper concludes with a summary in section five.

2. Background and Previous Work

In theory, if spot and futures markets are functioning efficiently, then in the absence of market frictions, futures contracts should be trading at a price known as the fair value. There have appeared various theoretical models of market efficiency for oil futures. The starting point of most studies is the arbitrage free or cost-of-carry model in which the futures price is represented as

$$F_t = S_t e^{(r+u-d)(T-t)} \tag{1}$$

where F_t is the futures price at time t, S_t is the spot price at time t, r is the risk-free interest rate, u is the storage cost, d is the convenience yield , T is the expiration date of the futures contract and T-t is the time to expiry of the futures contract. In practice, researchers have had difficulty testing the arbitrage relationship embodied in (1) due to the unobservable nature of storage costs and convenience yields in the oil markets.[2] Hence, most studies have focused on the Keynes-Hicks and Fama (1970) ***weak form market/speculative market efficiency*** tests of the form:

$$S_t = \alpha + \beta F_{t-i} + \varepsilon_t \qquad (2)$$

In this approach, market efficiency requires that futures prices should be unbiased predictors of future spot prices. Otherwise, risk-neutral speculators could make consistent profits on long or short futures positions through time. Simple empirical tests of the ***speculative efficiency hypothesis*** are based on tests of the joint hypothesis $\alpha = 0, \beta = 1$ in (2). For example, Crowder and Hamed (1993) examine the NYMEX crude oil contracts and conclude that accounting for the cointegration between spot and futures, one cannot reject the speculative efficiency hypothesis during the period March 1983 – September 1990. In contrast, Moosa and Al-Loughani (1994)'s reject futures market speculative efficiency for the West Texas Intermediate (WTI) contracts for the period January 1986-July 1990, which antedates the volatility spike that

[2] For example, Crowder and Hamed (1993) test a limited arbitrage version of (1) that includes a test for cointegration between oil futures prices, spot prices, and the risk free rate, ignoring storage costs and convenience yields. As they note, their rejection of this form of arbitrage efficiency cannot be explained by the behavior of convenience yields, as identified by Gibson and Schwartz (1990). In particular, since the risk free rate is non-stationary, it cannot be cointegrated with the stationary convenience yield shown by Gibson and Schwartz (1990).

occurred during the Iraqi invasion of Kuwait in August 1990. They suggest that their results may be consistent with rational expectations with a time varying risk premium. However, Peroni and McNown (1998) note that the Moosa and Al-Loughani conclusion may be unwarranted, as a result of the shortcomings of the test statistics employed.[3] Using monthly data, and the Phillips and Loretan (1991) approach, Peroni and McNown (1998) support the speculative efficiency hypothesis for the WTI for the 1984-1996 period.

A basic question that we address in this paper is whether oil futures prices are consistent with speculative market efficiency during periods of significant uncertainty. Such periods are associated with extreme volatility. Figure I provides a plot of conditional volatility in the price of the nearby contract of the NYMEX Light Sweet, Crude Oil futures contract using a GARCH (1,1) model, estimated over the period January 1, 1986 - April 30, 2005. We define extreme values of these estimates in the conventional statistical sense of extreme outliers, as estimates that exceed three times the inter-quartile range for the data over this period. For our sample, this corresponds to volatilities in excess of .49. Episodes of extreme volatility are fairly concentrated in time, and have been most evident over the recent period coinciding with the onset of the Iraqi war in March 2003.

[3] Specifically, Perroni and McNown(1998) demonstrate that the stationary regressors do not have a drift component, and hence the standard error adjustments used by Moosa and Al-Loughani (1994) are problematic.

Our tests of the speculative efficiency hypothesis provide two extensions to the work of Peroni and McNown (1998): a) we test whether the estimation that includes the recent episodes of extreme volatility leads to pricing biases that are inconsistent with speculative efficiency; and b) in contrast to who use the single equation Phillips and Loretan (1991) NLS procedure we employ the Johansen 's (1988) cointegration tests that have been shown to produce superior inference relative to such estimators, and are robust to alternative error structures (Gozalo (1995)).

Given time-varying volatility of the oil markets that is observed, one might expect that much attention would be devoted to devising appropriate hedging models for such markets. This does not appear to be the case, however. Baillie and Myers (1991) and Moschini and Myers (2002) are among the few studies that have looked at hedging oil contracts. Both studies are based on symmetric GARCH models and conclude that time varying hedge ratios outperform the constant hedge model. We will reexamine this issue using more recent data that encompasses a more volatile period in the market. In addition, we will analyze the relative performance of hedging models that incorporate the observed asymmetric responses of volatility to shocks that is found for these contracts.

3. Data

3.1 - Data Description

The data employed in this study consist of closing daily prices (unless specified otherwise) for both the spot prices and the nearby futures prices for the world's most liquid and heavily traded oil futures contract, the NYMEX's Light Sweet, Crude Oil contract.[4] The data are obtained from the U.S. Energy Information Administration and from Bloomberg.[5] The data period extends from January 1986 to April 2005 (4819 observations), and embraces the recent subperiod of extreme conditional volatility, that covers the onset of the Iraq war (March 2003) to the installation of the new Iraqi government (April 2005).

3.2 - Statistical Characteristics of the Data

Figure II plots the nearby contract prices and daily spot prices against time. As noted in Figure I, oil returns experience volatility clustering around periods of heightened uncertainty (Gulf War, Iraq War).

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[4] This contract is also the world's largest-volume futures contract trading on a physical commodity. These contracts trade on a 30 consecutive month basis.

[5] The analyses presented use contracts that are rolled over at maturity. The contracts cease trading at the close of business on the third business day prior to the 25th calendar day of the month proceeding the delivery month. If the 25th calendar day of the month is a non-business day, trading ends on the third business day prior to the business day proceeding the 25th calendar day. We also constructed futures series with a roll over to the next contract one week prior to maturity. The results are very similar to the ones reported here and are available upon request.

Table I shows the distribution of the daily closing nearby futures contract prices. As is evident, the price series indicate strong evidence of leptokurtosis and skewness, which is consistent with a generalized error distribution GED (Nelson (1988)) or a Student-t-distribution (Bollerslev (1987)).

- Insert Table I here -

4. Methodology

4.1 – Testing Speculative Market Efficiency

We conduct two sets of tests for speculative market efficiency. First we test whether the futures contracts are unbiased predictors of future spot prices. Second, we examine the nature of the cointegration relationship between spot and futures contracts.

4.1.1 – Future Contracts as Unbiased Predictors, Monthly Horizons

To test for unbiasedness of futures prices, two approaches are taken. First, as per West (1997) we look at how well futures and the spot prices on the day immediately after the expiration of the contract are used as the best available forecast for the coming month. Although this involves a sacrifice in usable observations, it avoids problems associated with autocorrelation of overlapping series.

We implement Fama's (1984) regression approach to test whether the basis at any period contains information about future spot prices or contains information about the risk premium at the expiration of the future contract. Two equations are estimated.

The first is:

$$S_{t+1} - S_t = \alpha_1 + \beta_1(F_t - S_t) + \varepsilon_{1,t+1} \quad (3)$$

The second is:

$$F_t - S_{t+1} = \alpha_2 + \beta_2(F_t - S_t) + \varepsilon_{2,t+1} \quad (4)$$

where ($F_t - S_t$) is the basis at time t, S_{t+1} is the observed spot price at time t+1 and F_t is the futures contract price at time t, and $\varepsilon_1(t+1)$ and $\varepsilon_2(t+1)$ are residual terms.

If β_1 is significantly different than zero then we can deduce that ($F_t - S_t$) contains information about the changes in spot price. Moreover, if β_2 is significantly different than zero then the premium, $F_t - S_{t+1}$ has variations that shows up in the basis.

Estimation of (3) and (4) requires that the data series be stationary. In order to test for stationarity, we use the Dickey and Fuller (1981), augmented Dickey Fuller (ADF), and Phillips-Perron (PP) tests.

The results in Table II show that the basis, the premium, and the change in the future spot prices are indeed stationary, and hence the regressions are well-specified.

- Insert Table II here -

Table III reports the results of the estimation of (3) and (4). Based on the estimates of (3), we can conclude that the basis at time t contains some information regarding future changes in the spot market. Unbiasedness of the futures as predictors of spot prices is supported, since the estimated constant term is not significantly different from zero, and the slope coefficient is not significantly from one. For regression (4), the results are consistent with a time varying risk premium.

- Insert Table III here -

Table IV reports the Wald test results for both models in which we examine the expectation hypothesis by restricting the coefficients $\alpha_1 = 0, \beta_1 = 1$ in (3) and $\alpha_2 = 0, \beta_2 = 1$ in (4).

The results show that for both models the expectation hypothesis cannot be rejected.

- Insert Table IV here -

4.1.2 - Futures Contracts vs. Random Walk Predictors, Daily Horizons

The previous tests for unbiasedness of futures prices are based on monthly series. An alternative approach for testing market efficiency is to examine the prowess of futures prices relative to random walk predictors using daily data. As per Park and Switzer (1997) we estimate:

$$S_T^i = \alpha_0 + \alpha_1 F_{t,T}^i + \alpha_2 MAT_t^i + \varepsilon_t^i \qquad (5)$$

where S_T^i is the prevailing spot price for contract i that matures at time T; $F_{t,T}^i$ is the futures price of contract i at time t; MAT is the number of days for contract i to mature as of time t, and ε_t^i is the error term. If α_1 is found to be significantly different than 0, then the current contract prices are good predictors of future spot prices.

The above model is compared with the simple random walk model:

$$S_T^i = \beta_0 + \beta_1 S_{t,T}^i + \beta_2 MAT_t^i + \varepsilon_t^i \qquad (6)$$

where $S_{t,T}^i$ is the spot price at time t that matures at T.

In the analyses, we examine the period from January 2000 to March 2005 (61 contracts), as well as a subset of this period, that focuses only on the period of extreme conditional volatility, from March 2003 to January 2005 (25 contracts). The results are reported in Tables V and VI.

- Insert Tables V and VI here -

Estimates of (5) and (6) for both datasets show that current future contracts as well as spot prices are significant predictors of future spot prices. The futures contract prices slightly outperformed the random walk although both α_1 and β_1 are found to be significantly different than zero.[6] This result is consistent with Moosa and Silvapulle (1999) who found a bi-directional causality or in simpler words a changing pattern in leads and lags over time. The interpretation is that both futures and spot prices play a significant role in price discovery including during periods of extreme conditional volatility.

4.2 – Cointegration Tests

Our final set of tests of efficiency we examine the nature of the cointegration of spot and futures prices spot during period of extreme conditional volatility.

We first test for the order of integration in each of the spot and the futures series using various unit root tests. Based on detrended Dickey Fuller tests, Augmented Dickey-Fuller tests, and Phillips-Perron tests, the results show that

[6] According to the Wald Test results, α_1 and β_1 are found to be significantly different than zero with an F-stat of 12955 and 12479 respectively.

the series have a stochastic trend in their univariate time-series presentations (non-stationary), while first differences are stationary.

- Insert Table VII here -

Based on the results derived from estimation of equations (3) and (4), futures contract prices are found to be an unbiased predictor of future spot prices. This implies that there exists a linear relationship between the spot and the futures series that is expected to be stationary. In other words, a cointegrating relationship is expected to exist between the two series as represented in (2).

Cointegration is considered as a necessary condition for market efficiency (Lai and Lai, 1991). However, in order to conclude efficiency, we should also examine whether futures contracts are unbiased predictors of futures spot markets i.e. $\alpha = 0$ and $\beta = 1$. If the oil spot and futures contract prices are cointegrated, then a long-run relationship must exist between these two series.

Johansen's (1988) approach is employed in order to test for cointegration. We consider a general VAR model of order k,

$$\Delta \mathbf{X}_t = \mathbf{D} + \mathbf{\Pi} \mathbf{X}_{t-1} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{X}_{t-i} + \varepsilon_t \qquad (7)$$

where $\Delta \mathbf{X}_t = \mathbf{X}_t - \mathbf{X}_{t-1}$; $\mathbf{D}$ is a deterministic term; $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ are matrices of coefficients. The cointegration relationship is examined by looking at the rank of the coefficient of matrix $\mathbf{\Pi}$. If $\mathbf{\Pi} = 0$, there is no cointegration vector, hence no cointegration relationship.

If $\mathbf{\Pi} = 1$, then the two series are cointegrated (Johansen and Juselius, 1990). The trace and maximum statistics are used[7].

- Insert Table VIII here -

Both test statistics give the same result and rejecting the assumption of no-cointegration. Looking at the cointegrating vectors, we can see that there exist a relationship between spot and futures prices that shows that one of the series contains some information that can help predict its counterpart.

- Insert Table IX here –

Table X tests whether the futures contracts are efficient predictors of future spot prices i.e. testing oil market efficiency by examine the joint hypothesis of $\alpha = 0$ and $\beta = 1$. Using Likelihood Ratio tests, we are unable to reject the null that the cointegrating vector is given by (1,-1). Future contract prices are found to be unbiased predictors of future spot prices, confirming the results from the previous section and the theory of market efficiency. These results are consistent with those of Crowder and Hamed (1993), as well as Peroni and McNown (1998) who examined a less volatile period in the oil markets.

- Insert Table X here -

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[7] The trace statistic tests the null that the number of cointegrating vectors is less than or equal to *r* against and unspecified hypothesis; whereas the maximum eigenvalue statistic tests the null that the number of cointegrating vectors is *r* against an alternative of *r +1*, where *r* is the canonical correlation coefficient between the two series. Both tests are formulated as:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{g} Ln(1-\hat{\lambda}_i),$$

$$\lambda_{\max}(r, r+1) = -TLn(1-\hat{\lambda}_{r+1})$$

4.3 - Volatility and Hedging

Energy prices are characterized by high, time-varying volatility with ARCH/GARCH features[8]. The symmetric GARCH model assumes that a negative shock ($\varepsilon_t \prec 0$) and a positive shock ($\varepsilon_t \succ 0$) have the same effect on the conditional variance. To allow for asymmetric effects of shocks (i.e. that depend on the sign of the shock) on conditional variance, Glosten et al (1992) (GJR) introduced the asymmetric GARCH variant:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 \varepsilon_{t-1}^2 I_{t-1}, \qquad (8)$$

$$\text{where } I_{t-1} = \begin{cases} 1, \varepsilon_{i,t} \geq 0 \\ 0, \varepsilon_{i,t} \prec 0 \end{cases} \qquad (9)$$

The short-run persistence of positive shocks is given by α_1 and short-run persistence of negative shocks is given by $\alpha_1(\alpha_1 + \gamma_1)$.

Estimates of the GARCH (1,1) model and for the GJR-GARCH model for spot and futures prices are reported in Tables XI and XII respectively, using a Student t- distribution of the error terms. Both models appear to provide a good explanation for both series. The Student *t* distribution is found to be appropriate

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8 Autocorrelation of the variance of daily returns is reflected in the significant Box-Ljung statistic Q statistic of 142.93 (for j=36). The Lagrange Multiplier statistic for ARCH/GARCH effects in spot returns also has a highly significant value of 81.88.

in all the cases with a highly significant degree of freedom coefficient. Both series exhibit statistically significant conditional heteroscedasticity. Table XI also reveals strong evidence for the presence of persistence in volatility (Integrated GARCH) where the sum of α_1 and β_1 is close to one.

- Insert Table XI here –

Table XII displays estimates of the asymmetric GARCH model. Significant positive asymmetry in the futures series is found: positive prices shocks are associated with greater volatility increases than negative price shocks. This contrasts with typical results for equity markets, where negative asymmetry is observed – i.e. volatility increases more on price declines due to leverage effects (e.g. Glosten et al (1993)). In contrast, for oil, price increases are often associated with production shocks and /or during periods of growing demand. Recent volatility shocks have occurred during periods in which demand has increased at a faster pace than production from existing sources and from new discoveries of oil. [9]

- Insert Table XII here -

[9] From the U.S. Energy Information Administration estimates, we note that world demand for oil has grown consistently from 2001-2004, with excess world demand appearing in 2003-04. See: http: //www.eia.doe.gov/emeu/ipsr/t21.xls.

4.4 – Hedging During Periods of Extreme Conditional Volatility

How effective is hedging during periods of extreme volatility? To address this issue, we examine the performance of several hedging procedures.

The return on an unhedged portfolio can be written as:

$$R_u = S_{t+1} - S_t \tag{10}$$

while the return on a hedged portfolio is:

$$R_h = (S_{t+1} - S_t) - h'(F_{t+1} - F_t) \tag{11}$$

where F_t and S_t are the futures and spot prices at time *t,* and h' is the hedge ratio. R_h is the return generated when going long on one unit of spot and short on h' units of futures at time *t*.

Similarly, the variance of an unhedged portfolio is:

$$Var\,(U) = \sigma_s^2, \tag{12}$$

and the variance on a hedged portfolio is :

$$Var(H) = \sigma_s^2 + h'^2\,\sigma_f^2 - 2h'\sigma_{s,f}, \tag{13}$$

where σ_s, σ_f represent the standard deviation of the spot and futures prices and $\sigma_{s,f}$ represent the covariance of both series.

Following Ederington (1979) and Park and Switzer (1995), hedging effectiveness can be measured by the percentage reduction in variance of the hedge portfolio to the unhedged portfolio:

$$HE = \frac{Var(U) - Var(H)}{Var(U)} \tag{14}$$

We assume a weekly horizon for the hedging, and focus on Friday closing prices for the extreme conditional volatility period March 2003 - April 2005. For the futures contracts, the price of the nearest contract is used and rolled over to the week prior to expiration. The sample consists of 102 observations.

We examine four alternative hedge ratios:

a) Naïve or 1-1

b) OLS

c) Symmetric bivariate GARCH:

The model for the first two conditional moments for the bivariate distributions of spot and futures series is:

$$\begin{aligned} S_t &= \alpha_0 + \beta_0 (S_{t-1} - \lambda F_{t-1}) + \varepsilon_{st} \\ F_t &= \alpha_1 + \beta_1 (S_{t-1} - \lambda F_{t-1}) + \varepsilon_{ft} \end{aligned}$$

where

$$\begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} | \Omega_{t-1} \sim N(0, H_t), \text{ and } H_t = \begin{bmatrix} h_{ss,t} & h_{sf,t} \\ h_{sf,t} & h_{ff,t} \end{bmatrix} \tag{15}$$

The term $(S_{t-1} - \lambda F_{t-1})$ is the error correction term that accounts for the cointegration between the spot and the futures series with λ as the cointegration parameter. The terms ε_{st} and ε_{ft} represent the residuals obtained from the spot and futures mean equations. The conditional covariance dynamics are modeled with the BEKK parameterization, which ensures a positive semi-definite conditional variance-covariance matrix. The distribution of the residuals is:

$\varepsilon_t \sim N(0, H_t)$,

$$H_t = C'C + A'H_{t-1}A + B'\varepsilon_t\varepsilon_t'B \qquad (16)$$

where H_t is the 2x2 variance-covariance matrix, A and B are matrices of coefficients, and C is an upper triangular matrix of intercept coefficients. ε_t is the vector of residuals with conditional mean 0 and conditional variance-covariance H_t.

d) Aymmetric bivariate GARCH :

This approach differs from the symmetric bivariate GARCH approach in that the covariance matrix (21) is replaced by:

$$H_t = C'C + A'H_{t-1}A + B'\varepsilon_t\varepsilon_t'B + G'\eta_{t-1}\eta_{t-1}'G \qquad (17)$$

where and G is a matrix of coefficients, and η_t is the additional quadratic form of the vector of negative return shock. H_t is a linear function of its own past values as well as of values of squared shocks. The inclusion of η_t in the above form not only accounts for asymmetry in the conditional variances but also allows for an asymmetric effect in the conditional covariance. Because this methodology implies no restriction of constant correlation between the futures and the spot series, it allows us for time variation in the correlations across the two series over time.

Parameter estimates are obtained by maximizing the log-likelihood function. Conditional log-likelihood functions are computed as:

$$L_t(\theta) = - \log 2\Pi - ½ \log |H_t| - ½\, e_t'(\theta)H_{t-1}(\theta)e_t(\theta) \qquad (18)$$

where θ is the vector of all parameters β_{ij} for i = oil spot and futures series, and j = 1 or 2 whether it is variance or covariance respectively. To maximize this log-likelihood function, we use the simplex and Berndt, Hall, Hall, and Hausman (1974) algorithms.

Table XIII shows the estimates of the symmetric and asymmetric Bivariate GARCH models for the entire period. The likelihood ratio statistic comparing the asymmetric vs. symmetric model is 19.996, which is exceeds the χ^2 critical value with three degrees of freedom at the 1% level (11.3). This demonstrates that the asymmetric model provides significant improvement over its symmetric counterpart.

-Insert Table XIII here-

Hedging effectiveness is then measured in an out of sample setting. We use rolling windows of 70 observations for both bivariate GARCH models, to ensure sufficient data for the estimation of the parameters. Out of sample hedge ratios are thus computed for observations 70-102, and are displayed in Figure III.[10]

-Insert Figure III here-

As with the naïve 1-1 hedge, the OLS hedge ratios are constant, and are based on the first 70 observations of the sample. For the symmetric bivariate GARCH and asymmetric bivariate GARCH models, the estimated parameters are based on rolling windows as described above.

The time-varying hedge ratios, h_t^*, can be obtained from the variance estimated of models (16) and (17).

$$h_t^* = {h_{sf,t}}\big/{h_{f,t}} \tag{19}$$

[10] The first out of sample hedge ratio uses the first seventy observations to compute the seventy first hedge ratio. The second out-of-sample hedge ration uses observations two to seventy one, and so forth.

As is evident, the asymmetric bivariate GARCH hedge ratios are higher than their symmetric counterparts.

As shown in Table XIV, the time-varying asymmetric Bivariate GARCH hedge ratios outperform the OLS and naïve counterparts. This is consistent with previous work for commodity and financial markets (e.g., Baillie and Myers (1991), Park and Switzer (1995)). Given the reaction of financial markets to news and the corresponding need to adjust off-setting hedges, this result should be obvious.[11] What is a novel and intuitive finding is that the asymmetric bivariate GARCH hedge model for in which positive prices shocks are associated with greater volatility increases than negative price shocks are shown to provide the best performance. This result is also consistent with recent work by Brooks et al. (2002) who demonstrate that or asymmetries in time-varying hedge ratios perform well for financial instruments.

- Insert Table XIV here -

5. Conclusion

This paper examines the efficiency of the oil market over the past two decades, and focuses on periods of extreme volatility in the markets, particularly from the onset of the Iraqi war in 2003 to the formation of the new Iraqi government

[11] We would like to thank the referee for this point.

in 2005. We also analyze the performance of alternative hedging models during periods of extreme conditional volatility.

The results are consistent with market efficiency, even during the recent episodes of extreme conditional volatility. Crude oil futures contract prices behave as unbiased predictors of future spot prices; in addition, the cointegration relationship between the futures and the spot series is consistent with efficiency.

Univariate GARCH models of the distribution of the spot and futures series reveal evidence of long-term volatility persistence and volatility clustering. When GJR-GARCH models are examined, significant volatility asymmetries in the futures and spot series are also found. Such asymmetries are incorporated in an asymmetric multivariate GARCH hedging model that is estimated for the first time, to our knowledge, for oil futures contracts. Out of sample tests demonstrate the superiority of this model relative to alternative models, including the symmetric bivariate GARCH model.

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Figure I - Daily GARCH Variance Series of Log Futures Contract Prices

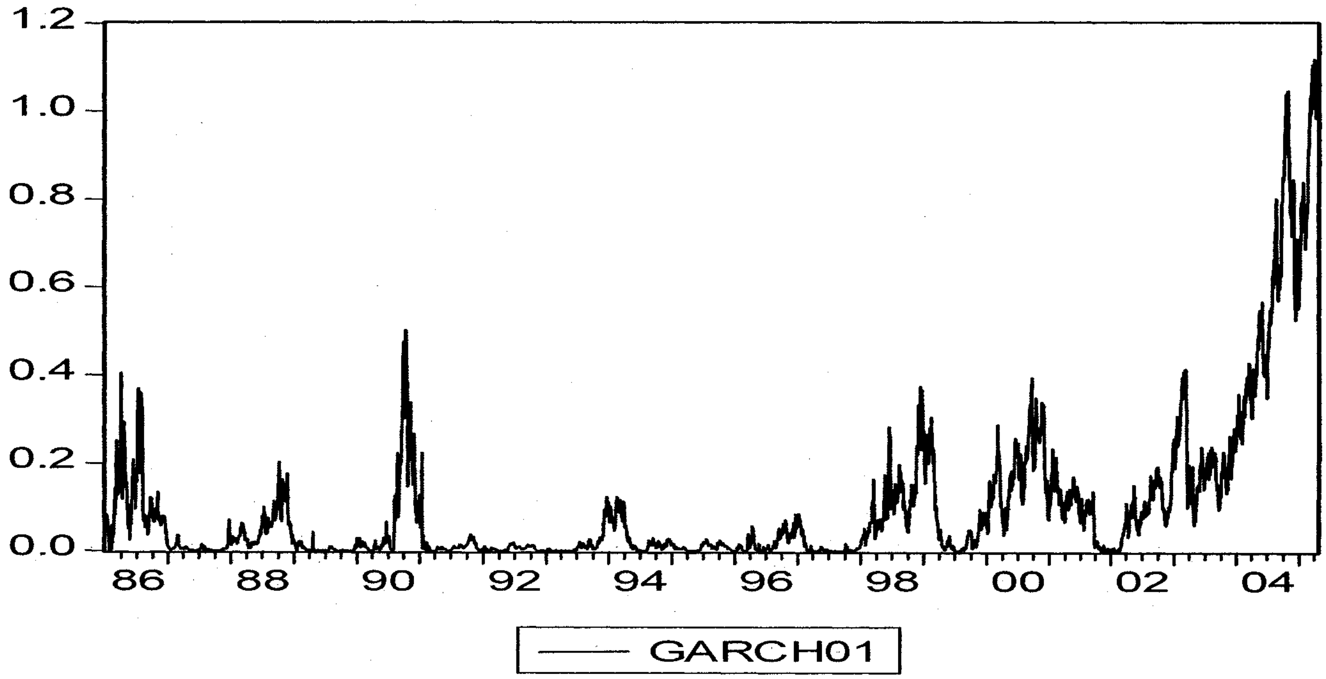

Figure II - Daily Futures Contract vs. Spot Prices

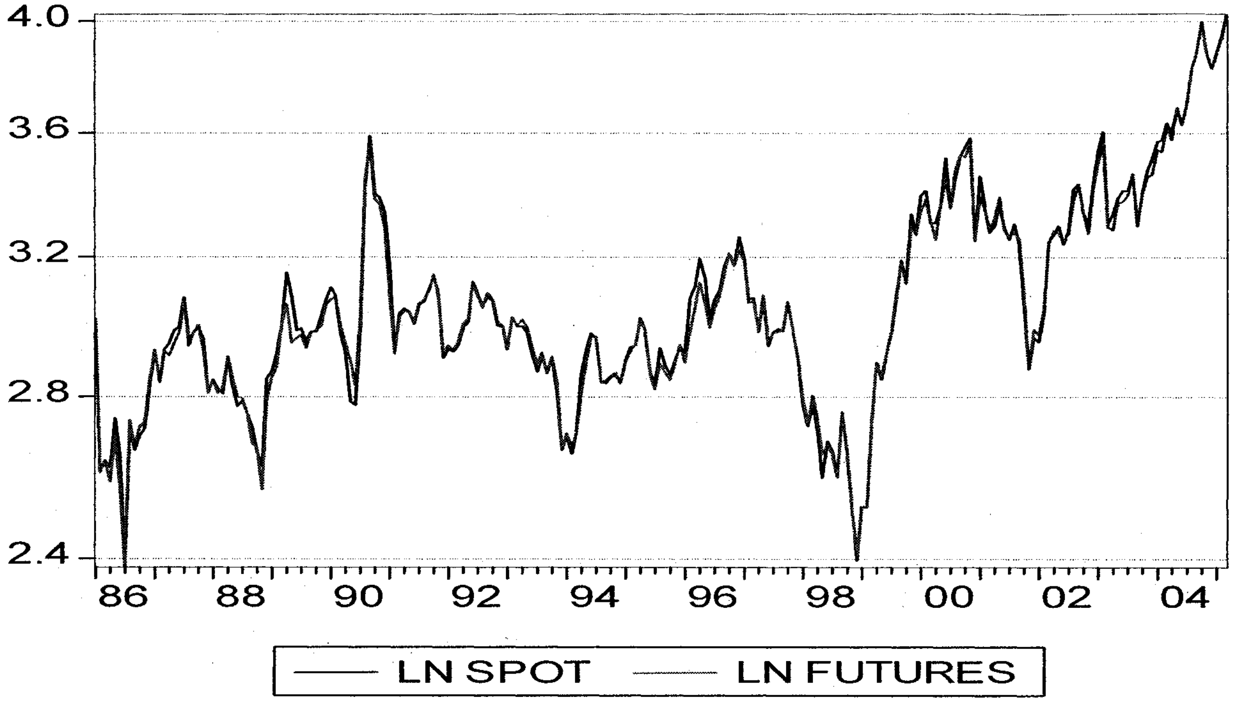

Figure III – Out of Sample Hedge Ratios, OLS, Bivariate Symmetric GARCH (SYMMETRIC), and Bivariate Asymmetric GARCH (ASYMMETRIC)

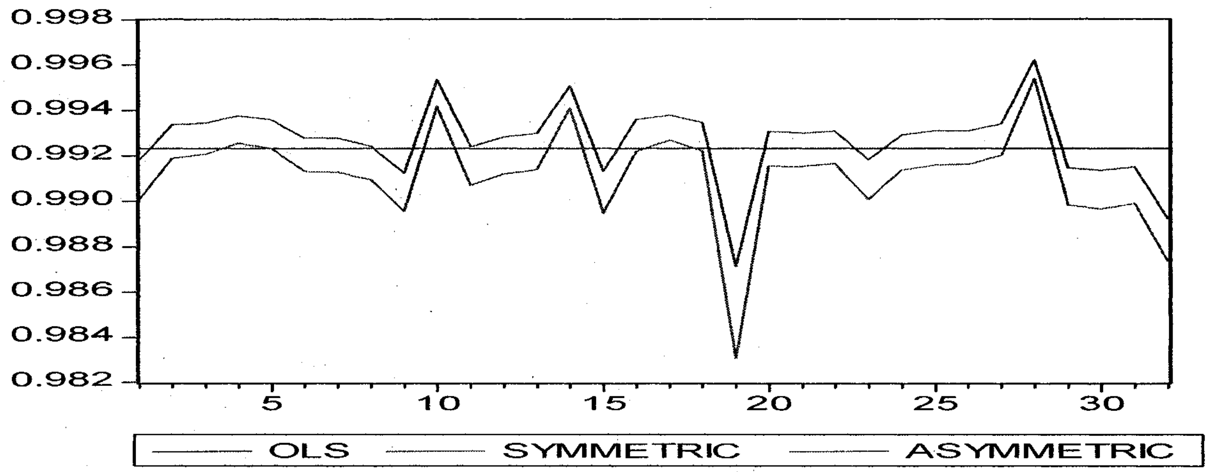

Table I – Distribution of Daily Contract Prices (in Logarithms)

Series: Jan. 1986 – April 2005	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Futures Prices	3.067	4.0477	2.3437	0.305	0.679	3.431	408.457
Spot Prices	3.068	4.0476	2.327	0.305	0.675	3.409	399.89

Table II - Unit Root Test Statistics for Fama Model Variables

Series: Jan. 1986 – April 2005	ADF	DF-GLS	PP
Change in Spot	-6.233685*	-1.100388	-6.17111*
Basis	-6.348805*	-6.363539*	-8.80031*
Risk Premium	-5.955168*	-1.082402	-5.95517*

Note - ADF, DF, and PP denote augmented Dickey Fuller, Dickey Fuller and Phillips Perron respectively. The values reported in the table represent the t-statistics for the ADF and DF test and the adjusted t-statistic for the PP test. The asterisk denotes significance at a 1% level. Critical values at a 1% level are -3.458719, -2.575189 and -3.74 for ADF, DF, and PP respectively from MacKinnon (1996).

Table III - Results of Fama's Model

Estimation Period: January 1986 – April 2005	α_1	β_1	F-Stat
Regression (3):			
$S_{t+1} - S_t = \alpha_1 + \beta_1(F_t - S_t) + \varepsilon_{1,t+1}$	0.000281	0.649067*	6.596267*
	[0.00704]	[0.28355]	
	α_2	β_2	**F-Stat**
Regression (4):			
$F_t - S_{t+1} = \alpha_2 + \beta_2(F_t - S_t) + \varepsilon_{2,t+1}$	-0.00346	1.129062*	21.73576*
	[0.00675]	[0.2615]	

Note - Robust standard errors are reported inside parentheses. * denotes significance at a 5% level

Table IV - Wald Test Results of Fama Model

Estimation Period: January 1986 – April 2005	$\alpha_1 = 0, \beta_1 = 1$	$\beta_1 = 1$	$\alpha_1 = 0$
Regression (3):	2.107178	1.928274	0.00165
$S_{t+1} - S_t = \alpha_1 + \beta_1(F_t - S_t) + \varepsilon_{1,t+1}$	[0.3487]	[0.1663]	[0.9676]
	$\alpha_2 = 0, \beta_2 = 1$	$\beta_2 = 1$	$\alpha_2 = 0$
Regression (4):	0.37826	0.28401	0.272439
$F_t - S_{t+1} = \alpha_2 + \beta_2(F_t - S_t) + \varepsilon_{2,t+1}$	[0.6855]	[0.5946]	[0.6022]

Note - F values reported. *p-values* reported in parentheses.

Table V - Oil Futures Contracts as Predictors of Futures Spot: Daily Data

Panel A: OLS Estimates of
$S_T^i = \alpha_0 + \alpha_1 F_{t,T}^i + \alpha_2 MAT_t^i + \varepsilon_t^i$
Estimation Period: January 2000 - March 2005

Independent Variable	Coefficient	t-statistics
$F_{t,T}^i$	0.978101*	98.83
	[0.0098]	
MAT	0.000983*	4.5
	[0.000218]	
α_0	0.064752	1.87
	[0.0345]	
F-statistic	6257.005	
Prob(F-statistic)	0	

Panel B: OLS Estimates of $S_T^i = \alpha_0 + \alpha_1 F_{t,T}^i + \alpha_2 MAT_t^i + \varepsilon_t^i$
Estimation Period March 18, 2003 till March 31, 2005

Independent Variable	**Coefficient**	**T-statistics**
$F_{t,T}^i$	0.9477*	55.361
	[0.017]	
MAT	0.001071*	2.856
	[0.0132]	
α_0	0.17578	2.787
	[0.586]	
F-statistic	2071.60	
Prob(F-statistic)	0	

Note - * denotes significance at a 5% level or better. Robust standard errors are reported in parentheses. S_T^i is the prevailing spot price for contract i that matures at time T; $F_{t,T}^i$ is the futures price of contract i at time t; MAT is the number of days for contract i to mature as of time t, and ε_t^i is the error term.

Table VI - Random Walk Model Estimates: Current Spot Market Prices as Predictors of Future Spot Prices: Daily Data

Panel A: OLS Estimates of

$S_T^i = \beta_0 + \beta_1 S_{t,T}^i + \beta_2 MAT_t^i + \varepsilon_t^i$

Estimation Period: January 2000 - March 2005

Independent Variable	Coefficient	T-statistics
$S_{t,T}^i$	0.9676* [0.0115]	83.927
MAT	0.0236* [0.007]	3.334
β_0	0.8115 [0.3428]	2.367
F-statistic	6443.92	
Prob(F-statistic)	0.0000	

Panel B: OLS Estimates of

$S_T^i = \beta_0 + \beta_1 S_{t,T}^i + \beta_2 MAT_t^i + \varepsilon_t^i$

Estimation Period: March 2003-March 2005

Independent Variable	Coefficient	T-statistics
$S_{t,T}^i$	0.944* [0.0172]	54.898
MAT	0.0288* [0.01334]	2.1587
β_0	1.7767 [0.582]	3.048
F-statistic	1873.547	
Prob(F-statistic)	0.0000	

Note - * denotes significance at a 5% level or better. Robust standard errors are reported in parentheses. S_T^i is the prevailing spot price for contract i that matures at time T; MAT is the number of days for contract i to mature as of time t, and ε_t^i is the error term.

Table VII - Unit root test statistics for futures and spot series

Series	ADF	DF-GLS	PP
Part A: Price Levels			
Futures	-0.99711	0.238519	-0.96049
Spot	-1.13615	0.064633	-1.07128
Panel B: First Differences of Prices			
Futures	-22.76708	-8.739519	-22.76708
Spot	-22.45641	-2.187894	-22.47778

Note - The values reported in the table are the t-statistics (Adjusted t-statistics for PP). The 5% critical levels for ADF (Augmented Dickey Fuller), DF – GLS (Dickey Fuller detrended residuals), and PP (Phillips Perron) are -2.876, -1.94, and -2.87 respectively(MacKinnon (1996)).The AIC criterion was used (Max Lag Specified is 17).

Table VIII – Johansen Cointegration Tests

Panel A: Johansen Cointegration Tests (Trace Statistics)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
r = 0 *	0.204361	107.7532	15.49471	0.0001
r ≤ 1	0.002123	0.992570	3.841466	0.3191

Panel B: Johansen Cointegration Tests (Max Statistics)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
r = 0 *	0.204361	106.7606	14.26460	0.0001
r ≤ 1	0.002123	0.992570	3.841466	0.3191

Note – Trace test indicates 1 cointegrating equation at the 0.05 level. *denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values. Max-eigenvalue test indicates 1 cointegrating equation at the 0.05 level.

Table IX– Cointegrating Vector

Log Spot	Log Futures
1.000000	-0.997281
	(0.00341)

Note - Normalized cointegrating coefficients (standard error in parentheses).

Table X – Test of Cointegration Restrictions

Hypothesized No. of CE(s)	Restricted Log-likehood	LR Statistic	Probability
1	-806.9715	0.310966	0.577088

Table XI -Univariate GARCH (1, 1) Model Estimates

$$\Delta S_t = \mu_s + \varepsilon_t$$

$$\Delta F_t = \mu_f + \varepsilon_t, \text{ where } \varepsilon_t \mid \Omega_{t-1} \sim td(0, \sigma_t^2, v)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

	Spot Series		Futures Series	
	Jan 86 - Apr 05	**May 03 - Apr 05**	**Jan 86 - Apr 05**	**May 03 - Apr 05**
μ_s, μ_f	0.000515*	0.001803	0.000397	0.001599
	[0.000258]	[0.000976]	[0.000253]	[0.000979]
ω	0.00000701*	9.85E-05	0.00000564*	5.23E-05
	[0.00000157]	[0.00016]	[0.00000135]	[0.0000743]
α_1	0.072481*	0.024555	0.067015*	0.017118
	[0.007753]	[0.027603]	[0.007412]	[0.026163]
β_1	0.918777*	0.787879*	0.926014*	0.874044*
	[0.008032]	[0.324762]	[0.007638]	[0.169498]
T-DIST. DOF	5.25653*	6.402665*	5.223548*	9.891065*
	[0.378498]	[1.657025]	[0.408256]	[5.353408]
Log likelihood	11644.34	1127.064	11771.41	1141.945

Note - * denotes significance at a 5% level. Robust standard errors reported in parentheses

Table XII - Univariate GJR-GARCH Model Estimates

$$\Delta S_t = \mu_s + \varepsilon_t$$

$$\Delta F_t = \mu_f + \varepsilon_t, \text{ where } \varepsilon_t \mid \Omega_{t-1} \sim td(0, \sigma_t^2, v)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 \varepsilon_{t-1}^2 I_{t-1}, \text{ where } I_{t-1} = \begin{cases} 1, \varepsilon_{i,t} \geq 0 \\ 0, \varepsilon_{i,t} \prec 0 \end{cases}$$

	Spot Series		Futures Series	
	Jan 86 - Apr 05	May 03 - Apr 05	Jan 86 - Apr 05	May 03 - Apr 05
μ_s, μ_f	0.000516	0.001625	0.000385	0.001341
	[0.000261]	[0.000975]	[0.000256]	[0.000978]
ω	0.00000701*	9.48E-05	0.00000563*	5.51E-05
	[0.00000157]	[0.0000701]	[0.00000135]	[0.0000296]
α_1	0.072957*	-0.058609	0.064017	-0.073647*
	[0.010874]	[0.036673]	[0.009741]	[0.028224]
γ_1	-0.000813	0.131368	0.00541*	0.150128*
	[0.013386]	[0.069029]	[0.012357]	[0.063718]
β_1	0.918733*	0.808466*	0.926211*	0.882354*
	[0.008064]	[0.144276]	[0.007619]	[0.06947]
T-DIST. DOF	5.257597*	6.214766*	5.21572*	9.249676*
	[0.381099]	[1.540381]	[0.407855]	[4.606078]
Log likelihood	11644.34	1129.045	11771.5	1145.823

Note - * denotes significance at a 5% level. Robust standard errors reported in parentheses.

Table XIII- Bivariate GARCH Models Output: March 2003-April 2005

Panel A

Bivariate GARCH with positive definite parameterizations:

$H_t = C'C + A'H_{t-1}A + B'\varepsilon_{t-1}\varepsilon_{t-1}'B$

Variable	Coefficients	T-Stat	Significance
C_{11}	65.41765 [0.0096]	6745.191	0
C_{21}	65.36872 [0.00118]	55253.82	0
C_{22}	65.12832 [0.0017]	37447.04	0
A_{11}	0.051703 [0.0001]	440.9789	0
A_{21}	0.049301 [0.00004]	1228.81	0
A_{22}	0.04786 0.00006]	733.1889	0
B_{11}	0.050571 [0.00004]	1154.162	0
B_{21}	0.049586 [0.00002]	1988.179	0
B_{22}	0.051787 0.00011]	467.85	0
Log Likelihood	-1777.548		

Note – Robust standard errors are reported in parentheses

Panel B

Asymmetric Bivariate GARCH:

$H_t \ = C'C + A'H_{t-1}A + B'\varepsilon_{t-1}\varepsilon_{t-1}'B + G'\eta_{t-1}\eta_{t-1}'G$

Variable	Coefficients	T-Stat	Significance
$\mathbf{C_{11}}$	65.558386 [0.0653]	1002.90863	0
$\mathbf{C_{21}}$	66.278058 [0.00967]	6852.98009	0
$\mathbf{C_{22}}$	65.698383 [0.04534]	1448.8802	0
$\mathbf{A_{11}}$	0.0535357 [0.00019]	270.41279	0
$\mathbf{A_{21}}$	0.0500588 [0.00003]	1660.01114	0
$\mathbf{A_{22}}$	0.0473983 [0.00019]	241.14175	0
$\mathbf{B_{11}}$	0.0529187 [0.0003]	171.19364	0
$\mathbf{B_{21}}$	0.0466974 [0.0002]	188.60973	0
$\mathbf{B_{22}}$	0.0593932 [0.0005]	104.9803	0
$\mathbf{G_{11}}$	0.0006852 [0.00009]	7.10489	0
$\mathbf{G_{21}}$	-0.001441 [0.00000048]	-2997.14118	0
$\mathbf{G_{22}}$	-0.002374 [0.000062]	-379.6871001	0
Log Likelihood	-1767.55		

Note – Robust standard errors are reported in parentheses

Table XIV. Out-of-Sample Hedging Results: Hedging Effectiveness as measured by % of variance reduction relative to unhedged position.

	Naïve	OLS	BV-GARCH	GJR-GARCH
Hedging Effectiveness	0.8170	0.8097	0.8699	0.8732