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Modelling Long Memory in Volatility of Oil Futures Returns

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Abstract

This paper examines long memory in the West Texas Intermediate (WTI) and Brent crude oil futures markets using the GARCH-class models. The results provide strong evidence of long term dependence in returns for both markets at different maturities. Also, the presence of asymmetric leverage effect was detected in the oil futures prices for all markets. The findings suggest that the two oil futures markets have similar pattern in their returns volatility at different maturities which violates the market efficient hypothesis.

Keywords: Crude Oil Prices, Futures Markets, GRACH Models, Long Memory

1. Introduction

One of the important non-linear dynamics properties of oil prices is long-term dependence. Long memory (or long-term dependence) is a special form of non-linear dynamics where a time series has non-linear dependence in its first and second moments and between distant observations, and a predictable component that increases its forecast ability (Thupayagale, 2010). It also means that a time series displays slow decay in its autocorrelation functions (Belkhouja and Boutahary, 2011). Consequently, "the presence of long memory implies that energy prices and in particular oil prices (actually returns) tend to be highly volatile, with price changes that often partially cancel out, although the original shock takes a long time to work through the system" (Arouri et al, 2011). The existence of long memory also invalidates the weak-form efficiency of the oil markets because the oil price returns can be predictable (Elder and Serletis, 2008).

A large body of literature has examined long memory in the crude oil markets. However, majority of the previous studies have focused on the volatility of oil spot prices (see e.g; Alvarez-Ramirez et al, 2008; Ayadi et al, 2009; Kang et al, 2009; Cheong, 2009; Gui et al, 2010; Wang et al, 2010; Power and Turvey, 2010; Fernandez, 2010; Wei et al, 2010; Mohammadi and Su, 2010; Wang et al, 2011; Hou and Suardi, 2011). To our knowledge, there are only a handful of studies that have examined long memory using oil futures prices (see e.g; Tabak and Cajueiro, 2007; Cunado et al, 2010; Wang et al, 2011; Arouri et al, 2012; Ozdemir et al, 2013).

This paper contributes to the literature as follows: First, the existing literature has been devoted on the West Texas Intermediate (WTI) crude oil market. As an extension, this paper examines long memory in the WTI and Brent crude oil futures markets to find whether these prices have similar pattern or can serve as alternative. Second, it investigates long memory in these markets at different maturities because it is well known that futures contracts for different maturities can exhibit dissimilar patterns since they are traded for delivery on different periods. To our knowledge no previous study has examined whether oil futures markets have similar pattern of persistence across maturities. These results can help in making investment decisions, portfolio diversification and risk management. Third, the paper investigates whether the response of oil prices to shocks are similar across the markets and maturities.

The rest of the paper is organized as follows. Section 2 discusses the methodology employed. Section 3 describes the data used and its properties for this paper. Section 4 presents the empirical results and Section 5 concludes and make some recommendations.

2. Methodology

This paper examines long memory in oil futures markets using the generalized autoregressive conditional heteroskedasticity (GARCH) models. The GARCH model was introduced by Bollerslev (1986) where the current conditional variance depends on its own lagged values and the variance includes both autoregressive and moving average elements. The model can be described as follows:

$$r_t = \mu_t + \varepsilon_t \tag{2.1}$$

where, $\varepsilon_t / \psi_t \sim iid \quad N(0, \sigma_t)$

$$\sigma^2{}_t = \omega + \beta\sigma^2_{t-1} + \alpha\varepsilon^2_{t-1} \tag{2.2}$$

where r_t represents the dependent variable which is return, μ_t is the conditional mean, σ_t^2 is the conditional variance, ω is the unconditional mean value which is constant, σ^2_{t-1} is the GARCH term which capture information on the past forecast error variance, ε^2_{t-1} is the ARCH term which capture information on volatility from the past period. The parameters α and β are expected to be positive with the restrictions $\omega > 0, \alpha > 0, \beta > 0$ to ensure positive conditional variance. The sum of the parameters $\alpha + \beta$ measures the persistence of shock on volatility; where $\alpha + \beta > 1$ implies that shock to volatility would be unstable. As an extension, Nelson (1991) proposed the exponential GARCH (EGARCH) model that allows for asymmetric response of the conditional variance to both positive and negative shocks, and non-negativity in the parameters of the conditional variance. The EGARCH (1, 1) model can be written as:

$$\log \sigma_t^{\ 2} = \omega + \alpha z_{t-1} + \gamma\left(\left|z_t\right| - E\left|z_{t-1}\right|\right) + \beta \log\left(\sigma^2_{t-1}\right) \tag{2.3}$$

where, γ is the parameter that captures the asymmetric effect of shock to conditional variance. The condition $\gamma < 0$ means that positive shock leads to less volatility than negative shock while $\gamma > 0$ is the reverse condition of high volatility than negative shock (Mohammadi and Su, 2011). Ding et al (1993) developed the asymmetric power autoregressive conditional heteroskedasticity (APARCH) model to capture asymmetric effect of shock on conditional variance and assumes that the effect on residuals follow exponential rate of decay. The APARCH model can be written as:

$$\sigma_t{}^2 = \omega + \beta\sigma_{t-1}^{\delta} + \alpha\left(\left|\varepsilon_{t-1}\right| - \gamma\varepsilon_{t-1}\right)^{\delta} \qquad (2.4)$$

where γ is the coefficient that captures the asymmetric leverage effect on conditional variance and δ determines the best specification of the model. The restrictions $\delta > 0$ and $-1 < \gamma < 1$ are imposed on the parameters and the model takes the form of GARCH (1, 1) when $\delta = 2$ and $\gamma = 0$. The condition $\delta = 1$ means that the conditional standard deviation is the best for modelling shock to volatility while $\delta = 2$ suggest conditional variance.

The models discussed above deals with short memory because they assume exponential decay in their conditional variance. Baillie et al (1996) developed the fractionally integrated GARCH (FIGARCH) model which captures the long memory in conditional variance and allows the autocorrelation in volatility to die at slow hyperbolic rate. The FIGARCH $(1, d, 1)$ can be written as:

$$\sigma_t{}^2 = \omega + \left[1 - \beta(L)\right]^{-1} + \left\{1 - \left[1 - \beta(L)^{-1}\right]\phi(L)(1-L)^d\right\}\varepsilon^2{}_t \qquad (2.5)$$

where d is the fractional integrated parameter that captures long memory and L is the lag operator. The parameters must take the form $0 \le d \le 1$ and $\omega > 0, \phi < 1, \beta < 1$ to ensure positive conditional variance. The superiority of the FIGARCH model is that it permits three different conditions: the intermediate range of persistence (long memory) when $0 < d < 1$, infinite persistence when $d = 1$ and geometric decay when $d > 1$. Bollerslev and Mikkelsen (1996) extend the EGARCH model to capture both asymmetric response and long memory in the conditional variance. However, the fractional integrated EGARCH (FIEGARCH) model assumes non-negativity in the parameters of the conditional variance not as in the case of FIGARCH model. The FIEGARCH model can be written as:

$$\ln\sigma_t{}^2 = \omega + \phi(L)^{-1}(1-L)^{-d}\left[1 + \psi(L)\right]g_t(z_{t-1}) \qquad (2.6)$$

where $d < 1$ means that shock on conditional variance decay at slow hyperbolic rate. Tse (1998) further proposed the fractional integrated APARCH (FIAPARCH) model to capture long memory and asymmetric effect of shock on conditional variance. The FIAPARCH $(1, d, 1)$ model can be written as:

$$\sigma_t{}^2 = \omega + \left[1 - \beta(L)\right]^{-1} + \left\{1 - \left[1 - \beta(L)^{-1}\right]\phi(L)(1-L)^d\right\}\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^{\delta} \qquad (2.7)$$

where $0 \le d \le 1$, $\omega > 0, \delta > 0$, $\varphi, \beta < 1$ and $-1 < \gamma < 1$. The model reduces to APARCH model when $d = 0$ and FIGARCH when $\delta = 2$ and $\gamma = 0$. Davidson (2004) developed the hyperbolic GARCH (HYGARCH) model which is more powerful than the FIGARCH in accounting for long memory in conditional variance. The HYGARCH $(1, d, 1)$ model can be written as:

$$\sigma_t{}^2 = \omega + \left[1 - \beta(L)\right]^{-1} + \left\{1 - \left[1 - \beta(L)^{-1}\right]\phi(L)(1+k)\left[\left((1-L)^d - 1\right)\right]\right\}\varepsilon^2{}_t \qquad (2.8)$$

where $0 \le d \le 1, \omega > 0, k \ge 0$, $\varphi, \beta < 1$. The model reduces to GARCH when $d = 0$, FIGARCH when $k = 1$, IGARCH when $d = 1$ and $k = 1$, nonstationary $k \ge 1$ and stationary $k < 1$.

3. Data

The paper used daily closing futures prices for West Texas Intermediate and Brent at one and three-month contract to maturities from 3, January 2000 to 5, October 2013. Data for the study were obtained from the Data Stream International. All the price series were converted into log returns series calculated as $r_t = \log(p_t / p_{t-1}) \times 100$, where r_t is the futures return, p_t is the current futures price and p_{t-1} is lagged futures price for one period. The following notations: WTI-C1, WTI-C3, Brent-C1, and Brent-C3 are used to denote futures price returns at one and three-month maturities.

4. Empirical Results

Table 1 and Table 2 reports the results of the conditional mean and variance equations estimated from the GARCH models along with their diagnostic tests for the oil markets. First, the results of the GARCH (1, 1) model show that the parameter estimates for the conditional variance equation α and β are positive and significant in all markets at the different maturities. The estimates of the measure of persistence parameter $\alpha + \beta$ are about the same and very close to unity in the two oil futures markets within the maturities. The results show that the values are between 0.996 and 0.980 across the markets, suggesting that the oil futures markets have high degree of persistence consistent with those of Arouri et al (2012) and Wang et al (2010) who studied the WTI futures market. However, the results of the EGARCH model show that the estimated value of the measure of persistence is greater than unity in all markets except Brent at one month maturity. The values reported are between 1.212 and 1.576 across the markets and maturities which suggest permanent persistence in the returns series, supporting Wang et al (2010). Secondly, the results reported for the asymmetric parameter, γ in the EGARCH, APARCH, FIEGARCH and FIAPARCH models are positive and significantly different from zero in each case except at Brent one-month maturity. The results indicate that the estimates range across the models between 0.063 and 0.424 within the markets and maturities. This implies that there is strong evidence of a leverage effect in the oil markets except Brent one-month maturity. Thirdly, the results indicate that the estimates of the power parameter δ which select the best specification for modelling oil futures returns across the APARCH and FIAPARCH models are between 1.006 and 1.975 across the markets. The results cannot reject the null hypothesis of $\delta = 1$ at the 5% significance level in all the markets, suggesting that their returns are better investigated with conditional standard deviation which supports the presence of long memory.

Fourthly, the results of the estimated values of the long memory parameters d show that the fractional integrated coefficient are all significant and different from zero in the FIGARCH, FIEGARCH, FIAPARCH and HYGARCH models. For the WTI market, the values of the estimates range from 0.392 to 0.678 across the models within the maturities, results consistent with Arouri et al (2012) and Wang et al (2010). In the Brent market, the values reported ranges from 0.379 to 0.696 across the models within the maturities. These suggest that the oil futures returns for both markets have long memory in their conditional variance. The results also fail to support the hypothesis of $d = 0$ and $d = 1$, implying that the FIGARCH model does not reduce to either the IGARCH or GARCH models in each market. Both oil markets therefore have similar pattern of long term dependence in their returns at the different maturities. The results support Tabak and Cajueiro (2007) and Cunado et al (2010) that reported long memory in the oil futures market using a different approach. Finally, the Box-piers test and ARCH test for serial correlation are conducted to confirm the fitness of the models. Both tests cannot reject their null hypothesis of no serial correlation at the 5% level. In sum, the analysis using the different GARCH models show evidence of long memory in the WTI and Brent crude oil futures markets at the different maturities.

Table 1: Estimated Results for WTI Market

Panel A: Results for WTI 1-month futures contract

	GARCH	EGARCH	APARCH	FIGARCH	FIEGARCH	FIAPARCH	HYGARCH
μ	0.079**(0.037)	0.048(0.036)	0.040(0.035)	0.090**(0.036)	0.040(0.034)	0.056(0.036)	0.091**(0.036)
ω	0.068(0.037)	1.814*(0.166)	0.032**(0.014)	0.148(0.081)	2.193*(0.315)	0.169*(0.059)	0.191(0.120)
α	0.059*(0.019)	-0.227(0.205)	0.064*(0.016)				
β	0.930*(0.022)	0.985*(0.006)	0.936*(0.016)	0.624*(0.095)	0.530**(0.265)	0.708*(0.085)	0.637*(0.099)
γ		0.181*(0.048)	0.419*(0.143)		0.191*(0.042)	0.368*(0.168)	
δ			1.006*(0.217)			1.191**(0.395)	
d				0.410*(0.074)	0.678*(0.066)	0.508*(0.095)	0.444*(0.099)
φ				0.313*(0.082)	-0.425(0.255)	0.314*(0.070)	0.301*(0.078)
$\alpha+\beta$	0.989	1.212					
Q(20)	15.99[0.717]	16.08[0.712]	14.61[0.798]	16.81[0.665]	16.08[0.712]	16.49[0.686]	16.95 [0.656]
ARCH(10)	0.556[0.850]	0.583[0.829]	1.299[0.225]	0.234[0.993]	0.583[0.829]	0.430[0.933]	0.043[0.999]
Log(L)	-7506.88	-7500.91	-7489.72	-7504.65	-7500.91	-7490.19	-7504.53

Note: Figures in bracket are the standard errors in parenthesis beside the parameters. Q (20) is the Box-piers test Q-statistics of order 20 for the standardised residuals. ARCH (10) is the t-statistics of the homoscedasticity test with 10 lags. P-values are reported in the square bracket. Significant at 1% and 5% level are represented by * and **, respectively. Log (L) represents the logarithm maximum likelihood function.

Panel B: Results for WTI 3-month futures contract

	GARCH	EGARCH	APARCH	FIGARCH	FIEGARCH	FIAPARCH	HYGARCH
μ	0.077**(0.033)	0.051(0.031)	0.044(0.039)	0.089*(0.032)	0.041(0.028)	0.054(0.031)	0.089*(0.032)
ω	0.074**(0.035)	1.492*(0.126)	0.044**(0.019)	0.119**(0.056)	1.786*(0.306)	0.151*(0.045)	0.179**(0.094)
α	0.060*(0.017)	-0.418*(0.127)	0.058*(0.015)				
β	0.922*(0.023)	0.984*(0.006)	0.934*(0.018)	0.657*(0.075)	0.547(0.338)	0.705*(0.061)	0.673*(0.074)
γ		0.199*(0.043)	0.402*(0.142)		0.205*(0.039)	0.424*(0.173)	
δ			1.227*(0.255)			1.336**(0.286)	
d				0.392*(0.068)	0.670*(0.070)	0.413*(0.075)	0.457*(0.104)
φ				0.377*(0.065)	-0.548*(0.237)	0.413*(0.065)	0.092*(0.100)
$\alpha+\beta$	0.982	1.402					
Q(20)	15.60[0.741]	16.85[0.663]	15.35[0.756]	16.13[0.709]	16.27[0.700]	16.81[0.665]	16.17[0.706]
ARCH(10)	0.919[0.514]	0.855[0.575]	1.419[0.165]	0.464[0.914]	0.833[0.597]	0.704[0.721]	0.502[0.890]
Log(L)	-7102.64	-7095.84	-7089.82	-7099.95	-7080.44	-7085.04	-7099.60

Note: Figures in bracket are the standard errors in parenthesis beside the parameters. Q (20) is the Box-piers test Q-statistics of order 20 for the standardised residuals. ARCH (10) is the t-statistics of the homoscedasticity test with 10 lags. P-values are reported in the square bracket. Significant at 1% and 5% level are represented by * and **, respectively. Log (L) represents the logarithm maximum likelihood function.

Table 3: Estimated Results for Brent Market

Panel A: Results for Brent 1-month futures contract

	GARCH	EGARCH	APARCH	FIGARCH	FIEGARCH	FIAPARCH	HYGARCH
μ	0.066**(0.031)	0.054(0.031)	0.055(0.032)	0.075**(0.032)	0.051(0.032)	0.069**(0.032)	0.075**(0.02)
ω	0.025**(0.012)	1.780*(0.227)	0.019**(0.010)	0.055(0.030)	2.063(0.442)	0.055(0.057)	0.037(0.051)
α	0.048*(0.010)	-0.007(0.428)	0.051*(0.011)				
β	0.948*(0.010)	0.991*(0.004)	0.951*(0.010)	0.727*(0.058)	0.585(1.440)	0.726*(0.051)	0.710*(0.061)
γ		0.114**(0.048)	0.122(0.101)		0.127(0.078)	0.063(0.072)	
δ			1.551*(0.353)			1.975*(0.200)	
d				0.486*(0.074)	0.683*(0.207)	0.476*(0.057)	0.463*(0.092)
φ				0.307*(0.054)	-0.312(1.339)	0.319*(0.079)	0.317*(0.058)
$\alpha + \beta$	0.996	0.998					
Q(20)	19.07 [0.517]	18.21 [0.573]	19.12 [0.514]	17.97 [0.589]	20.23 [0.443]	18.09[0.582]	17.94 [0.591]
ARCH(10)	2.050[0.025]	1.989[0.031]	2.157[0.018]	1.360[0.193]	1.757[0.063]	1.369[0.188]	1.360[0.193]
Log(L)	-7238.93	-7247.01	-7236.65	-7237.10	-7237.47	-7236.32	-7237

Note: Figures in bracket are the standard errors in parenthesis beside the parameters. Q (20) is the Box-piers test Q-statistics of order 20 for the standardised residuals. ARCH (10) is the t-statistics of the homoscedasticity test with 10 lags. P-values are reported in the square bracket. Significant at 1% and 5% level are represented by * and **, respectively. Log (L) represents the logarithm maximum likelihood function.

Panel B: Results for Brent 3-months futures contract

	GARCH	EGARCH	APARCH	FIGARCH	FIEGARCH	FIAPARCH	HYGARCH
μ	0.067**(0.031)	0.063**(0.029)	0.054(0.030)	0.078*(0.030)	0.062**(0.029)	0.065**(0.033)	0.078*(0.041)
ω	0.057(0.034)	1.547*(0.172)	0.025(0.016)	0.111(0.068)	1.692*(0.298)	0.151*(0.064)	0.310(0.030)
α	0.053*(0.017)	-0.585*(0.082)	0.051*(0.016)				
β	0.986*(0.024)	0.991*(0.004)	0.948*(0.019)	0.660*(0.081)	-0.729*(0.118)	0.709*(0.090)	0.673*(0.083)
γ		0.209*(0.041)	0.347**(0.179)		0.204*(0.030)	0.327(0.183)	
δ			1.047*(0.347)			1.317*(0.334)	
d				0.379*(0.073)	0.696*(0.042)	0.432*(0.094)	0.427*(0.120)
φ				0.367*(0.067)	0.380**(0.274)	0.384*(0.070)	0.348*(0.076)
$\alpha+\beta$	0.980	1.576					
Q(20)	12.72[0.889]	12.21[0.908]	13.22 [0.868]	12.28[0.906]	13.69[0.846]	13.27[0.865]	12.31[0.905]
ARCH(10)	1.729[0.069]	0.796[0.632]	3.779[0.000]	0.778[0.651]	0.722[0.705]	0.781[0.648]	0.759[0.669]
Log(L)	-7005.55	-6988.52	-6994.43	-6999.53	-6999.53	-6975.4	-6999.32

Note: Figures in bracket are the standard errors in parenthesis beside the parameters. Q (20) is the Box-piers test Q-statistics of order 20 for the standardised residuals. ARCH (10) is the t-statistics of the homoscedasticity test with 10 lags. P-values are reported in the square bracket. Significant at 1% and 5% level are represented by * and **, respectively. Log (L) represents the logarithm maximum likelihood function.

5. Conclusion

In this paper, we examine long memory property of the WTI and Brent oil futures prices using GARCH-class models. Empirical results provide strong evidence of long memory in the oil prices for both markets at different maturities suggesting that shock on their conditional volatility disappear slowly at hyperbolic rate. The presence of asymmetric leverage effect is detected in the oil futures returns series. The implication of these findings is that the markets reject the weak form efficient hypothesis because their returns are predictable. Second, the presence of long memory suggests that these oil markets will have low returns in the long term because their future prices are predictable. Lastly, hedging activities will not be effective while speculative activities will be profitable because past information can be used to help exploit arbitrage opportunities in these markets.

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