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THE RELATION BETWEEN WTI AND BRENT CRUDE OIL PRICES: COINTEGRATION, VOLATILITY, AND BIAS

BY

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AN ABSTRACT OF THE THESIS OF

Angelic Raja Salha for Master of Business Administration and Economics

Title: The Relation Between WTI and Brent Crude Oil Prices: Cointegration, Volatility, and Bias

The main purpose of our thesis is to examine the short term and long term relationship between the spot prices of two crude oil benchmarks, West Intermediate Texas (WTI) crude oil and Brent crude oil. We analyze the daily, weekly, and monthly spot price of WTI and Brent crude oil for the last 30 years in the period starting in May 1986 till May 2016. We start by testing for stationarity and find that the data has one unit root. After that, we test if the prices of WTI and Brent move together with a stable difference between them by applying Johansen, Engle-Granger, and ARDL tests.

Then, we test the data for biasness by interpreting the coefficients in the regression equation and GARCH model. The empirical analysis shows that there is high evidence of short term and long term bias. Additionally, we test for volatility and whether good news and bad news affect the prices of WTI and Brent in the same way.

We link the results to a tentative theory of production of two firms that produce WTI and Brent crude oils and each act as a monopoly in its product market. We prove the assumptions of the theory to be true and illustrate the results of the tests using it.

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I. Introduction

A. An Overview of Crude Oils

Most of the material in the subsequent section is taken from the Deutsche Bank's report (2013) and Fattouh (2011).

Crude oils are nonrenewable resources and with different origins and qualities. There are two characteristic that classifies the quality of crude oil. It is the American Petroleum Institute (API) gravity and sulfur content. The API gravity index identifies the density of crude oils, those with high densities are heavy crude oils and those with low densities (35 and 40 degrees) are light crude oils. The heavier the crude oil, the more difficult and costly it is to extract and transport through pipeline. As for the sulfur content, it is also more difficult and costly when the sulfur content is high, as sulfur should be removed before refining. The higher the percentage of sulfur, the sourer the crude oil is. The crude oil is said to be sweet if the sulfur content is less than 0.5%. WTI and Brent have an API of 39.6° and 38.3° and they have a sulfur content of 0.24% and 0.37%, respectively. This makes them both light crude oils and very similar in quality, where WTI has slightly a better quality as it has less sulfur percentage. Usually, light crude oils are used to get the following refined products: Gas oil/diesel (Middle distillates) 36%, gasoline 21%, fuel oil 19%, others (Residual, lubricants) 9%, Naptha 6%, Kerosene 6%, and Petroleum Gas 3% .

Brent crude oil is extracted from the North Sea and is mixed with several other crude oils, which are Ninian, Forties, Oseberg, and Ekofisj. Brent is considered as a benchmark due to several reasons such as: its location, it can be easily transported, made up of several crude oils leading to high production volumes, in addition to legal and regulatory body provided by the UK government for Brent (Horsnell & Mabro, 1993). Unlike Brent, WTI is landlocked and a surge in production. WTI is extracted from the fields of Texas, Oklahoma, New Mexico, and Kansas. It is also a mixture if the following crude oils including Light Louisiana Sweet (LLS) and West Texas Sour (WTS).

B. An Overview of the History of Crude Oil Prices

Most of the material in the subsequent section is taken from Fattouh (2011).

The factors that affect crude oil prices in the 1950 are different from the factors that affect it today. In 1950, the Seven Sisters, a multinational company that makes up a high percentage of oil production controlled the prices of crude oils. In 1970, multinational companies controlled prices in such a way that tax liabilities are reduces. In 1960, the Organization of the Petroleum Exporting Countries (OPEC) was established to manage the decline in profits of some companies and the tax and royalties issues. In the 1980s the crude oils prices decreased due to the global recession.

The crude oil market is studied by several researchers to indicate whether the market is globalized, crude oil prices move with a stable difference between them (also referred to as cointegrate), or regionalized, crude oil prices don't maintain a stable difference between each other. Weiner (1991) asserts that the crude oil market is regionalized, whereas Gulen (1997, 1999), Bentzen (2007), Fattouh (2010), and Wilmot (2013) found that the crude oil market is globalized. On the other hand, Ji and Fan (2015) illustrate that the spot prices of WTI and Brent don't cointegrate.

C. The Purpose of the Thesis

The objective of this thesis is to test if the crude oil spot prices, WTI and Brent, cointegrate in the long term and if there is short run and long run bias between them. The thesis will also test for price efficiency and volatility. It will present the results for different time frequencies: monthly, weekly, and daily.

D. The Methodology of the Thesis

We conduct our study on WTI and Brent crude oil spot prices, extracted from the US Energy Information, on the following periods:

- The period starting May 20, 1987 till May 9, 2016 for daily spot prices
- The period starting May 15, 1987 till May 6, 2016 for weekly prices
- The period starting May 1987 till April 2016 for monthly prices

We will test whether WTI and Brent prices cointegrate in the long run. We will also test the existence of volatility and short run and long run bias in both oils.

E. The Structure of the Thesis

The thesis is organized as follows: The second part is the survey of the literature where we discuss the empirical findings of the different researchers. The third part is the theory that we will use in our empirical analysis. The fourth part is the empirical analysis, which analyzes the statistical findings of the study. The fifth part is the conclusion that includes the limitations of the study and recommendations.

II. Literature Review

Most of the early literature, to the best of our knowledge, that considers the relation between crude oil spot prices generally and the relation between WTI and Brent relation will be discussed in this section. Some articles take into consideration the influence of volatility on the crude oil market and others debate the efficiency between them. In some cases, researchers classify crude oil prices according to their quality (sulfur content and API gravity) or origin before conducting the tests. Researchers started by testing the relation between crude oil markets and identifying it as regionalized or globalized in 1984. Regionalized markets are markets where crude oil prices react to local circumstances (ex. demand and supply) independent of other crude oils of similar quality in other regions. On the other hand, globalized markets-sometimes called unified- are where the prices of similar crude oils in different regions move together in a way that the spread between them is almost stable (Fattouh, 2010). Researchers throughout the literature test for regionalization and globalization using several types of cointegration tests on different models. If the tests show that the tested crude oil prices are cointegrated then the crude oil market is globalized, if the tests show that the tested crude oil prices are not cointegrated then the market is regionalized.

Regionalization vs. Globalization:

A. Empirical Analysis of Weiner (1991)

Weiner (1991) tests if the crude oil market is integrated or fragmented, using monthly landed prices from 1/1980 toll 3/1987 of six crude oils, which are: Mexican Isthmus, Nigerian Bonny Light, Saudi Arabian Light, UK Generic, Indonesia Generic, and Soviet Ural. Weiner justifies his use of monthly price, instead of daily or weekly prices, by the following: availability of data, time required for delivery of oils, enough time for prices to integrate and adjust, and realistic for policy application and effects. Weiner uses correlation and regression tests. He applies correlation and autocorrelation tests. Autocorrelation shows the dependence of present prices on past price. The degree of correlation in the correlation test shows the level of market integration, but it doesn't take into consideration that shocks could affect crude oil prices in different regions. Due to the low level of correlation, crude oil markets seem to be not unified.

After that, he applies regression test and takes into consideration the transaction costs (ex. freight and insurance expenses) and the probability that two crude oils, in different regions, belong to different markets. He forms two equations to make up a switching regression system, equation (1) shows the relation between crude oil prices in a unified market and equation (2) shows the relation in a regionalized market. In equation (1), the prices of two crude oils (in percent) in two regions vary by the transaction costs and error of the regression.

Whereas in equation (2), they vary by transaction costs plus error of the regression minus a variable, which diminishes the difference between the prices and shows that the difference is less than the transaction cost. After that, he applies maximum-like hood estimation to observe the probabilities that different oils are regionalized. The high probabilities displayed in more than half of the tested crude oils confirm that the crude oil markets are regionalized.

B. Empirical Analysis of Gulen (1997, 1999)

In 1997, Gulen (1997) contradicts Weiner's (1991) findings and proves that the crude oil market is unified. Gulen groups 15 crude oils according to their API gravity and sulfur content and applies the tests on their monthly spot prices (data used is prior to 1/1995). Gulen tests for unit root to check if the series is stationary or non-stationary. So he refers to Perron's (1989) method, which inserts dummy variables to Dickey-Fuller test, and treats structural breaks. After that, he employs bivariate test (Engle and Granger's model), on crude oils from same group and different groups, to test cointegration between two crude oils and multivariate test (Johansen's model) to test cointegration between three or more oils.

Furthermore, Gulen (1999) verifies the result of globalization achieved by Gulen (1997) when he repeats the same tests on 11 crude oils, but uses weekly prices instead of monthly prices. He observes the whole sample data from 1991 till 1996, and then he divides it into two parts according to progress of prices: the first period from 1991 till 1993 when prices were decreasing and the second period is from 1994 till 1996 when they were increasing. He studies those subparts to observe the result under different market conditions and in small periods.

C. Empirical Analysis of Bentzen (2007)

Similarly, Bentzen (2007) confirms globalization in crude oil market, after he uses daily prices from 1/1988 till 12/2004 of the following crude oils: WTI, Brent, Dubai, and OPEC. As these crude oils have different quality, price differentials might arise, so he employs vector error correction model (VECM) to treat it. Dickey Fuller (DF), DF-GLS (DF with higher power properties), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) are applied to test for unit root. Engle and Granger bivariate cointegration and Johansen multivariate cointegration tests are used to find that there is cointegration. The estimate of the slope of WTI and Brent is 1.046 leading to a DF/ADF statistic of -11.367, where the critical value for ADF/DF test is -3.339 rejecting the null hypothesis of no cointegration.

After that, he applies VECM and determines the lags using Akaike's Information Criterion (AIC). GARCH and integrated GARCH are applied to make efficient estimations in four different samples. The first includes all selected data and the other three are divided according to periods affected by economic factors like Gulf war, OPEC decisions… He tests for causality (weak and strong exogeneity) using F-test, for autocorrelation using Lagrange Multiplier, for heteroscedasticity using ARCH, and for regression using R squared. The variables in the VECM equation show the type of exogeneity, if the error correction term in the equation is close to zero then the P1 (price of crude oil 1) will not be affected by P2 (price of crude oil 2) and the relation is weak exogeneity. Besides that, if variable beta (tests null hypothesis as not Grangers causality) is zero then there is strong exogeneity. F-test is applied to test the null hypothesis. He applies the tests among three couples; one of them is WTI and Brent. The results for WTI and Brent specifically, reveal that they will cointegrate and that they possess bidirectional causality. Moreover, he uses time varying parameter estimation to remove the constant parameters and replace it with recursive estimations using Kalman filter and confirm previous results.

D. Empirical Analysis of Fattouh (2010)

Fattouh (2010) examines the behavior of crude oil differentials, which are caused by different quality of crude oils, regional events, and demand for refined products. He groups Sahara, Bonny, Maya, WTI, Lliod, Brent, WTI, and Dubai into seven pairs according to their quality only, and then according to the availability of future market and quality. Then, he calculates the differential by finding the logarithm form of the spread that is the difference between prices of two crude oils. He uses spot prices from 1/1997 till 12/2008. Fattouh applies the threshold autoregressive model (TAR) to find the oil price differential and estimates the model using Least Squares (LS). He uses AIC to find the number of lags, and Breusch Godfrey and Ljung and Box Q-statistics to test for serial correlation and confirm the number of lags chosen. He tests the delay of the selected pairs with Wald test to see if the model is linear or there exists nonlinear effect. In case of the former, ADF, PP, and ADF-GLS test (special for those with threshold effect) are applied to test for unit root, whereas in case of the latter, one sided and two sided Wald test statistics are used. The use of tests is justified by Caner and Hansen (2001) that the standard unit root tests might be ineffective in case of nonlinearity. The tests for unit root show that the market is globalized, after they calculate the critical values using bootstrap method and reject the null hypothesis of being nonstationary.

Additionally, the TAR estimates divided the regression function into two systems: system 1, the lagged value is below threshold estimate, and system 2, the lagged value is above the threshold estimate. The results reveal that shifting to long-run equilibrium is faster in system 2 than in system 1. Additionally, oil price spreads follow a random walk in system 1 and a stationary manner in system 2. Wald test on Sahara-Bonny (crude oil prices of similar quality) confirm the previous results, whereas the test on Maya-Lloyd Blend shows that the threshold doesn't affect the shifting.

Overall the tests reveal that crude oil spreads are stationary, where the switching to long run equilibrium change according to the quality of couple (same or different quality). Furthermore, the threshold effect point out that there are transaction costs. While crude oils that are traded as contracts have lower threshold, pointing out to lower transaction costs. Fattouh also links the price differential of WTI and Brent to their logistic infrastructures and locations.

E. Empirical Analysis of Hammoudeh, Ewing, and Thompson (2008)

Hammoudeh, Ewing, and Thompson (2008) use daily prices of WTI, Brent, Dubai, and Maya crude oil prices from 1/1990 till 6/2006. They use ADF, Phillips-Perron (PP), and Kwiatkowski-Phillips–Schmidt–Shin (KPSS) to test for unit root. Then they apply momentum-threshold autoregression cointegration method (M-TAR) to the spreads of coupled benchmarks. Hammoudeh et al. prefer M-TAR over Engle and Granger (1987) error correction model as it enables spread to change in the long-run equilibrium, and doesn't presume that the data acts in symmetry. After they check four different spreads, the four crude oils achieve long term equilibrium. Specifically, testing the WTI-Brent spread, Brent reacts to the prices of WTI and it is own historical spot prices, whereas WTI reacts to its own historical prices only, in the short-run. When they examine the long run reaction of WTI and Brent, WTI adjusts it prices faster when the WTI-Brent spread is widening than when it is narrowing. While, Brent adjusts it price only when the spread is decreasing.

F. Empirical Analysis of Reboredo (2011)

Reboredo (2011) supports regionalization in crude oil market by applying copula approach and combining ARMA and EGARCH on weekly data of WTI, Brent, Maya, and Dubai from 1/9997 till 6/2010. He applies ARMA (p, q)-t-EGARCH(r, m) on spot price returns to find the most significant unique attributes and uses AIC to detect number lags (p, q, r, m). He uses several models to confirm that the best marginal model is MA (1)-t-GARCH (1, 1), the models are serial correlation, Cramer-von Mises, Anderson-Darling test, and Kolmogorov-Smirnov. And the copula approach represents the dependence structure, dependence degree, and tail dependence measure between different crude oils. The tail dependence computes the tendency of crude oil prices to increase or decrease together. Copula approach also provides more flexibility in estimations and models than multivariate distribution does. Five copula functions are employed, where each of them detects a different style of tails. The copula functions used are: Gaussian copula, Student-t-copula, Clayton copula, Gumbel copula, and symmetrized-Joe-Clayton copula. Two tests are used to confirm the results: AIC shows that Student-t-copula presents the best results due to the low degrees of freedom it has. And the goodness fit test that follows pseudo likelihood ratio test and the results show that WTI and Brent are more dependent and integrated than other pairs as they have greater symmetric tail dependence.

The results support globalization in crude oil market since there is proof of symmetric tail dependence in which crude oil price studied progress simultaneously regardless of the events taking place. Additional results reveal the presence of tail dependence that shows higher risk than in the absence of tail dependence. And that tail dependence plays an important role in pricing assets and showing level of safety in investments.

G. Empirical Analysis of Wilmot (2013)

Wilmot (2013) shows that Canadian Crude, WTI, Brent, Edmonton Par Maya, Dubai, and Bonny are cointegrated with structural breaks, according to monthly data from 1991 to 6/2012. He tests for unit root and confirms cointegration using ADF, PP, and KPSS. He calculates the critical values in Gregory- Hansen approach, compares it to the ADF-statistics and Z-statistics, and rejects the hypothesis alternative to the unit root hypothesis (in other words “the series is integrated of order one”). He proves regional spot prices to be cointegrated using bivariate residual based cointegration test (Gregory-Hansen), under four models that apply OLS regression on four different models: the standard cointegration model, the second model is standard cointegration model that permits the intercept to shift (C), the third adds a trend to the model (C/T), and the fourth allows both the intercept and slope to shift (C/S). This test allows for structural change without having the date identified. ADF and Z-test statistics reject the null hypothesis of no cointegration and are also used to determine break date (when test statistic is the lowest negative). The events of structural breaks caused by direct and indirect events are based on Maslyuk and Smith (2009) article and some are obtained from EIA (not available online).

H. Empirical Analysis of Kim, Kim, and Heo (2013)

Likewise, Kim, Kim, and Heo (2013) use Gregory and Hansen residual based cointegration test to examine WTI, Brent, and Dubai weekly prices from 1/1997 till 7/2012. They justify the use of weekly prices that they eliminate the time difference between different regions and remove sensitivity to specific days of the week. ADF and KPSS test are used to test for unit root. The residual based cointegration test launches with Engle and Granger bivariate cointegration test and indicate cointegration among the couples. The test is applied on four models: three of them are used by Wilmot (2013), C, C/S, C/T, and a fourth model that has a regime shift with trend (C/TS). ADF, Z (t), and Z (alfa) test statistics are used to point out the dates of breaks (ADF shows results different than those of Z test).

Generally, the test shows that most breaks take place between 2008 and 2010 in the couples. Specifically, the test proves that WTI and Brent are cointegrated in three models C, C/S, and C/TS, while there is no proof of cointegration in model C/T. They use AIC, SIC, HQIC, and final prediction error (FPE) to choose the best lag. As a result, the full data is divided into two subsamples, subsample 1 from 1/1997 till 12/2008 and subsample 2 from 1/2009 till 7/2012. Then Granger causality test developed from vector error correction mechanism (VECM) is applied on the two periods to show the impact of the structural breaks on the crude oil market and its leader. The VECM formula is the error correction variable in terms of the long run variable and short run variable.

They test the null hypotheses of no Granger causality using chi-squared distribution on three types of causality is described as: short run, long run, and strong causality. The null hypotheses in case of short run are when the short run term is equal to 0 in both causal cases (x causes y, y causes x), in case of long run causality the long-run term is equal to 0, and in case of strong causality both short-run and long-run terms equal 0.

The outcomes confirm Bentzen's (2007) findings, in which couples formed from WTI, Dubai, and Brent have bidirectional relationships and include a strong Granger causal effect in the period prior to 2009, in the short run; whereas in the long run, Brent leads WTI and Dubai. However, starting 2009, in the short run WTI and Brent have bidirectional relation, and Dubai leads WTI and Brent. In the long run in the same period, WTI and Dubai lead Brent. (This also shows that Dubai is the leader in benchmark after 2009). The results confirm that structural breaks affect the causal relation between benchmark crude oil studied.

I. Empirical Analysis of Liao, Lin, & Huang (2014)

Liao, Lin, & Huang (2014) show the crude oil market is unified. They use augmented Dickey-Fuller (ADF) to test for unit root and adjust the structural breaks using Fourier series. The model they use enables them to test for unit root without specifying the breaks previously.

They employ the Quantile Kilmogorov-Smirnov (QKS) test on monthly logarithm of WTI-Brent spread from 5/1987 till 4/2013. They repeat QKS on weekly and daily spreads to eliminate effect of data frequency and achieve the same result.

J. Empirical Analysis of Ji and Fan (2015)

Ji and Fan (2015) utilize daily prices of WTI, Brent, Bonny, Tapis, and Dubai from 1/2000 till 3/2014. After starting with descriptive statistics, they extend to studying correlation between the five crude oils. Then they apply Johansen cointegration to examine the long term relationship between them. The number of cointegrating equations is assured by Johansen Tracing test and Johansen Maximum Eigenvalue test. The results reveal that WTI doesn't co-integrate with the rest of crude oils in the long term. They apply varying correction estimation using a correlation coefficient formula that takes into consideration the time, window width, and crude oil price. The window width is taken as 250 days. Double Maximum and Schwarz Information Criterion (SIC) specify that WTI breaks with the other 4 crude oils and the break date is specified using Bai and Perron (1998, 2003) (ADF is used). For example, the correlation between WTI and Brent in the full sample is 0. 9824 which is less than the mean of the time varying correlation between them. This signifies that crude oil prices diverge less in long term than in the short term. Additionally, in the time carrying correlation the ADF value for WTI-Brent confirms that there is no integration between them; similar results also apply to the relation between WTI and other crude oil prices.

The overall results show that the other four crude oil markets keep their cointegration, even after WTI's divergence in September 2010. Then the distance between the coefficients is calculated to confirm these results. The less distant the coefficients are, the more integrated and cointegrated the crude oils. They estimate abnormal return (AR) in crude oil prices by subtracting normal return (return under normal conditions) from the actual return, using ARCH. The volatility seems to be high between WTI, Brent, and Nigeria, where it seems to be low between Dubai and Tapis.

Since the market reacts in two different dynamics, the data is divided according to structural break identified above, from 1/2000 till 20/9/2010 and 21/9/2010 till 3/2014 (according to break date). ADF, PP, and KPSS are used to test for unit root. They apply Johansen cointegration, VAR, and SIC to examine the long term relationship. The results show that there is a long term relationship between the crude oils, so they involve error correction model (ECM) to identify the structure. In the first case, they assume the cointegrating vector of the ECM formula to be 0 to test if any variable can be excluded from the cointegrating vector. The results of Chi-squared distribution reject the null hypothesis of no cointegration in sub-period 1 and indicate that the studied crude oils have a long term relationship. In the second case, they test the null hypothesis that the reaction to market changes and the adjustment speed are both zero in purpose of observing the weak exogeneity. The null hypothesis is rejected using Chi-squared distribution and confirms the long term equilibrium between the crude oil prices.

Additionally, they test the reaction of one of the crude oils to the other according to certain information using directed acyclic graph (DAG). The result shows that prior to September 2010, WTI and Dubai directly lead Brent, while Brent directly leads WTI and Dubai after that. The overall result indicates that WTI and Brent are the least affected by other prices, whereas Tapis is the most affected. The variance decomposition shows that WTI lead the market in volatility in the first period where Brent did that in the second period. The variance decomposition of sub-period 1 and sub-period 2 separately show the comparison between the five crude oils and the percentage in which each leads the others. Finally, they sum up that during global crisis the market is more integrated, where it is less integrated during localized events.

Variance Estimation:

Some articles observe the WTI-Brent relation and their reaction to macroeconomic factors closely. As for the relation between WTI and Brent, Choi et Hammoudeh (2008) illustrate that Brent has greater variance than WTI, but converges more quickly to long term equilibrium.

K. Empirical Analysis of Hammoudeh, Bhar, and Thompson (2010)

Hammoudeh, Bhar, and Thompson (2010) examine whether WTI and Brent could be substitutes and how they are affected by the real macroeconomic factors. He tests the relation under two conditions, regime 1 with low volatility and regime 2 with high volatility. He uses monthly data for Brent, WTI, federal fund rate (FFR), default risk variable (DFR), US dollar effective exchange rate (FX), and industrial production (IP). The range of data used includes structural breaks at unidentified dates and a linear time varying model isn't unsuitable, therefore they use Markov Chain. They compose the logarithmic formula of WTI and Brent by adding short term variables and long term variables.

The unconditional variance is varying, so they use a regime dependent model rather than GARCH. They apply VAR to the four macroeconomic variables once with WTI and the other with Brent under Markov switching (MS) in variances and intercepts for the two regimes. The results confirm that MS model is the right choice. They indicate that WTI isn't affected by any of the studied macroeconomic variables, but is by other non-fundamental factors like: weather, OPEC decisions…Whereas Brent is affected by default risk. After all, according to the oil-macroeconomic cycle in the US economy, Brent and WTI aren't perfect substitutes. Hammoudeh et al. use smooth probability tests to confirm that the right regimes are used. The test has a regime classification measure (RCM), the lower the measure, the better the regime.

The results reveal that WTI is more persistent than Brent in case of low volatility case, where Brent is less persistent in case of high volatility. This indicates that Brent is more affected by the macroeconomic factors than WTI. The periods that experience volatility are: Gulf war (1990), US recession (1991), Asian crisis (1997), change in OPEC' oil pricing oil (2000), September 9/11 (2001), Iraq war (2003), and Katrina Hurricane (2005).

L. Empirical Analysis of Cheong (2009)

Further studies regarding WTI and Brent discuss the volatility of these crude oils and how is it affected by events and news. Cheong (2009) uses WTI and Brent daily returns prices from 1/1993 till 12/2008. He applies four different GARCH types under ARCH model. The first one with zero asymmetric effect, zero fractional integrated operator, and Box-Cox transformation of 2 (transforms to normality). The second is AP-GARCH (asymmetric power GARCH, tested for both normal and student-t-distribution) takes only fractional integrated operator as zero. The third is Fractionally Integrated GARCH (FI-GARCH) with Box-Cox of 2 and zero asymmetric effect. And the fourth is FI-AP-GARCH. According to results based on the values of the power coefficient 1 and 2, Cheong rejects the null hypothesis at 5% only when the power coefficient is 1 for Brent and reject the null hypothesis for WTI only when the power coefficient is 2 in the case of APARCH- student-t. And fails to reject the null hypothesis in both cases in WTI in normal APARCH. The power coefficient is the exponential value of the estimate.

Therefore, the results show that: Brent is more precise in conditional variance modeling than conditional standard deviation, while WTI is more accurate while using conditional standard deviation in student-t-APARCH and shows to be unresponsive in both cases in normal-APARCH. Additionally, conditional variance is more suitable for FIGARCH and FI-APA-GARCH too. He uses the asymmetric coefficient to observe the influence of good and bad news on the WTI and Brent, each influence Brent prices differently, unlike WTI prices. Bad news affect Brent more than good news does.

The fractional difference parameter shows that the price variations have are more tenacious in WTI than in Brent. To make sure the right model is used, he employs AIC, SIC, and log-likelihood. As for Brent, AIC and SIC show different results, the former prefers FIARGARCH-student-t model and the latter shows that GARCH-normal is the best model for Brent. Cheong checks the model again using Ljung-Box statistics (tests the null hypothesis of no serial correlation) for residuals to test for autocorrelation and LM to test for ARCH effect. These tests show that FIGARCH type is the best models to portray volatility for both WTI and Brent.

M. Empirical Analysis of Hassan (2011)

Hassan (2011) uses data used of daily returns of WTI and Brent data from 5/2000 till 4/2010. ADF and PP confirm the presence of unit root. He applies GARCH and GARCH-in-mean (linear) to check the persistence of news to volatility and EGARCH (nonlinear) to evaluate the consequence of positive and negative shocks. GARCH (1, 1) (first term AR and moving ARCH) uses the sum of alfa and beta, which respectively show the volatility and the forecasted variance in the previous period. The sum is close to 1 and indicates high persistence of instability aftershocks and will last in the long memory. M-GARCH confirms the previous results and adds to it that the relation between expected return and expected risk are insignificant. Finally, EGARCH results indicate that the effect of negative shocks is higher than the effect of positive news on the data.

N. Empirical Analysis of Salisu and Fasanya (2013)

Salisu and Fasanya (2013) test for unit root and spot structural breaks using Narayan and Popp (2010) (NP) instead of PP. They point out two events the Kuwait/Iraq issue (1990) and global financial crisis (2008). They also test for volatility using ARCH-LM. They use daily prices of WTI and Brent from 4/2000 till 3/2012. They calculate the return of the prices and reveal fat tails, therefore generalized error distribution (GED) and student-t-distribution, they use the same tests using fixed parameters and degrees of freedom respectively. Then, according to AIC, HQC, and SIC, they choose student-t-distribution as the best model.

They detect the existence of volatility by using ARCH LM as suggested by Engle (1982). They do this by getting the fitted residuals, regressing their squares on lags and a constant, and testing the ARCH effect using Lagrange Multiplier (LM) and Chi-squared distribution. The tests assure the presence of ARCH effect. They prove using NP the existence of stochastic and deterministic constituents in the price returns, and apply the formula of each to two models. A model that permits break in the intercept and another that permits the break to be in the slope of the trend in addition to the level, respectively, according to the innovative outlier (IO). They follow this method to slow down the effect of shocks and make it gradual instead of immediate.

They allocate GARCH (1, 1) to test if there is volatility and GARCH-M (1, 1) to watch the effect of conditional variance (both treat symmetrical volatility- GARCH is better). These two tests prove that WTI and Brent both follow a gradual mean reverting variance in the two models listed above, where that of Brent is slower, which points out to high persistence in volatility. Also, they use E-GARCH and T-GARCH to treat asymmetrical volatility (EGARCH is better). These two tests explain the effect of leverage that suggests that the worse the news the more volatile the crude oil market. They repeat the chi-squared distribution at the end to confirm the ARCH effect. Generally, the use of asymmetric models seems to be more suitable for studying crude oil volatility.

O. Empirical Analysis of Salisu (2014)

Similarly, Salisu (2014) studies the volatility of Brent and WTI using daily prices from 1/2000 till 2/21012. He divides the data into three periods: before, during, and after the financial crisis in 2008. First, starts by calculating the return using AR, the return formula takes into consideration the risk premium of long term securities and the error term (calculates difference in rate of return before and after). The presence of volatility is tested using ARCH LM. They test for the ARCH hypothesis using chi-distribution test.

After that, he calculates the estimations of conditional and unconditional variance that indicates volatility, using ARCH, GARCH, ARCH in mean, GARCH in mean (ARCH-M and GARCH-M identify the effect of conditional variance), exponential GARCH (EGARCH takes into consideration the leverage effect) models, and threshold GARCH (T-GARCH). Then, he uses AIC, Hannan Quinn Information Criterion (HQIC), and Schwatz Information Criterion (SIC) to decide on the most convenient model that estimates volatility.

Finally, ARCH LM is used to confirm the models. The results reveal that Brent and WTI are affected by the financial crisis and show high volatility, but Brent keeps it after that period more than WTI, showing higher persistence. T-GARCH and E-GARCH show that negative news have higher impact than positive news on the studied prices. In some cases mean reverting was done since the standard deviation was insignificant. T-GARCH (1, 1) seems to be more effective in finding the volatility in Brent, while GARCH (1, 1) in WTI.

Weak-Form Efficiency:

In addition to cointegration and volatility in crude oil market, some articles discuss the efficiency of the market that considers the effect of the accessible related data on the prices of assets (Fama 1970, 1991), specifically crude oil prices in our study. The efficiency market hypothesis (EMH) has three kinds, in which each considers the effect of a certain type of information on the current prices. EMH could be semi-strong form efficiency, strong form efficiency, and weak form efficiency. The semi-strong form and strong form show the effect of public available data and both (public and private) on current data, respectively. In this section, we will discuss the weak form efficiency, the category which illustrates that present prices of crude oil rely on historical prices only.

P. Empirical Analysis of Tabak and Cajueiro (2006)

Tabak and Cajueiro (2006) test the efficiency of the crude oil market using Hurst Exponent (Rescaled Range Hurst) by R/S analysis on original data and shuffled data using rolling samples, the results reveal that efficiency of the market seems to increase with time. The use of shuffled data is important, to alter the short term sensitivity of R/S method and observe long term effects. The daily spot return prices of WTI and Brent are used from 5/1983 till 7/2004. The calculation of Hurst exponent shows that efficiency in 1990s is higher than it is in the 1980s (Hurst exponent decreased).

Additionally, the study reveals that GARCH isn't the proper model to test this series, since Hurst exponent decreases and moves away from 0. 5 showing high persistence in variance, where GARCH and EGRACH don't show the same results. Lastly, they illustrate that WTI is likely to be in a more weak efficient form than Brent, as it has a higher Hurst exponent for variation than Brent.

Q. Empirical Analysis of Charles and Darne (2009)

Charles and Darne (2009) observe the data of WTI and Brent returns from 6/1982 till 7/2008. The descriptive statistics and LM show that the data is not normal and has ARCH effect. To test for weak form efficiency in the crude oil market, variance ratio test (VR) is employed on Random Walk Hypothesis (RWH). The following VR methods are used: Wright, Belaire-Contreras, Kim, and Deo and Richardson, in which the last two reject the RWH (Random Walk Hypothesis). VR tests are repeated after dividing the data into two periods, one prior to NAFTA and the other after it, to test weak form efficiency.

The outcomes show that Brent is efficient in both periods since it rejects the RWH in both periods, whereas WTI is efficient in the first period only, since it rejects RWH in the second period only. The latter results indicate that the NAFTA didn't affect WTI positively, where Brent shows no change in efficiency. This indicates that WTI is disturbed by factors like pipeline issues and infrastructure logistics and thus proves that Brent is more weak efficient than WTI.

R. Empirical Analysis of He (2011)

He (2011) uses daily and monthly WTI and Brent prices in the logarithmic form from 7/1996 till 8/2005, and employs phase space reconstruction technique (PSRT), Largest Lyapunov Exponents (LLE), Kolmogorov Entropy, and fractal integral methods. Using the fractal dimensions, He shows that there exist fractals in the crude oil market. LLE test shows that there is chaos in the market and long term forecast is not feasible, but short term forecast is possible. He shows that the prices of WTI and Brent are qualitatively similar. The same findings apply to daily and monthly data, except for LLE test that shows higher effect of chaos in WTI than Brent's daily prices; hence prediction error and risk are higher in WTI.

S. Empirical Analysis of Aloui, Hamdi, Mensi, and Nguyen (2012)

On the other hand, Aloui, Hamdi, Mensi, and Nguyen (2012) mingle Shannon entropy and Symbolic Time Series Analysis (STSA-changes series to representative series) on daily return of prices of WTI and Brent from 1/1986 and 5/1987, respectively, till 7/2007 to test whether crude oil market is in weak form efficient. Daily returns are calculated using successive logarithmic prices. In descriptive statistics, Jarque-Berra and Ljung-Box confirm non-normal characteristic and autocorrelation in WTI and Brent. ADF, PP, and KPSS are used to test for unit root. They estimate Shannon entropy (H) on a rolling sample such that a four year time window is used and new data will be added till they observe the full data.

Additionally, the efficiency aspect of WTI seems to be less volatile than Brent, since the standard deviation of WTI is 0.02% less than that of Brent. This implies that Brent acts more efficiently than WTI, as the value of H for Brent is closer to 1 than that of WTI, and both of them reject the hypothesis of normal distribution, where Brent has a higher value of Jarque-Berra test than WTI (Brent is less normal than WTI). Nonparametric tests, like testing equality of medians, are done and confirm the high efficiency of Brent over WTI.

They refer the reason of the results to certain factors like: NAFTA, Iraq invasion of Kuwait, 9/11 attack, Gulf war, and Asian crisis, besides stock and logistic infrastructure. They assert that the level which weak form efficiency reaches can't be confirmed, especially that the efficiency of WTI seems to increase and that of Brent seems to decrease at the end of 2007, and that the degree of efficiency (how efficient the market is measured by the Shannon entropy) is affected by several factors.

T. Empirical Analysis of Zhang (2013)

Zhang (2013) uses daily return prices of WTI, Brent, Daqing, and Dubai, each according to the available data, but no data later than 4/2013 is used. The use of ARCH test and descriptive statistics show that the data is not normally scattered and the WTI has the highest variance. Zhang employs generalized spectral analysis to test the significance of efficiency market hypothesis (EMH) and prove if the crude oils listed above are in weak form efficiency. The general spectral test uses a test statistic that takes into consideration the effect of "conditional heteroscedasticity" and "other time-varying higher order conditional moments", defined by M1. M1 captures nonlinear and linear drifts and can calculate more lags. He finds out that WTI and Brent are in weak form efficiency, where efficiency varies according to different periods in the case of Daqing and Dubai. To eliminate the consequence of serial dependence and conditional heteroscedasticity on the result of efficiency, he uses ARMA and GARCH to remove the latter effects respectively and then repeats the GS.

The result shows that non-efficiency of Dubai is due to heteroscedasticity and that of Daqing is due to linear serial dependence. He uses rolling sample model to demonstrate secular besides repeated progress of efficiency. M1 tests are repeated on the rolling sample of different window lengths. According to the results of WTI and Brent, efficiency doesn't have a higher level (the higher the p-value of M1 the more efficient the market is) in 1990s than in 1980s, in both cases the p-values of the test statistic M1 used are higher than 5% and fail to reject the null hypothesis of weak form efficiency.

Unlike Charles and Darne's (2009) results, Zhang declares that neither WTI nor Brent permanently has a higher efficiency. WTI can have a weaker form efficiency than Brent before 2005, and Brent has a weaker form efficiency after 2005. He concludes that the short term efficiency in markets is due to shocks and crisis.

III. Methodology:

A. The Theory

The tentative model settings are highly simplified, and should be considered as only illustrative. They are as follows:

1. A Cobb-Douglas production function, i. e. production (Q) is a function solely of labor (L) and capital (K), such that $Q = L^{\alpha}K^{\beta}$. There are two firms producing each a different category of crude oil, and they have the same technology.

2. Constant returns to scale. Therefore $Q = L^{\alpha}K^{1-\alpha}$. Firms cannot grow or shrink forever. This assumption is not crucial and can be relaxed without affecting materially the results. For this sake we can replace $1 - \alpha$ by β .

3. The two firms are price takers in the factor input market with a given wage rate w and with a given interest rate r.

4. The two firms act each as a monopoly in the product market. They are faced by different demand curves, and, consequently by different price elasticities of demand, denoted as $\square_1^d$ and $\square_2^d$. Hence, the two firms have different price elasticities of demand for crude oil, where the price elasticity of each firm alone is constant over time. The firms are operating in different countries, one in the US and the other in UK. Therefore, they have different price elasticity of demand for crude oil (Cooper, 2003).

The Lagrangian is therefore as follows:

$$Minimize\ wL + rK + \lambda(Q - L^{\alpha} - K^{1-\alpha})$$

After many manipulations the result is that Total Cost is a linear function of quantity, implying that the Marginal Cost (MC) is constant:

$$Total\ Cost = Q\left(\frac{w}{\alpha}\right)^{\alpha}\left(\frac{r}{1-\alpha}\right)^{1-\alpha} \Rightarrow \quad MC = \left(\frac{w}{\alpha}\right)^{\alpha}\left(\frac{r}{1-\alpha}\right)^{1-\alpha} = constant$$

Since each monopolist maximizes profits in its product market, then Marginal Revenue (MR) must be equal to Marginal Cost (MC), which is equal to a constant. And since the two firms have the same production technology, producing each a different category of crude oil, then:

$$MR = MR_x = MR_y = P_x(1 - 1/\in_x^d) = P_y\left(1 - 1/\in_y^d\right) = MC$$

Hence, $P_x = P_y\left[\left(1 - 1/\in_y^d\right)/\left(1 - 1/\in_x^d\right)\right]$

and

$$Log(P_x) = Log\left[\left(1 - 1/\in_y^d\right)/\left(1 - 1/\in_x^d\right)\right] + Log\left(P_y\right)$$

The first equation on the LHS predicts that the slope of a regression of P_x on P_y has a slope different from +1, whereas the equation in logs on the RHS predicts a slope of a regression of $Log(P_x)$ on $Log\left(P_y\right)$ of +1. There is unibiasness in the log specification.

How realistic are the assumptions of this theoretical and tentative model?

Our last assumption is that the price elasticities of demand for Brent and of WTI are different. Ideally, we would like to have direct estimates of these elasticities. Unfortunately, only elasticities by country are available. One might argue that the US and Canadian price elasticities are closer to a WTI price elasticity, and that a European price elasticity is closer to a

Brent price elasticity. Cooper (2003) estimates the US price elasticity to be -0.061 in the short run and -0.453 in the long run, and the Canadian price elasticity to be -0.041 and -0.352 respectively. This contrasts with a short run elasticity of -0.068 for the United Kingdom, and a long run elasticity of -0.182. Italy's short run price elasticity is -0.035, and its long run one is -0. 208.

Javan and Zahran (2015) illustrate more recent estimate. They assert that the US short run elasticity is -0.05 and the long run is -0.18. While, they state that the Canadian price elasticity is -0.02 in the short run and -0.08 in the long run. However, Italy's price elasticity is estimated as -0.16 in the short run and -0.27 in the long run, both higher than their US counterparts. The UK, relative to the US, has a higher short run elasticity of -0.10, but a lower long run elasticity of -0.16. These data present evidence on how disparate the price elasticities are. Hence assuming that the elasticities are not constant is indeed realistic.

Regarding the assumption about the Marginal Revenue (MR) and the Marginal Cost (MC). We assume that the MC of producing Brent and WTI are the same, and are equal to their MR. We calculate MR and MC for two firms that produce WTI and Brent based on the following formulas:

$$MR = \frac{\Delta TR}{\Delta Q}$$

$$MC = \frac{\Delta TC}{\Delta Q}$$

TR is the annual total revenue

TC is the annual total cost

Q is the quantity produced annually

The two firms we will base our calculations on are: EOG Resources, Inc. that produces mostly a WTI blend and TOTAL, a French company, which produces mostly a Brent blend. Referring to the annual reports of EOG Resources, Inc. (2004, 2007, 1010, 2013, & 2014), we estimate the MR to be $41 per barrel and the MC to be $35 per barrel. Moreover, we refer to Factbook 2015 on the website of TOTAL to estimate its MR and MC. We find the MC of TOTAL to be $36.5 per barrel on average for the years 2013 to 2015 (Factbook 2015, p. 30). Also, we find the average margin revenue for the years 2010 to 2015 to be $27.65 per metric ton (Factbook 2015, p. 7), which is equivalent to a margin of $3.87 per barrel, making the MR equal to $40.4 per barrel.

Hence, although the MR and the MC are different for each firm, and therefore for each blend, with the MR higher than the MC, the two MR and the two MC for the two firms are quasi the same. Since the model hinges on the fact that price elasticities of demand are different, but that, nevertheless, the MR of the two blends are equal, the assumptions of the model are met with great success. As a conclusion, and although the model is simple and little sophisticated it can describe the crude oil market with much exactitude.

B. The Significance Level

According to Lind, Marchal, and Wathen (2005) we must choose the level of significance before we apply the tests and before gathering the data. The level of significance is the range in which the null hypothesis is true, but rejected. Each type of data has a certain level of significance according to statistical rules and traditions. As we are using financial data, the best significance level to use is 5%.

C. Unit Root Tests

We will start by identifying the stationarity of the data and whether it has a unit root I(1) or more roots as unit root is a restriction for using some tests.

The data is stationary if the joint distribution of the corresponding data at different times (t) {xt 1, xt2, …, xt m} is identical to the joint distribution of the data {x t 1 + r , x t 2 +r, …, x t m +r} where r ≥1, otherwise the data is nonstationary (Wooldridge, 2009). Dickey and Fuller (DF) (1979) start with the following regression formula that includes a linear trend and an intercept to derive the DF formula that test for unit root and allows a linear trend:

$$y_t = X_t'\beta + \delta y_{t-1} + \epsilon_t;$$

$X_t'\beta$ is a linear trend

δ is the slope

ϵ_t is white noise

Dickey and Fuller (1979) add the term " $-y_{t-1}$" to both sides to differentiate the above formula leading to:

$$\Delta y_t = X_t'\beta + \Pi y_{t-1} + \epsilon_t \text{ ; } \Pi = \delta - 1$$

We take into consideration that the data might be highly correlated, therefore we use Augmented Dickey Fuller test (ADF) with an intercept and a trend derived by Said and Dickey (1984), instead of simple DF test.

The ADF formula including a linear trend and a drift is as follows:

$$\Delta y_t = X_t'\beta + \Pi y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-i} + \epsilon_t;$$

$\sum_{i=1}^{p} \emptyset_i \Delta y_{t-i}$ is the parametric term that adds p lags of the dependent variable to allow higher-order serial correlation

The ADF test the following hypothesis:

H_0: $\Pi = 0$ (y_t has a unit root)

H_a: $\Pi < 0$ (y_t has no unit root)

We use Eviews to test for unit root where we can identify the level of the test, this means the number of roots we are testing. In the first step we will test if the data is stationary of order 0, *I(0)*. If not then we test for stationarity after the 1st differential, *I(1)*. So the first time we test the null hypothesis for *I(0)*, if we fail to reject the null hypothesis, then the data is nonstationary and we differentiate equation and test for unit root in *I(1)*. If we reject the null hypothesis then it is stationary now, which indicates that the data has one unit root only.

Sjo (2008) asserts that this model of ADF is less limited than other models as it permits quadratic and linear trends, but still it doesn't permit segmented trends. Therefore, we will utilize Phillips-Perron (PP) unit root test to confirm previous results. PP is based on non-augmented Dickey Fuller test and the Π coefficient is adjusted so that serial correlation doesn't affect the asymptotes (Phillips and Perron, 1988). PP tests the same hypothesis as ADF. We also test for unit root at the zero level and first differential using the method Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (1992) that has the null hypothesis and alternative hypothesis reversed to that of ADF and PP as follows:

H_0: $\Pi < 0$ (y_t has no unit root)

H_a: $\Pi = 0$ (y_t has a unit root)

KPSS relies on the residuals form the Ordinary Least Squares on the exogenous variable, which we took as a constant and linear trend.

D. Variance Ratio Test

Variance ratio Lo and MacKinlay (1988, 1989) tests the following hypothesis:

H_0: *The data is martingale*

H_a: *The data is martingale*

Martingale implies that the historical data is not useful to predict that current price, which is expected to be equal to previous prices according to the following formula Lo and MacKinlay (1988):

$E\ [P_t - P_{t-1} | P_{t-1}, P_{t-2}, \ldots] = 0$; P_t is the price at time t.

The martingale test is similar to the market efficiency test and a starting point to test for Random Walks. Market efficiency is how accurate and quick the market behavior is to new information (Fama, 1965). Specifically, Fama (1970) asserts that in weak form efficiency the analysis of historical prices doesn't lead to precise and accurate forecasts of future prices. Brealey, Myers, and Allen (2008) assure that if investors fail to forecast future prices, then the data follows Random Walks. Fama (1970) states few assumption for the random walk theory, they are:

- The data is stationary
- The sequence of prices and probability distribution aren't constant implying that successive price variances are independent

In our study, variance ratio test tests the null hypothesis of martingale, which permits for general conditional heteroscedasticity and dependence according to Lo and MacKinlay (1988). This implies that this hypothesis also tests heteroscedasticity random walks hypothesis.

The following Kernel Estimator is used by the variance ratio test:

$$s^2(q) = \sum_{j=1}^{q-1} \left(\frac{2(q-j)}{q}\right)^2 . \ \delta_j \ ;$$

$$\delta_j = \frac{\left\{\sum_{t=j+1}^{T} (y_{t-j}-\hat{\mu})^2 (y_t-\hat{\mu})^2\right\}}{\left\{\sum_{t=j+1}^{T} (y_{t-j}-\hat{\mu})^2\right\}^2};$$

$$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} (Y_t - Y_{t-1})$$

q is the order of the difference

$\hat{\mu}$ is the estimator of the mean of first difference

E. Cointegration Tests

As we stated above, the data is assumed to have a unit root in the cointegration tests used. We will test for cointegration using Johansen cointegration test, Engle and Granger cointegration test, Phillips Ouliaris, and ARDL adjusted for GARCH effects.

It is worth noting that throughout our study we will use Schwarz Information Criterion (SIC).

a. Johansen Cointegration Test

The main disadvantage of Johansen cointegration test is that it is sensitive to errors when the samples are small and the lags are long. In this case, Johansen cointegration test might lead to inefficiency. This test uses the canonical form (defined below).

In this test, the number of stationary connections resemble the number of cointegrating vectors in the matrix. If the rank of the matrix (Π) is 0, then there is no cointegration. If the ADF, PP, and KPSS tests show that the data has a unit root, then the number of cointegrating vectors is less than the number of variables Johansen (1991, 1995), which is two in our study.

Johansen test undergoes two likelihood ratio tests: the trace test (J_{trace}) and the maximum eigenvalue test (J_{max}).

$$J_{trace} = -T\sum_{i=r+1}^{n} \ln(1 - \lambda_i);$$

r is the number of cointegrating relations and is equal to 0

n is the number of endogenous variables 1

i is the largest eigenvalue of the matrix

The formula above is the test statistic of the Trace Test and tests the hypothesis below:

H_0: $it\ has\ r\ cointegrating\ vectors$

H_a: $it\ has\ n\ cointegrating\ vectors$

This formula below represents the test statistic of the Maximum Eigenvalue test and it tests the following hypothesis:

$$J_{max} = -T\ln(1 - \widehat{\lambda_{r+1}});$$

H_0: $it\ has\ r\ cointegrating\ vectors$

H_a: $it\ has\ r + 1\ cointegrating\ vectors$

b. ARDL Cointegration Test

Autoregressive Distributed Lag (ARDL) is a cointegration method based on least squares regression where it add lags to the dependent variables and some independent variables. The specification of lags is essential and could rely on either SIC or AIC. As discussed above, we will follow the SIC lags indicator in our study. Though unlike Johansen and Engle-Granger cointegration tests, in ARDL the number of lags doesn't have to be the same for all the variables. Additionally Pesaran, Shin, Smith (2001) state that having one unit root only isn't an assumption in ARDL cointegration test, it can be used with both I(0) and I(1). ARDL relies on the following formula (the terms are identified above):

$$y_t = \alpha + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_i} X'_{j,t-1} \beta_{j,i} + \epsilon_t;$$

X_j is the dynamic regressor (explanatory variable)

q is the number of lags for the first explanatory variable

k is the number of lags for the k-th explanatory variable

In our study, we will test the long run coefficients of the dynamic regressors for long run cointegration and long run bias. We test the following hypotheses:

H_0: There is no long run cointegration (coefficient (WTI) = 0)

H_a: There is no long run cointegration (coefficient (WTI) ≠ 0)

H_0: There is no long run cointegration (coefficient (WTI) = 1)

H_a: There is long run cointegration (coefficient (WTI) ≠ 1)

Additionally, we will use the ARDL cointegrating equation coefficient in the error correction model to calculate the period required for long term cointegration. Let Z be the cointegration coefficient on the lagged cointegration residual, and TR be the time required for long term cointegration in terms of the data frequency (months/weeks/days).

$$TR = \left|\frac{1}{Z}\right|$$

c. Engle and Granger Cointegration Test

In testing for cointegration, Engle and Granger (1987) also assume that the series has a unit root, I(1). Its disadvantages are:

- It assumes that there is only one cointegrating vector, which isn't a problem in our case.
- Similarly to ADF, the number of lags should be chosen cautiously.
- It assumes that the dynamic formulas have a common term.

Based on the regression formula used by ADF above the hypothesis for Engle-Granger cointegration test are:

H_0: The cointegration residual is non-stationary (There is no cointegration)

H_a: The cointegration residual is stationary (There is cointegration)

d. Phillips-Ouliaris Cointegration Test

Phillips Ouliaris (1990) test is similar to Engle-Granger, but instead of relying on ADF it relies on PP. This test also has a null hypothesis of no cointegration.

Engle-Granger and Phillips-Ouliaris tests are performed under the three systems: DOLS (Dynamic Ordinary Least Squares), FMOLS (Fully Modified Ordinary Least Squares), and CCR

(Canonical Cointegrating Regression). Each of the three estimators have certain characteristics. FMOLS uses a semi-parametric correction that solves the obstacle of long run correlation (Phillips and Hansen, 1990). After that in 1992, Park adjusts FMOLS, approximates the least squares, forms CCR, and uses stationary transformations to overcome the long run reliance between regressors and cointegrating equation. Both FMOLS and CCR have normal unbiased asymptotes and are efficient. Finally, the DOLS adds lags and leads to the previous equations to absorb the effect of long run correlation.

F. Granger Causality

The first differential of the prices of Brent (*D(Brent))* is said to Granger cause the first differential of the prices of WTI *(D(WTI))* if D(Brent) aids in forecasting the prices of D(WTI), and vice versa. Though, the price difference of WTI is Granger caused by the price difference of Brent, but this doesn't mean that its price change is the result of change in Brent price, it only indicates precedency (Granger, 1969). In the econometric program used in our study, EViews, bivariate regression form is used to test the following hypotheses.

Set A:

$H_0: D(WTI)\ doesn't\ cause\ D(Brent)$

$H_a: D(WTI)\ causes\ D(Brent)$

Set B:

$H_0: D(Brent)\ doesn't\ cause\ D(WTI)$

$H_a: D(Brent)\ causes\ D(WTI)$

The formulas used are:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-l} + \beta_1 x_{t-1} + \cdots + \beta_l x_{t-l} + \epsilon_t$$

and

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \cdots + \beta_l y_{t-l} + \omega_t;$$

y_t and x_t are D(WTI) and D(Brent) respectively

G. GARCH

GARCH (1, 1) is the simplest form of the GARCH (q, p). GARCH(q, p) has an autoregressive (AR) GARCH term of order *q* and a moving average ARCH term of order *p* Bollerslev (1986*)*. Therefore, GARCH(1, 1) has a first-order AR GARCH term and a first-order moving average (MA) ARCH term, respectively.

Using GARCH models we will test for short run biasness by observing the coefficient of D(WTI) and calculating its t-statistic:

$z_{stat} = \frac{\bar{x}-\mu}{s_{\bar{x}}}$; $\bar{x}$ is the coefficient, $\mu = 1$ and $s_{\bar{x}}$ is the standard error

The critical values we will rely on are at the significance level of 5%. Therefore, the 95% confidence interval is -1.96 < z_{stat} <1.96.

The hypothesis we test is:

H_0: *There is no bias in the short run* (Coefficient =1)

H_a: *There is bias in the short run* (Coefficient ≠1)

We observe the z_{stat} the test displays and consider a confidence level of 95% to test if the cointegrating vector equals 0. The hypothesis we test is:

H_0: *There is no long run cointegration* (Cointegrating vector =0)

H_a: *There is long run cointegration* (Cointegrating vector ≠0)

The GARCH model relies on the following formula:

σ_t^2 is the conditional variance and it is the one-period ahead forecast variance based on past information:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2;$$

ω: constant

α: ARCH coefficient

ϵ_{t-1}^2: news about volatility from previous period (lag of the squared residual) (the ARCH term)

β: GARCH term

σ_{t-1}^2: the previous period's expectation (the GARCH term)

There are some conditions required for the GARCH model to be valid. The standardized residuals of the first differential of the data (*D(WTI) and D(Brent))* studied shouldn't be serially correlated, the standardized residuals squared should show that there is no ARCH effect, and finally normality should hold (Sjo, 2011). Though normality isn't a serious condition to worry about. We change the residuals to standardized residuals as we deal with huge samples. When the sample size is large using non-standardized residuals might lead to errors in estimation of the model (Engle, 2001). Therefore, to check for the two conditions of applying GARCH, serial correlation and heteroscedasticity, we find the correlogram of standardized residuals and standardized residuals squared, respectively.

Standardized equation residual = $\frac{\epsilon_t}{\sigma_t}$;

ϵ_t is the equation residual

Engle (2011) illustrates that upon testing large samples and daily data for more than ten years, we better use the generalized form of GARCH (q, p). Engle (2011) explains that GARCH (q, p) allows "slow and fast" deterioration of information. The formula of this model is Bollerslev (1986):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2;$$

In TARCH and EGARCH, we can test the following null hypothesis:

H_0: *There is no asymmetric effect*

H_a: *There is asymmetric effect*

A more general form of GARCH is TARCH that takes into consideration the threshold term (I_{t-k}) as proposed by Glosten, Jaganathan, and Runkle (1993) and Zakoïan (1994). The formula used by TARCH is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \epsilon_{t-k}^2 I_{t-k};$$

$I_t = 1 \text{ if } \epsilon_t < 0 \text{ and } I = 0 \text{ otherwise}$

TARCH is the general autoregressive conditional heteroscedasticity test that allows asymmetric effect of volatility, where good news and bad news effect σ_t^2 differently. If γ_i =0, then we fail to reject the null hypothesis, hence there no asymmetric effect. When $\gamma_i < 0$ the effect of bad news is revealed in α_i + γ_i, if γ_i>0 then there's a leverage effect, i. e. bad news increases volatility more than good news. These tests are carried out by looking upon the z-statistics on the coefficient γ_i.

Nelson (1991) asserts another GARCH model that transforms TARCH and leverage effect to a exponential model such that γ_i<0, where it is used to test for leverage effect. This model is known as EGARCH. If γ_i=0, then the asymmetric term is insignificant. If $\gamma_i \neq 0$, then we reject the null hypothesis of no asymmetric effect, hence there is an asymmetric effect of good and bad news. If $\gamma_i < 0$ there is a leverage effect, i. e. bad news impact volatility more than good news. If $\gamma_i > 0$ there is an asymmetric effect. If $\gamma_i = 0$ there is no asymmetry. These tests are carried out by looking upon the t-statistics on the coefficient γ_i.

The disadvantage of EGARCH is that it doesn't accept negative input as it is in logarithmic form and this doesn't exist in our study as price inputs are positive. The formula used is:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}$$

IV. Empirical Analysis

A. Data

In our study, we will use daily, weekly, and monthly data of WTI and Brent spot prices that we took from US Energy Information Administration. We remove all missing values so that the data will be continuous and ready for testing. Additionally, we will take the logarithmic form of the data to eliminate possible skewness and stabilize the variance. We use the following periods for different data frequencies:

- The period starting May 20, 1987 till May 9, 2016 for daily spot prices

- The period starting May 15, 1987 till May 6, 2016 for weekly prices
- The period starting May 1987 till April 2016 for monthly prices

We will use EViews to conduct the tests in this study.

B. Unit Root Tests Results

Table 1a and Table 1b show the results of testing the prices of WTI and Brent for unit root using ADF method. The results show that both Brent and WTI, the original data and logarithmic data, fail to reject the null hypothesis at 5% at level zero and indicate that the series is non-stationary thus has a unit root. Therefore, we find the first difference of the data and repeat the ADF test. The results now reject the null hypothesis of non-stationarity at 5% and indicate that the first difference of the data doesn't have a unit root. We find out that the series have a unit root of order I(1). Moreover, one of the random walks conditions is satisfied.

Similarly for PP, the daily, weekly, and monthly data of WTI and Brent in both forms (original data and logarithmic form) are non-stationary at the zero level and fail to reject the null hypothesis of unit root at 5%. We report the results in Tables 2a and 2b, which show that when the test is repeated on the data of first differential, the null hypothesis of unit root is rejected and again reveals that the data is stationary of root I (1). Our results coincide with most of the literature we discuss above, starting from the results deduced by Gulen (1997) till those explained by Ji and Fan (2015).

We report the value of the statistic of KPSS in tables 3a and 3b and test null hypothesis of stationarity (no unit root). The critical values of this test are 0. 119, 0. 146, and 0. 216 at 10%, 5%, and 1%, respectively. We reject the null hypothesis at zero level at 5% in all data frequencies and both forms. This implies that the series is non-stationary at zero level. And we fail to reject its first differential at 5%. This denotes that the first differential of the series is stationary. Hence, the results of KPSS test coincide with the results of ADF and PP.

In the three unit root tests we apply, we choose the exogenous factors to be a constant and a linear trend.

C. Variance Ratio Test Results

Tables 4a and 4b indicate whether the historical available data is useful to predict future spot price changes of Brent and WTI respectively. The results in tables 4a and 4b show that the null hypothesis of martingale is rejected in monthly and weekly prices for both WTI and Brent, in normal form and logarithmic form. These results indicate that the spot prices of WTI and Brent on monthly or weekly basis are serially correlated. This implies that using the available monthly and weekly changes spot prices of WTI and Brent, you can predict accurately the changes in spot prices for the coming month or week respectively. These results show that WTI and Brent spot prices are not weak form efficient on monthly and weekly basis and do not follow random walks.

On the other hand, the results of variance ratio test on daily prices of Brent show that the daily spot price differentials of Brent and logarithmic daily spot price differentials of Brent fail to reject the null hypothesis of martingale. Consequently, this shows that past price changes are not efficient in predicting future prices and this affirms weak form efficiency. In this case, studying historical daily price changes of Brent does not aid in forecasting future price changes accurately.

The results of variance ratio test on daily spot price differentials of WTI show that it fails to reject the null hypothesis of martingale for daily spot prices, but rejects the nulls hypothesis in case of logarithmic data. This indicates that the effect of martingale on WTI daily spot prices correlates with skewness. Thus, predicting daily spot prices differentials of WTI using past prices differentials isn't efficient.

The above results agree with Charles and Darne (2009) that Brent is more weak efficient than WTI, and contradict Tabak and Cajueiro (2006).

D. Cointegration Tests Results

a. Johansen Cointegration Test Results

We report the results of the coefficients, tests statistics, and its p-value of Johansen cointegration test in table 5 to test the null hypothesis of whether the coefficient of WTI equals 0 to test for long term cointegration. We reject the null hypothesis at 5% and confirm there exists a relation between WTI and Brent. In table 6 we report again the coefficient of WTI, the Chi-squared distribution statistic, and its p-value to test the null hypothesis of no long term bias, such that the coefficient of WTI is equal to 1. We reject the null hypothesis of no bias as the coefficients are obviously different from one and the probabilities are less than 0.05 in all data frequencies, monthly, weekly, and daily. This indicates that there is long term biasness in the relation between WTI and Brent. This biasness could be linked to localized events that happen and effect the crude oil prices as Ji and Fan (2015) demonstrate. Fattouh (2010) also illustrates that the price differences between WTI and Brent is linked to their locations and logistic infrastructure.

We proceed to test for cointegration using the two tests of Johansen cointegration test. ADF, PP, and KPSS test show that the process has one unit root. This indicates that the number of cointegrating equations is less than two (the number of variables), so it is either zero or one. Trace test (tables 7a and 7b) and Maximum Eigenvalue test (tables 8a and 8b) both reject the null hypothesis of "no cointegrating equations" and fail to reject the null hypothesis of "one cointegrating equation at most" at 5%. We got similar outcomes upon testing WTI and Brent in all data frequencies in logarithmic form and original form. This shows that the WTI and Brent spot prices cointegrate in one equation at most. Thus WTI and Brent spot prices move together with a stable difference between them, they almost decrease and increase together throughout the 30 years period studied. These results confirm the results achieved by several researchers such as Bentzen (2007), Wilmot (2013), and Kim, Kim, and Heo (2013). On the other hand, it contradicts other literature like Roboredo (2011) and Ji and Fan (2015).

b. ARDL Test Results

To double check the cointegration results, we perform the most recent cointegration test, ARDL. We start this test by applying error correction model to test for cointegration and specifically to identify the periods required to adjust to long term cointegration. Table 9 shows the outcomes we get from the absolute value of the reciprocal of the error correction model coefficient. The outcomes show that for WTI and Brent it requires 15. 15 months to achieve monthly cointegration, such that their monthly prices move together. They require around 46. 82 weeks to adjust to weekly cointegration and 108 days to adjust to daily cointegration. Additionally, the periods required by the logarithmic data to adjust to long term cointegration in monthly, weekly, and daily series are 6 months, 17 weeks, and 38 days, respectively.

We display the results of long run cointegration in ARDL in table 10. The low p-value gives evidence to support the alternative hypothesis, so we reject the null hypothesis of no long term cointegration. This proves that WTI and Brent spot prices cointegrate in the long term and move together with a stable difference between them and confirm the results we achieve by Johansen cointegration test.

In table 11, we report the results of testing the null hypothesis of no lung run bias by calculating the t-statistics such that:

$t_{stat} = \frac{x-\mu}{s}$; μ=1,s is the standard error, and x is the WTI coefficient

In all the cases we tests, we reject the null hypothesis of no long run bias. This implies that there is long run bias between WTI and Brent in data frequencies.

c. Engle and Granger Test Results

Tables 13, 15, and 17 show the results of Wald test for three different systems: Canonical Cointegrating Regression, Dynamic Ordinary Least Squares, and Fully Modified Ordinary Least Squares respectively. The three tests in both data forms reject the null hypothesis of no bias with coefficient different from 1 in monthly, weekly, and daily data. This confirms the result of previous tests that there is biasness between the prices of WTI and Brent and their slope isn't exactly 1. We also observe the t-stat that is greater than the critical value 1. 96 to confirm the latter observation. Therefore, we can figure that the biasness that appeared in FMOLS isn't the result of the dependence between the regressors and cointegrating equation, since it proceeds in the CCR and DOLS where lags are also added. We interpret the p-value and test statistic in each of CCR, DOLS, and FMOLS in tables 12, 14, and 16 respectively and find high evidence to support the alternative hypotheses of cointegration and bias.

When we perform Engle-Granger and Phillips-Ouliaris cointegration tests in the three systems CCR, DOLS, and FMOLS, and we get the same results reported in tables 18 and 19.

The Engle-Granger test (table 18) tests for the null hypothesis of no cointegration in monthly, weekly, and daily spot prices in original data and logarithmic data. In the three frequencies, we reject the null hypothesis and confirm that there is cointegration in the WTI and Brent prices.

d. Phillip-Ouliaris Test Results

Phillip-Ouliaris test results in table 19 confirm the cointegration of the prices of the two crude oils in both forms and in the three chosen frequencies.

E. Granger Causality Test Results

As we have previously interpreted, WTI and Brent spot prices cointegrate in the long run according to the tests we applied on monthly, weekly, and daily prices in its normal form and logarithmic form. Now, we will determine whether one of the prices lead the other using Granger Causality. The results of this test are displayed in table 20. Both null hypotheses of "WTI doesn't cause Brent" and "Brent doesn't cause WTI" are rejected when Granger test for causality is applied on daily and weekly spot price in normal and logarithmic form. This implies that both Brent and WTI lead each other and the causality is bidirectional and confirms the results of Bentzen (2007). And if the spot prices of Brent increase or decrease, then the spot prices of WTI follow and increase or decrease, respectively. And if the spot prices of WTI increase or decrease, then the spot prices of Brent increase or decrease respectively.

This bidirectional causality applies in the case of weekly and daily data only. In the case of monthly prices, we fail to reject the null hypotheses listed, thus neither the price of WTI nor the price of Brent leads the other. The absence of causality could be justifies by Weiner's (1991) proposal that monthly prices reveal the prices after adjustments and integration, where one month is enough for it to take place. Therefore, we failed to observe the causality process on monthly spot prices of WTI and Brent.

F. GARCH Test Results

Applies on D(WTI) and D(BRENT).

As the WTI and Brent are cointegrating according to our results, we can proceed to test for volatility on the returns of WTI and Brent. We started our GARCH test by testing the residuals to check whether they satisfy the condition of absence of serial correlation, absence of heteroscedasticity, and normality. We chose three GARCH models to test our data. The GARCH (1, 1) is the "typical" GARCH model that has an AR (1) and MA (1) (Engle, 2011) and we apply it to our monthly and weekly data. As for daily data, we use GARCH (q, p) as it has a high frequency, specifically we found that GARCH (4, 1) is the best model. We use the listed GARCH models to test for volatility of spot prices. To test for asymmetric volatility, we use TARCH and EGARCH which show whether bad news and good news affect volatility differently. We didn't report the result of few tests that show insignificance. The results we didn't report are:

-Monthly data: EGARCH (1, 1) on original data

-Weekly data: EGARCH (1, 1) on logarithmic data

-Daily data: EGARCH (1, 1) on logarithmic data

We start by testing if the conditions of using GARCH models are satisfied. We display the results of testing the D(Brent) and D(WTI) for serial correlation and heteroscedasticity in Tables 21a → 23b on all three models (GARCH, TARCH, and EGARCH). We reject the null hypotheses of "no serial correlation" and "no heteroscedasticity", respectively, in all the data. We used the following different lags for different time frequencies relying on the Ljung-Box Q-statistic for different lag lengths.

-For monthly data we use the following lag lengths: 3 months, 6 months, 12 months, and 24 months.

-For weekly data we use the following lag lengths: 1 week, 2 weeks, 3 weeks, 4 weeks, and 5 weeks.

-For daily data we use the following lag lengths: 1 day, 5 days, 10 days, and 20 days.

The series in all frequencies and both forms show that there exists serial correlation and heteroscedasticity in the residuals. But the samples we are testing are large in size; we have 343 observations for monthly data, 1,510 observations for weekly data, and 7,240 observations for daily data. The huge sample size justifies the incorrect estimation and presence of serial correlation and heteroscedasticity. As Engle (2011) illustrates, large sample size data requires testing standardized residuals.

Therefore, we repeat the serial correlation and heteroscedasticity tests, in addition to the normality test on the standardized WTI and Brent differential residuals. We display the test results of monthly, weekly, and daily data in tables 24, 25, and 26 for all GARCH models. In table 24, in monthly data, we fail to reject the null hypothesis of no serial correlation in all the cases we study. As for the null hypothesis of no heteroscedasticity in the standardized residuals squared, we reject the null hypothesis only in the original form in GARCH and TARCH at the first two lags, at 3 months and 6 months. But, in the logarithmic form of the data at the same lags, we fail to reject the null hypothesis.

In Table 25, in the weekly data study, we fail to reject the null hypothesis of no serial correlation and no heteroscedasticity in all cases, which is a good sign for the model. Lastly, Table 26, in testing daily data, we reject the null hypothesis of no serial correlation only in case of GARCH (1, 4) and EGACRH (1, 4), in original data, at the lags of 5 days, 10 days, and 20 days in both models. And as for the null hypothesis of no heteroscedasticity, we only reject it in the case of EGARCH (1, 4) in original data. Though for the same data under the same models, but in logarithmic form, we fail to reject the null hypothesis of no serial correlation and no heteroscedasticity.

We display the results of normality tests on monthly, weekly, and daily data in tables 27, 28, and 29. The results show that all three models, which we applied on all data frequencies and both forms, reject the null hypothesis of normal distribution. But this doesn't affect the interpretation of the asymptotes and hence doesn't affect the coefficient values and is expected to be non-normal (Sjo, 2008).

The previous results indicate that the condition of applying the GARCH (1, 1), TARCH (1, 1), and EGARCH (1, 1) models on monthly and weekly data are satisfied. Where we will apply GARCH (1, 4), TARCH (1, 4), and EGARCH (1, 4) on daily data as it shows better fit.

We use the coefficients of GARCH models to interpret short run biasness. Table 30 reports the coefficient of D(WTI) and the test statistic. If the coefficient is equal to 1 and the z-stat is between -1. 96 and 1. 96, then we fail to reject the null hypothesis and there is no short run bias. Otherwise, we reject the null hypothesis and find out that there is bias in the short run. We can see in table 30 that the coefficient of D(WTI) equals 1, only in the case of monthly data when we use GARCH (1, 1) and EGARCH (1, 1) on original data. This implies that there is no short term bias when these two models are applied on monthly data. On the other hand, there is short term bias whenever we use one of GARCH models on original weekly, original daily, logarithmic monthly, logarithmic weekly, and logarithmic daily data.

In tables 31 and 32, we interpret the cointegrating vector in GARCH models. We test if the coefficient is different from 0 to test the null hypothesis of no long run cointegration and report the results in table 31. And we test if the coefficient is different from 1 to test the null hypothesis of no long run biasness and report the results in table 32. In both tables, we can see that we reject the null hypotheses. This implies that presence of long term cointegration and long term biasness in all three GARCH models.

We test for asymmetric effect of news on WTI and Brent by interpreting the coefficients of the residuals. We report the results in table 33. We fail to reject the null hypothesis of no asymmetric effect in the following cases:

- Monthly data using TARCH in original data
- Weekly data using TARCH in original data and logarithmic data
- Daily data using TARCH in original data

In the data stated above, good news and bad news have the same effect on WTI and Brent spot prices. But at the same cases, except for logarithmic monthly prices, EGARCH reject the null hypothesis of no asymmetric effect. Which means, that under EGARCH good news and bad news affect WTI and Brent spot prices differently.

Hence TARCH and EGARCH are indicating opposite result sin weekly and daily prices. But the in logarithmic monthly prices, they both reject the null hypothesis of no asymmetric effect.

V. Conclusion

A. Research Findings

The empirical results we discuss in part IV show that there exists high evidence for short term and long term bias and long term cointegration. After we confirm that the data has a unit root, we proceed to test for weak form efficiency and cointegration. We find out that WTI, logWTI, Brent, logBrent are not weak form efficient on monthly and weekly basis. And logWTI is not weak efficient in daily data. But still, this may not lead necessarily to abnormal profits after transaction and turnover costs. Additionally, there is a margin of error, because the goodness-of-fit statistic is not perfect.

In tables 5, 7, 8, 10, 18, and 19 we use Johansen, ARDL, Engle-Granger, and Phillips-Ouliaris to test for cointegration and show that there is long term cointegration in all the studies series. Therefore, the prices of WTI and Brent converge in the long run.

We use the same tests and interpret different coefficients to test for bias. In tables 6, 11, 13, 15, and 17, we test for the null hypothesis of no long run bias and reject the null hypothesis in all the cases. Hence, we prove that there exists a long run bias in all cases. Therefore, as there is a joint hypothesis, we conclude that either the theory is unrealistic and wrong, or the data does not behave according to a correct theory, or both.

Besides that, we use ARDL to find the length of the period required by the series to achieve long run cointegration. As we report in table 9, in the monthly data, it requires the series 15 months to adjust to long term cointegration. In weekly data, it requires the series 46 weeks to adjust to long term cointegration. And finally in daily data, it requires the series 108 days to adjust to long term cointegration.

Furthermore, we use Granger causality in table 20 to show that there is bidirectional causality between WTI and Brent in weekly and daily data. This implies that either WTI or Brent can lead the other. Hereafter, the price information about one crude oil carries information about the other crude oil and they both move in tandem.

Additionally, we test for serial correlation and heteroscedasticity in the differenced series. We report the results in tables 21a → 23b. The results reject the null hypothesis of no serial correlation, as well as the null hypothesis of no conditional heteroscedasticity. This indicates that the data is serially correlated and volatile.

We repeat the GARCH (1, 1) estimate on the standardized residuals and report the results in tables 24 → 25. The monthly and weekly data show that the estimated model eliminates serial correlation and heteroscedasticity. This indicates that the estimates of the chosen GARCH model is efficient. We chose GARCH (1, 4) models for daily data as it shows a better fit than GARCH (1, 1) and report the results in table 26. We fail to reject the null hypothesis of no heteroscedasticity in most of the cases, but we reject the null hypothesis of no serial correlation in few cases in the original data. Hence, using GARCH is more efficient in monthly and weekly data.

In addition to that, we test for short run bias after GARCH's adjustment and report the results in table 30. Even after we test standardized residuals, we reject the null hypothesis of no bias in the short run. The results reveal that there is bias in the relation between WTI and Brent after we eliminate heteroscedasticity and serial correlation. Also, we test the null hypothesis of no long run bias and reject the null hypothesis (table 31). This affirms the presence of bias even after GARCH estimations. Moreover, we test the null hypothesis of no long run cointegration and the results are reported in table 32. We reject the null hypothesis of no cointegration and confirm previous results of long run cointegration.

Finally, we test the null hypothesis of no asymmetric effect and report the results in table 33. We reject the null hypothesis of no asymmetric effect using EGARCH in all data frequencies and forms and using TARCH in the logarithmic form in monthly data. Therefore, in monthly logarithmic data good and bad news affect the spot prices of WTI and Brent differently. For this reason, the investor must beware periods of high volatility and bad news, and be more risk averse in such cases.

B. Limitations

a. We didn't include structural breaks that might lead to shocks in crude oil prices.
b. The models used for testing asymmetric effect fail to converge in daily and weekly data.
c. The theoretical model may be unrealistic although it is described as tentative.
d. Same events may impact the two oil prices differently.
e. The two crude oils are not perfect substitutes.

f. The marginal cost may not be constant and the marginal revenues may be time-variable.

g. Price demand elasticities may change over time.

h. Other fundamental factors, ignored in this research, may impact the two crude oils differently.

C. Recommendations

a. It is not recommended to act on predictability of prices, because this may be due to the sample selection chosen. Other samples may or may not confirm the anomaly.

b. New information about one crude oil price spills over to the other. Hence observance of one oil price carries much information about the price of the other.

c. Since the two long run oil prices move in tandem in the long run, one may recommend substituting one crude oil for the other. This is highly risky because short selling is risky and because the time to full adjustment, or to the long run, is stochastic.

d. The relation between the two crude oils is non-linear due to GARCH effects. A linear forecast is therefore biased and inefficient.

e. For the best model fit, it is recommended to use GARCH on weekly data

f. The investor should beware of excess volatility of financial markets, because it has big impacts on the market of crude oils.

g. In the long run a one dollar increase in WTI increases Brent by more than one dollar. This should trigger a buy recommendation on Brent.

h. In the long run a 1% increase in WTI increases Brent by more than 1%. Again this should trigger a buy recommendation on Brent.

i. It is unclear whether these long run irregularities can lead to the creation of arbitrage, riskless and abnormal trading profits, once transaction costs and all other uncertainties involved in statistical analysis are accounted for.

VI. Tables

Table 1a: *Augmented Dickey-Fuller Unit Root Test*
H_0: Brent has a unit root (non-stationary)
H_a: Brent has no unit root (stationary)

	Brent		LogBrent	
	P-value at Level	P-value at 1st Diff.	P-value at Level	P-value at 1st Diff.
Monthly	0.199900	0.000000*	0.226800	0.000000*
Weekly	0.634400	0.000000*	0.414700	0.000000*
Daily	0.718600	0.000100*	0.409000	0.000100*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 1b: *Augmented Dickey-Fuller Unit Root Test*
H_0: WTI has a unit root (non-stationary)
H_a: WTI has no unit root (stationary)

	WTI		LogWTI	
Period	P-value at Level	P-value at 1st Diff.	P-value at Level	P-value at 1st Diff.
Monthly	0.093900	0.000000*	0.176300	0.000000*
Weekly	0.502700	0.000000*	0.336600	0.000000*
Daily	0.504900	0.000100*	0.227300	0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 2a: *Phillips Perron Unit Root Test*
H_0: Brent has a unit root (non-stationary)
H_a: Brent has no unit root (stationary)

	Brent		LogBrent	
	P-value at Level	P-value at 1st Diff.	P-value at Level	P-value at 1st Diff.
Monthly	0.515100	0.000000*	0.412600	0.000000*
Weekly	0.376700	0.000000*	0.362400	0.000000*
Daily	0.670800	0.000100*	0.448000	0.000100*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 2b: *Phillips Perron Unit Root Test*
H_0: WTI has a unit root (non-stationary)
H_a: WTI has no unit root (stationary)

	WTI		LogWTI	
	P-value at Level	P-value at 1st Diff.	P-value at Level	P-value at 1st Diff.
Monthly	0.351900	0.000000*	0.385400	0.000000*
Weekly	0.209600	0.000000*	0.315500	0.000000*
Daily	0.521300	0.000100*	0.332600	0.000100*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 3a: *KPSS Unit Root Test*
H_0: Brent has no unit root (stationary)
H_a: Brent has a unit root (non-stationary)

	Brent		LogBrent	
	Value of Statistic at Level	Value of Statistic at 1st diff.	Value of Statistic at Level	Value of Statistic at 1st diff.
Monthly	0.248320*	0.139091	0.254729*	0.094411
Weekly	0.450641*	0.072063	0.472248*	0.073519
Daily	0.937438*	0.103015	0.986588*	0.082659

Notes:
* denotes that we reject the null hypothesis at 5%, where the critical value is 0.146
We reject the null hypothesis when the value of the statistic > 0.146

Table 3b: *KPSS Unit Root Test*
H_0: WTI has no unit root (stationary)
H_a: WTI has a unit root (non-stationary)

	WTI		LogWTI	
	Value of Statistic at Level	Value of Statistic at 1st diff.	Value of Statistic at Level	Value of Statistic at 1st diff.
Monthly	0.2477460*	0.1152550	0.2405200*	0.0866740
Weekly	0.4164270*	0.0566840	0.4404800*	0.0667570
Daily	0.8504570*	0.0836140	0.9156860*	0.0686590

Notes:
* denotes that we reject the null hypothesis at 5%, where the critical value is 0.146
We reject the null hypothesis when the value of the statistic > 0.146

Table 4a: *Variance Ratio Test*

H_0: Brent is martingale

H_a: Brent is not martingale

	Brent	LogBrent
P-value in Monthly Data	0.013600*	0.019800*
P-value in Weekly Data	0.000000*	0.000000*
P-value in Daily Data	0.506300	0.556600

Notes:
* denotes that we reject the null hypothesis at 5%

Table 4b: *Variance Ratio Test*

H_0: WTI is martingale

H_a: WTI is not martingale

	WTI	LogWTI
P-value in Monthly Data	0.004800*	0.001900*
P-value in Weekly Data	0.000100*	0.022400*
P-value in Daily Data	0.862800	0.037500*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 5: *Johansen Cointegration Test (t-stat)*

H_0: There is no long term cointegration (coefficient (WTI) =0)

H_a: There is long term cointegration (coefficient (WTI) ≠0)

		Original Data	Logarithmic Data
Monthly	Coefficient of WTI	1.142942	1.096010
	t-stat	35.228700	76.415400
	P-value	0.000000*	0.000000*
Weekly	Coefficient of WTI	1.129529	1.090853
	t-stat	32.637700	83.764600
	P-value	0.000000*	0.000000*
Daily	Coefficient of WTI	1.124958	1.092539
	t-stat	42.621700	130.332000
	P-value	0.000000*	0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 6: *Johansen Cointegration Test (Chi-squared distribution)*
H_0: There is no long run bias (coefficient of WTI =1)
H_a: There is long run bias (coefficient of WTI ≠1)

		Original Data	Logarithmic Data
Monthly	Coefficient of WTI	1.142942	1.096010
	Chi-squared	10.254060	17.757200
	P-value	0.001364*	0.000025*
Weekly	Coefficient of WTI	1.129529	1.090853
	Chi-squared	8.010147	21.799990
	P-value	0.004652*	0.000003*
Daily	Coefficient of WTI	1.124958	1.092539
	Chi-squared	14.080600	59.869440
	P-value	0.000175*	0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 7a: *Johansen Test (Trace Test)*
(A): H_0: It has zero cointegrating vectors

	Brent/WTI	LogBrent/LogWTI
P-value in Monthly Data	0.0018000*	0.00010*
P-value in Weekly Data	0.0060000*	0.00000*
P-value in Daily Data	0.0000000*	0.00010*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 7b: *Johansen Test (Trace Test)*
(B): H_0: It has at most 1 cointegrating vector

	Brent/WTI	LogBrent/LogWTI
P-value in Monthly Data	0.0567000	0.10100
P-value in Weekly Data	0.1127000	0.14320
P-value in Daily Data	0.1367000	0.13610

Notes:
* denotes that we reject the null hypothesis at 5%

Table 8a: *Johansen Test (Maximum Eigenvalue Test)*
(A): H_0: It has zero cointegrating vectors

	Brent/WTI	LogBrent/LogWTI
P-value in Monthly Data	0.0041000*	0.00010*
P-value in Weekly Data	0.0091000*	0.00000*
P-value in Daily Data	0.0000000*	0.00010*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 8b: *Johansen Test (Maximum Eigenvalue Test)*
(B): H_0: It has at most one cointegrating vector

	Brent/WTI	LogBrent/LogWTI
P-value in Monthly Data	0.0576000	0.10100
P-value in Weekly Data	0.1127000	0.14230
P-value in Daily Data	0.1367000	0.13610

Notes:
* denotes that we reject the null hypothesis at 5%

Table 9: *Length of the Adjustment to the Long-run*

Data Period	Dependent	Coefficient of Brent	Coefficient of LogBrent
Monthly	Time (months)	15.1556485	6.2600552
Weekly	Time (weeks)	46.8274409	16.7358415
Daily	Time (days)	108.5658452	37.5361285

Table 10: *ARDL Long Run Cointegration*

H_0: There is no long run cointegration (coefficient (WTI) =0)

H_a: There is long run cointegration (coefficient (WTI) ≠0)

Dependent	Brent	LogBrent
(t-stat) P-value in Monthly Data	(25.407236) 0.000000*	(73.037232) 0.000000*
(t-stat) P-value in Weekly Data	(27.594396) 0.000000*	(75.750400) 0.000000*
(t-stat) P-value in Daily Data	(34.434650) 0.000000*	(98.006827) 0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 11: *ARDL*

H_0: There is no long run bias (coefficient (WTI) =1)

H_a: There is long run bias (coefficient (WTI≠1)

Dependent	Brent	LogBrent
(Coefficient(WTI)) t-stat in Monthly Data	(1.117466) 2.670774*	(1.092325) 6.173108*
(Coefficient(WTI)) t-stat in Weekly Data	(1.095630) 2.408513*	(1.082160) 5.751085*
(Coefficient(WTI)) t-stat in Daily Data	(1.098026) 3.074168*	(1.083921) 7.587794*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 12: *Canonical Cointegrating Regression*

	Variable	WTI	LogWTI
Monthly	P-value	0.000000	0.000000
	t stat	34.785210	79.887640
	Coefficient	1.148136	1.098352
Weekly	P-value	0.000000	0.000000
	t stat	37.080820	84.107030
	Coefficient	1.132159	1.090754
Daily	P-value	0.000000	0.000000
	t stat	45.511300	80.171100
	Coefficient	1.121822	1.090450

Table 13: *Wald Test (Canonical Cointegrating Regression)*
H_0: There is no long run bias (C(1)=1)
H_a: There is long run bias (C(1)≠1)

	Dependent	Brent/WTI	LogBrent/LogWTI
Monthly	t-stat	4.488184	7.153512
	P-value	0.000000*	0.000000*
Weekly	t-stat	4.328500	6.997931
	P-value	0.000000*	0.000000*
Daily	t-stat	4.942222	6.649957
	P-value	0.000000*	0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 14: *Dynamic Ordinary Least Squares*

	Variable	WTI	LogWTI
Monthly	P-value	0.000000	0.000000
	t stat	62.218680	117.710300
	Coefficient	1.107337	1.087913
Weekly	P-value	0.000000	0.000000
	t stat	104.864200	188.986900
	Coefficient	1.106028	1.087600
Daily	P-value	0.000000	0.000000
	t stat	190.411800	331.823800
	Coefficient	1.105610	1.087537

Table 15: *Wald Test (Dynamic Ordinary Least Squares)*
H_0: There is no long run bias (C(1)=1)
H_a: There is long run bias (C(1)≠1)

	Dependent	Brent/WTI	LogBrent/LogWTI
Monthly	t stat	6.031028	9.512014
	P-value	0.000000*	0.000000*
Weekly	t stat	10.052650	15.221810
	P-value	0.000000*	0.000000*
Daily	t stat	18.188510	26.708900
	P-value	0.000000*	0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 16: *Fully Modified Ordinary Least Squares*

	Variable	WTI	LogWTI
Monthly	P-value	0.000000	0.000000
	t stat	33.322020	79.200610
	Coefficient	1.152021	1.098767
Weekly	P-value	0.000000	0.000000
	t stat	36.470840	83.984310
	Coefficient	1.133094	1.090765
Daily	P-value	0.000000	0.000000
	t stat	45.296070	142.598600
	Coefficient	1.121990	1.091851

Table 17: *Wald Test (Fully Modified Ordinary Least Squares)*

H_0: There is no long run bias (C(1)=1)

H_a: There is long run bias (C(1)≠1)

	Dependent	Brent/WTI	LogBrent/LogWTI
Monthly	t stat	4.397175	7.119267
	P-value	0.000000*	0.000000*
Weekly	t stat	4.283902	6.988501
	P-value	0.000000*	0.000000*
Daily	t stat	4.924868	11.995940
	P-value	0.000000*	0.000000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 18: *Engle-Granger Cointegration Test*

H_0: There is no cointegration

H_a: There is cointegration

	Brent/WTI	LogBrent/LogWTI
P-value in Monthly Data	0.00060*	0.00000*
P-value in Weekly Data	0.00140*	0.00000*
P-value in Daily Data	0.00000*	0.00000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 19: *Phillips-Ouliaris Cointegration Test*

H_0: There is no cointegration

H_a: There is cointegration

	Brent/WTI	LogBrent/LogWTI
P-value in Monthly Data	0.01240*	0.00000*
P-value in Weekly Data	0.00040*	0.00000*
P-value in Daily Data	0.00000*	0.00000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 20: *Granger Causality*

		Original data		Logarithmic Data	
		P-value	Result	P-value	Result
Monthly	D(WTI) doesn't cause D(Brent)	0.0672	no causality	0.9146	no causality
	D(Brent) doesn't cause D(WTI)	0.2367		0.5933	
Weekly	D(WTI) doesn't cause D(Brent)	0.0004*	bidirectional causality	0.0001*	bidirectional causality
	D(Brent) doesn't cause D(WTI)	8.00E-05*		1.00E-10*	
Daily	D(WTI) doesn't cause D(Brent)	3E-153*	bidirectional causality	4.00E-167*	bidirectional causality
	D(Brent) doesn't cause D(WTI)	7E-13*		4.00E-12*	

Notes:
* denotes that we reject the null hypothesis at 5%

Table 21a: *Serial Correlation and ARCH Tests on Monthly D(Brent) and D(LogBrent)*
(A): H_0: There is no serial correlation
H_a: There is serial correlation
(B): H_0: There is no conditional heteroscedasticity
H_a: There is conditional heteroscedasticity

	D(Brent)		D(LogBrent)	
Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
3	0.0000*	0.0000*	0.0000*	0.0000*
6	0.0000*	0.0000*	0.0000*	0.0000*
12	0.0000*	0.0000*	0.0000*	0.0000*
24	0.0000*	0.0000*	0.0000*	0.0000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 21b: *Serial Correlation and ARCH Tests on Monthly D(WTI) and D(LogWTI)*
(A): H_0: There is no serial correlation
H_a: There is serial correlation
(B): H_0: There is no conditional heteroscedasticity
H_a: There is conditional heteroscedasticity

	D(WTI)		D(LogWTI)	
Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
3	0.0000*	0.0000*	0.0000*	0.0000*
6	0.0000*	0.0000*	0.0000*	0.0000*
12	0.0000*	0.0000*	0.0000*	0.0000*
24	0.0000*	0.0000*	0.0000*	0.0000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 22a: *Serial Correlation and ARCH Tests on Weekly D(Brent) and D(LogBrent)*
(A): H_0: There is no serial correlation
H_a: There is serial correlation
(B): H_0: There is no conditional heteroscedasticity
H_a: There is conditional heteroscedasticity

	D(Brent)		D(LogBrent)	
Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
1	0.0000*	0.0000*	0.0000*	0.0000*
2	0.0000*	0.0000*	0.0000*	0.0000*
3	0.0000*	0.0000*	0.0000*	0.0000*
4	0.0000*	0.0000*	0.0000*	0.0000*
5	0.0000*	0.0000*	0.0000*	0.0000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 22b: *Serial Correlation and ARCH Tests on Weekly D(WTI) and D(LogWTI)*
(A): H_0: There is no serial correlation
H_a: There is serial correlation
(B): H_0: There is no conditional heteroscedasticity
H_a: There is conditional heteroscedasticity

	D(WTI)		D(LogWTI)	
Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
1	0.0000*	0.0000*	0.0000*	0.0000*
2	0.0000*	0.0000*	0.0000*	0.0000*
3	0.0000*	0.0000*	0.0000*	0.0000*
4	0.0000*	0.0000*	0.0000*	0.0000*
5	0.0000*	0.0000*	0.0000*	0.0000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 23a: *Serial Correlation and ARCH Tests on Daily D(Brent) and D(LogBrent)*
(A): H_0: There is no serial correlation
H_a: There is serial correlation
(B): H_0: There is no conditional heteroscedasticity
H_a: There is conditional heteroscedasticity

	D(Brent)		D(LogBrent)	
Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
1	0.0020*	0.0000*	0.0010*	0.0000*
5	0.0150*	0.0000*	0.0030*	0.0000*
10	0.0030*	0.0000*	0.0010*	0.0000*
20	0.0000*	0.0000*	0.0000*	0.0000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 23b: *Serial Correlation and ARCH Tests on Daily D(WTI) and D(LogWTI)*
(A): H_0: There is no serial correlation
H_a: There is serial correlation
(B): H_0: There is no conditional heteroscedasticity
H_a: There is conditional heteroscedasticity

	D(WTI)		D(LogWTI)	
Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
1	0.0000*	0.0000*	0.1660	0.0000*
5	0.0000*	0.0000*	0.0000*	0.0000*
10	0.0000*	0.0000*	0.0000*	0.0000*
20	0.0000*	0.0000*	0.0000*	0.0000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 24: *Serial Correlation and ARCH Tests on the Monthly Standardized Residuals*
(A): H_0: There is no serial correlation in standardized residuals
H_α: There is serial correlation in standardized residuals
(B): H_0: There is no conditional heteroscedasticity in standardized residuals
H_α: There is conditional heteroscedasticity in standardized residuals

	Dependent	D(Brent)		D(LogBrent)	
	Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
GARCH	3	0.781	0.004*	0.410	0.234
	6	0.147	0.031*	0.196	0.229
	12	0.234	0.215	0.244	0.144
	24	0.392	0.724	0.411	0.430
TGARCH	3	0.828	0.003*	0.509	0.401
	6	0.093	0.028*	0.297	0.778
	12	0.193	0.207	0.455	0.768
	24	0.378	0.674	0.649	0.862
EGARCH	3			0.552	0.616
	6			0.319	0.620
	12			0.348	0.265
	24			0.525	0.676

Notes:
* denotes that we reject the null hypothesis at 5%

Table 25: *Serial Correlation and ARCH Tests on the Weekly Standardized Residuals*
(A): H_0: There is no serial correlation in standardized residuals
H_a: There is serial correlation in standardized residuals
(B): H_0: There is no conditional heteroscedasticity in standardized residuals
H_a: There is conditional heteroscedasticity in standardized residuals

	Dependent	D(Brent)		D(LogBrent)	
	Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
GARCH	1	0.773	0.454	0.717	0.835
	2	0.937	0.755	0.857	0.912
	3	0.903	0.770	0.951	0.966
	4	0.912	0.710	0.903	0.971
	5	0.957	0.796	0.879	0.975
EGARCH	1	0.980	0.069		
	2	0.726	0.190		
	3	0.787	0.278		
	4	0.823	0.249		
	5	0.881	0.337		

Notes:
* denotes that we reject the null hypothesis at 5%

Table 26: *Serial Correlation and ARCH Tests on the Daily Standardized Residuals*
(A): H_0: There is no serial correlation in standardized residuals
H_a: There is serial correlation in standardized residuals
(B): H_0: There is no conditional heteroscedasticity in standardized residuals
H_a: There is conditional heteroscedasticity in standardized residuals

	Dependent	D(Brent)		D(LogBrent)	
	Lag number	(A) P-value	(B) P-value	(A) P-value	(B) P-value
GARCH	1	0.966	0.355	0.879	0.444
	5	0.026*	0.536	0.518	0.411
	10	0.032*	0.328	0.287	0.458
	20	0.010*	0.504	0.053	0.588
TGARCH	1			0.963	0.449
	5			0.550	0.498
	10			0.315	0.502
	20			0.059	0.644
EGARCH	1	0.745	0.049*		
	5	0.012*	0.065		
	10	0.016*	0.128		
	20	0.003*	0.319		

Notes:
* denotes that we reject the null hypothesis at 5%

Table 27: *Normality Test on Monthly Data*
H_0: Standardized residuals are normally distributed
H_a: Standardized residuals are not normally distributed

Dependent Variable	D(Brent)	D(LogBrent)
Test	P-value	P-value
GARCH	0.041071*	0.003867*
TGARCH	0.051276	0.000006*
EGARCH		0.000002*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 28: *Normality Test on Weekly Data*
H_0: Standardized residuals are normally distributed
H_a: Standardized residuals are not normally distributed

Dependent Variable	D(Brent)	D(LogBrent)
Test	P-value	P-value
GARCH	0.00000*	0.00000*
EGARCH	0.00000*	

Notes:
* denotes that we reject the null hypothesis at 5%

Table 29: *Normality Test on Daily Data*
H_0: Standardized residuals are normally distributed
H_a: Standardized residuals are not normally distributed

Dependent Variable	D(Brent)	D(LogBrent)
Test	P-value	P-value
GARCH	0.00000*	0.00000*
TGARCH		0.00000*
EGARCH		0.00000*

Notes:
* denotes that we reject the null hypothesis at 5%

Table 30: *GARCH/TARCH/EGARCH*
H_0: There is no bias in the short run (coefficient of D(WTI)=1)
H_a: There is bias in the short run (coefficient of D(WTI)≠1)

		Original Data		Logarithmic Data	
	Model	Coefficient of D(WTI)	t-stat	Coefficient of D(WTI)	t-stat
Monthly	GARCH(1,1)	1.0031400	0.334220	1.0417700	2.704843*
	TGARCH(1,1)	1.0013590	0.140538	1.0622090	4.122258*
	EGARCH(1,1)			1.0540120	3.833901*
Weekly	GARCH(1,1)	0.8421150	-238.956415*	0.8901080	-12.761816*
	TGARCH(1,1)	0.8418940	-20.570648*	0.8891390	-12.828165*
	EGARCH(1,1)	0.8495810	-21.692474*		
Daily	GARCH(1, 4)	0.5584520	-84.458301*	0.5766860	-77.629562*
	TGARCH(1, 4)	0.5581160	-84.652107*	0.5760220	-77.340022*
	EGARCH(1, 4)	0.5575350	-72.989937*		

Notes:
* denotes that we reject the null hypothesis at the critical values, such that $t_{0.05}$>1.96 or $t_{0.05}$<-1.96

Table 31: *GARCH/TARCH/EGARCH*

H_0: There is no bias in the long run (cointegrating vector=1)

H_a: There is bias in the long run (cointegrating vector≠1)

		Original Data		Logarithmic Data	
	Model	Coefficient	z-stat	Coefficient	z-stat
Monthly	GARCH(1,1)	-1.016310	1.03424223	-1.066358	5.09036514*
	TGARCH(1,1)	-1.019311	1.05484241	-1.056944	3.84730761*
	EGARCH(1,1)			-1.063078	4.47520397*
Weekly	GARCH(1,1)	-0.824406	3.68215142*	-1.069459	5.88935052*
	TGARCH(1,1)	-0.044862	3.40882258*	-2.069488	5.83834650*
	EGARCH(1,1)	-1.045314	3.18395166*		
Daily	GARCH(1, 4)	-1.076801	5.73141791*	-1.088436	8.86132265*
	TGARCH(1, 4)	-1.075275	5.46500653*	-1.088194	9.00766010*
	EGARCH(1, 4)	-1.074341	5.64686669*		

Notes:

* denotes that we reject the null hypothesis at the critical values, such that $z_{0.05}>1.96$ or $z_{0.05}<-1.96$

Table 32: *GARCH/TARCH/EGARCH*

H_0: There is no long run cointegration (cointegrating vector=0)

H_a: There is long run cointegration (cointegrating vector≠0)

		Original Data		Logarithmic Data	
	Model	Coefficient	z-stat	Coefficient	z-stat
Monthly	GARCH(1,1)	-1.016310	64.44428*	-1.066358	81.80225*
	TGARCH(1,1)	-1.019311	55.67959*	-1.056944	71.41045*
	EGARCH(1,1)			-1.063078	75.42133*
Weekly	GARCH(1,1)	-1.053741	72.20030*	-1.069459	90.68073*
	TGARCH(1,1)	-1.052547	68.27849*	-1.069488	89.86162*
	EGARCH(1,1)	-1.045314	73.44843*		
Daily	GARCH(1, 4)	-1.076801	80.35780*	-1.088436	109.0575*
	TGARCH(1, 4)	-1.075275	78.06666*	-1.088194	111.1410*
	EGARCH(1, 4)	-1.074341	81.60378*		

Notes:

* denotes that we reject the null hypothesis at the critical values, such that $z_{0.05}>1.96$ or $z_{0.05}<-1.96$

Table 33: *TARCH/EGARCH*

H_0: There is no asymmetric effect

H_a: There is asymmetric effect

		Original data		Logarithmic Data	
	Model	Coefficient	z-stat	Coefficient	z-stat
Monthly	TGARCH(1,1)	-0.1912200	-1.4484890	-0.2268560	-3.4748910*
	EGARCH(1,1)			0.1155460	2.0630900*
Weekly	TGARCH(1,1)	-0.0448620	-1.3312670	0.0164260	0.3921530
	EGARCH(1,1)	0.0430900	2.3438190*		
Daily	TGARCH(1, 4)	-0.006070	-1.1285550	0.0187740	3.4731930*
	EGARCH(1, 4)	0.0100170	2.3600250*		

Notes:

* denotes that we reject the null hypothesis at 5%, where the critical values are $z_{0.05}>1.96$ or $z_{0.05}<-1.96$

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