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Gauging Returns and Volatility of Crude Oil Using GARCH Approach

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ABSTRACT

This paper examines the returns and volatility of two distinct types of crude oil: Brent and West Texas Intermediate (WTI). The time series data, collected from the international market, spans from February 1, 2014, to February 1, 2024. It includes 2,537 observations for WTI and 2,542 observations for Brent. The study employs the E-Views software to analyze the secondary data and to investigate the impacts of ARCH and GARCH models at a significant level. The mean reversion of WTI is 0.993582, and Brent crude mean reversion is 0.956194. The results show that WTI has a slower mean reversion than Brent because it is closer to 1. Further half-life model analysis showed that WTI reverted to its mean position after 99 days and Brent after 16 days. This study concludes that WTI is more volatile than Brent crude oil.

1 Introduction

Crude oil plays a vital part in the international economy as one of the most significant energy sources on the planet and is sometimes referred to as "Black Gold." For this reason, crude oil is stated to be the cornerstone of a country or region's industrial and economy. The financial consequences of crude oil are becoming more significant as globalisation and international trade grow. The market's increased activity in producing financial derivatives, like crude oil futures and options, draws in more investors and financial organisations. However, variations in the price of crude oil discourage companies from investing and increase borrowing costs with a negative impact on predicted cash flow and market volatility (C. Zhang & Zhou, 2024)

Crude oil, the "lifeblood" of industries and the valuable "commodity, " is a fundamental energy resource and a significant raw material in contemporary society. It holds a crucial position in the economy, politics, and military, with numerous factors influencing its price fluctuations. The WTI, Brent, and Dubai crude oil futures markets set the benchmark price for the global oil market on a global scale (Su et al., 2020).

The economy's ability to function depends on the crude oil market. It is one of the most important energy sources for growing the local economy. Thus, researchers, governments, and investors are interested in learning more about the future of crude oil (X. Gong et al., 2017).

Natural organic oil derived from hydrocarbon reserves and other organic components is known as crude oil. Diesel, gasoline, and other petrochemicals are examples of refined crude oil derivatives frequently employed in industrial settings. Foreign crude oil price measurements and quotes are usually expressed in Brent barrels, Blend, OPEC-BR, and NMAX. Petroleum has economic importance due to its essential components. Many countries lack sufficient crude oil resources, are therefore highly dependent on oil imports from other countries, and are therefore highly vulnerable to oil price fluctuations. Because oil is a desirable and depleting resource, price fluctuations can also affect other variables, such as return on equity, exchange rates, inflation, and interest rates (Raheem Ahmed et al., 2017).

Crude oil is one of the most significant commodities in the world and is vital to the global economy as a valuable financial asset and energy source. For numerous studies, including those on risk management, asset pricing, and portfolio allocation, a vital factor is the volatility of crude oil returns. For an extended period, one of the main issues in finance has been the modelling and forecasting of crude return volatility, drawing in-depth study from scholars, investors, and asset managers. However, there is still much work in both theory and practice to create a more precise forecast for the volatility of crude oil returns (Ma et al., 2019).

Since the energy crisis of the 1970s, significant changes in oil prices have received considerable attention in the trade and business press. Both upward and downward movements appear to be receiving considerable attention, as the recent sharp decline in oil prices shows (Christoffersen & Pan, 2018).

Most research now focuses on return value and less on learning to associate them. Specifically, return volatility is typically expressed as observed variance or represented by the GARCH model; nevertheless, it is frequently discovered that implied volatility is more illuminating and indicative of volatility in the future (Bouri et al., 2017).

Crude oil has grown to be one of the most traded commodities worldwide in volume and level since it has been an essential energy source since the 19th century. Unlike refined products like heating oil or gasoline, crude oil makes up most of the global oil market. Local supply and demand variables are usually used to set prices. Crude oil is still used as a standard for the entire energy industry even though it has the potential to adversely impact the cost of heat and electricity as well as the supply and demand of all other energy sources (Z. Gong & Kappi, 2019).

Crude oil has a special place globally, but its price volatility is most noticeable. Over the past ten years, the oil market has garnered the interest of multiple financial stakeholders, market players, and the media concerning Hedging strategies, portfolio allocation, and option pricing. It is proven that precise modelling and prediction of the features that cause oil volatility are theoretically and practically critical to prevent oil volatility. It encourages the construction of energy-efficient infrastructure and upholds a healthy society by lowering energy risks and enhancing energy security. Growth of the capital market in the global economic system, crude oil holds a unique position, and the volatility of its price affects choice pricing, portfolio allocation, and hedging strategies. The oil market has drawn the interest of many financial stakeholders, market players, the media, industry participants, and an expanding range of economic practitioners throughout the past ten years. Consequently, it is clear that from a theoretical and practical standpoint, accurate modelling and prediction of oil volatility features is crucial. Standpoint for reducing and eliminating energy-related risks, enhancing the level of electricity security, encouraging the improvement of strength consumption shape, and maintaining the health of the improvement (Liang et al., 2020).

The Earth's sedimentary shell contains Crude oil, a naturally found combustible liquid with an oily texture. Water, mechanical impurities, asphaltene-resin, hydrocarbon, and ash compounds make up its significant constituents, with trace amounts of sulphur and oxygen compounds (Ryspaeva, et al., 2024).

There is a growing acknowledgement among academics and practitioners of the impact of crude oil price variation on government plans and policy decisions regarding sales revenue and subsidies in the traditional and renewable power sectors and the agricultural economy. Inflation and how it impacts the price of consumer goods and commercial products are also related to the volatility of crude oil prices. This seems to significantly affect the political structure of economies that rely on oil. Furthermore, how agricultural commodity prices are handled and how they relate to the price of oil affects global food supply and the sensibilities of many financial sellers, for whom oil serves as the primary input in the production system. Moreover, the instability of the impact of inflation on the price of goods and merchandise purchased in the industrial region is likewise linked to changes in oil prices (Oyuna & Yaobin, 2021).

Because it is essential to the operation of global transportation networks, industries, and economies, crude oil is regarded as a strategic commodity. It is an essential energy source necessary for the stability and expansion of national economies. Numerous scholars have focused on identifying the factors influencing precious metals or crude oil markets. For example, the positions of the traders have a significant effect on how WTI crude oil futures use economic indicators to forecast the pattern of exchanges in crude oil prices, such as US currency rates, producer pricing indices, and aspects pertaining to supply and demand (Foroutan & Lahmiri, 2024).

Crude oil is undoubtedly a vital commodity because it produces energy. Human activities involve distilling crude oil to create gasoline, heating oil, fuel oil, and jet fuel, all essential for home, industrial, and transportation needs. Thus, it should come as no surprise that crude oil is the commodity with the highest worldwide trading volume. As a result, problems with oil risk management are quite important. Long-term contracts were used in the past to set oil prices. However, since the 1970s, oil prices have experienced increased volatility, particularly after the first oil shock. Currently, two main markets serve as benchmarks for oil prices. It is a purified product on an international basis, WTI, which is a combination of America and London. These are Speed international prices based on premium or discount. These are indicative prices. This premium or discount reflects the quality features of the product. Various types of crude oil and local and worldwide supply and demand circumstances exhibit dissimilarities. Moreover, vital benchmark crude oil is the underlying asset in organised futures contracts. WTI is the recently established base grade for crude oil, known as "sweet light crude." In contrast, the basis of the Brent contract is both Brent and the New York Mercantile Exchange. Another critical player in this area is the London-based International Petroleum Exchange (IPE) (Alizadeh et al., 2004).

When accurately estimating the return volatility of financial assets, GARCH models have demonstrated a strong performance. The total performance is decreased even though these models deliver predictions in a different representation. While it yields more accurate in-sample estimates, the GARCH model is less precise. Alternatives to the outdated volatility model, implied volatility model, and GARCH that are frequently used are unexpected expectations (Agnolucci, 2009).

This thesis aims to gauge the Returns and Volatility of WTI and Brent crude oil and investigate international markets in dollars per barrel from February 2014 to February 2024. Applied ARRCH and GARCH models. This study gauges two crude oil returns and volatility between 2014-2024.

This research measures the returns and volatility of two crude oil markets by an empirical investigation into the volatility of crude oil prices during the last ten years, from 2014 to 2024. This study addresses the following research questions.

RQ1: Is there an ARCH effect in crude oil returns?

RQ2 Is there a GARCH effect in crude oil returns?

RQ3: Does the oil return series observe mean reversion?

2 Literature Review

Many studies have emphasised crude oil's significance in the world’s economy. Comprehending oil as a commodity necessitates a comprehensive review that considers various dimensions. Many scholars have investigated the relationship between economic activity and oil prices. Although it is well acknowledged that oil prices impact the economy, some research has looked primarily at how this relationship has changed during the 1980s (Floros & Galyfianakis, 2020).

By analysing monthly data from 2003 to 2020, fluctuations in oil production and prices make it evident that the uncertainty surrounding forthcoming interest rates directly impacts future adjustments in interest rates. The rising rates in the 10-year U.S. Treasury derivatives market are highly correlated with oil prices and volatility, suggesting a downward trend in oil prices and a persistent increase in market expectations. The extensive research background equips individuals with the necessary insights to navigate the challenges posed by escalating interest rates and the fluctuating real money markets, enabling them to optimise their financial strategies and effectively manage both high and low-risks (Qadan & Cohen, 2024).

The effects of different types of extreme occurrences vary. The crude oil market consults various sources when predicting the possible effects of particular, extreme events on crude oil prices. In terms of the oil market, these occurrences are usually divided into two categories. The first group consists of incidents like the first Persian Gulf War, the September 11 terrorist attacks, and the most recent COVID-19 epidemic that resulted in problems with the oil supply. Conversely, downturns in the economy, stock market, and finance are included in the second group. The financial crises in Asia, the US, and Europe in 1997–1998 and 2008–2009, respectively, are among them. A few of these tragedies had a long-term impact on crude oil prices. The study also examined the relationship between OPEC output announcements, hurricanes, and extreme weather events. The findings demonstrated that the global financial crisis significantly affected oil price returns (Q. Zhang et al., 2024).

The Central Bank of Iraq must intervene by using its monetary tools to influence the nation's economic activity and by using those foreign reserves to achieve stability in the Iraqi country's balance and the dinar's currency rate and overall level of governance. The influence of a drop in crude oil prices directly affects public revenues, which has a negative impact on the bank's foreign reserve size (Salman, 2024).

There have been significant fluctuations in the price of crude oil worldwide during the last 20 years. Abrupt peaks and declines, shortened boom cycles, and shorter intervals of gradual transition have all been characteristics of these swings. The global economy contracted in 2001 after the Internet bubble crashed. With a maximum loss of 40%, the Brent crude oil price fell from $29.43/barrel to $17.68/barrel between September and November. During the 2008 financial crisis, prices dropped by about 76% in just six months, from USD 140/barrel in June to roughly USD 33/barrel in December. The shale oil revolution caused a fall in crude oil prices, which peaked at the beginning of 2016. With the US-China trade conflict intensifying and oil companies stepping up output to close the supply shortfall created by US sanctions on Iran, oil prices fell by 42% in 2018. Due to the global coronavirus outbreak in 2020, the world's need for energy decreased by about 4.5%, and the oil demand fell by an astounding 9.3%. In May, the WTI crude oil futures settlement price dropped lower than it has ever closed, at USD -37.63/barrel, as market anxiety increased. Following 2021, the COVID-19 vaccine's widespread use and government-sponsored economic stimulus programs increased energy demand and raised energy costs globally. The price of oil rose by more than 60% globally in 2021 (Lu & Huang, 2024).

The exchanges in the oil prices are one indicator of changes in the overall economy. The crude oil price changes can significantly affect imports, inflation, and other economic indicators in the Croixes economy. Consequently, this can erode shareholder confidence and impact investment across different sectors. The influence of oil prices on a company's performance is contingent on the specific industry in which it operates. The VAR-BEKK-GARCH model examines monthly crude oil production and inventory levels. This analysis reveals that crude oil prices have a limited effect on stock market flotation, stock returns, and oil market returns. During periods of economic recovery, the Global Petroleum Reserve (GPR) may have a detrimental effect on crude oil inventories due to reduced international economic activities. It is essential to closely monitor the exchanges in crude oil prices and evaluate how they affect the economy (Behera et al., 2024).

Since its launch in late 2018, China's crude oil futures market, or INE, has drawn increasing interest. This study looks at how the market reacts to storage problems and whether or not it can replace WTI and Brent as a benchmark. The market's correlation, return, and volatility are examined across time using various GARCH models. It evaluates the combination of Chinese crude oil futures with global benchmark markets using VAR-DCC GARCH and VARBEKK GARCH models. The empirical results show market integration for China's crude oil futures is going well. Furthermore, the average correlation values between the two main markets and the INE market are approximately 0.7, irrespective of structural discontinuities. Moreover, a mutual correlation exists between crude oil pricing and the INE market. These findings demonstrate how the crude oil market in China affects the commodity's future. Interestingly, the INE market correlates more with the Brent market than the WTI market, highlighting Brent's current dominance in the crude oil futures market (Liu et al., 2019)

We consider daily and weekly observations of the crude oil volatility index (OVX) data depending on the data frequency. We use WTI oil price data and the OVX data between May 10, 2007, and December 31, 2017. the daily fluctuations in OVX and crude oil prices. We examine whether time-varying leaps exist in OVX using the GARCH-jump approach. Based on daily data, the results demonstrate signs of fluctuating jump intensity and time-varying jumps in OVX. The parameter representing the severity of the conditional jump's persistence is 0.9897. The GARCH-jump model specification seems accurate because the jump intensity parameters are positive (Dutta et al., 2021).

Events on a global scale, such as the pandemic and the conflicts in Europe, have caused noticeable inflation and heightened volatility in crude oil and gold prices. Monthly data on gold spot prices, WTI futures, and Brent futures are collected from May 1983 to December 2022. Three sophisticated data analysis methods are combined to generate the Rolling SARIMAX module: the Rolling Model, the SARIMAX model, and the Rolling Correlation approach. This newly developed model predicted the rolling correlation for Gold Spot Price-WTI Futures and Gold Spot Price-Brent Futures, with R-square values of 89.8% and 88.4%, respectively. Accordingly, the mean absolute percentage error was 10.84% and 10.33%. The price of crude oil and gold have a stronger association, which may provide helpful information for risk management and strategic investing (Pandit & Luo, 2024).

This study analyses the daily series of WTI and Brent crude oil prices, the same as in the first study. The US Energy Information Administration's (EIA) publically available data is the foundation for our analysis. While the Brent prices are available from May 20, 1987, to June 30, 2017, with 7,645 views, the WTI prices are available from January 2, 1986, to June 30, 2017. This extended dataset spans 13 years and starts about three years after the original, non-publicly accessible data. The value enhancement is what separates the original series from the extended series. It is worth noting that the original study concluded just before the significant price surge in 2008 when the oil price surpassed the $140 mark (compared to the $30 price range between 2000 and 2004). The price movement within the expanded sample is particularly intriguing, and we anticipate obtaining compelling results from a transparent market perspective (Kristoufek, 2019).

This research investigation examined the daily fluctuations of crude oil prices from April 1, 2000, to March 20, 2012. The price volatility of crude oil was examined using two different models: symmetric and asymmetric. In particular, it evaluated volatility three times: before, during, and following the global financial crisis. The data indicates that the Global Financial Crisis had the highest crude oil price volatility level compared to other periods. Based on the model selection criteria, asymmetric GARCH models perform better than symmetric ones in controlling the volatility of oil prices. The study shows that leverage effects occur in the oil market and highlights how important it is to account for these effects when determining oil prices (Salisu & Fasanya, 2012)

The statistical measure of volatility over a specified period has been used to estimate the possibility of an exponential increase or drop in the value of a securities or market. The standard deviation of the returns on an investment is used to calculate the amount since it shows the degree of variance. Volatile markets are characterised by high trading volume and substantial price volatility, which is usually the result of trade orders moving only in one direction (Sikandar & Ahmad, 2023).

Currently, there is a lack of consensus in predicting and projecting oil volatility. The traditional GARCH model does not capture the persistent character of crude oil price volatility. However, volatility models and forecasts are extensively utilised and documented in the stock and currency markets. Limited research has been conducted on the duration of these market fluctuations, emphasising that crude oil prices are subject to constant fluctuations (Kang et al., 2009).

Every week, starting in January 2008 and ending in October 2021, is subjected to an autoregressive model and stochastic volatility analysis (TVP-VAR-SV) using time-varying parameter vectors. We find that changes in WTI oil prices respond positively to shocks, unfavourably to shocks in U.S. economic activity, but positively to oil production, inventories, and the United States. Currency index and VIX. The reaction to the Economic Policy Uncertainty index started positive, turned slightly negative, and finally disappeared. The volatility index (VIX) has the most significant impact. Moreover, his WTI response to oil price fluctuations changes over time. As the COVID-19 pandemic has shown, economic downturns and crises often have severe consequences. These results could enhance our comprehension of the temporal dynamics and factors influencing swings in the price of WTI crude oil (Le et al., 2023).

This theory addresses the oil price modelling and builds upon previous work in this field by analysing the role of structural breaks and long memory in modelling and forecasting the conditional volatility of oil spot and futures prices using various GARCH-type models. Their conclusions are summed up as follows. Firstly, they demonstrate parameter instability in five of the nine GARCH-based conditional volatility processes for energy prices. Secondly, they show that all the series considered have a long memory, and the data seem to fit better into a FIGARCH model. That being said, the degree of volatility persistence significantly drops when structural fractures are considered. In the end, their out-of-sample study shows that volatility models consider the data's long memory and instability (Odu, Bilkisu, Sulaimon, & Charles, 2022).

2.1 Theories

Engle (2001) presented the use of ARCH and GARCH models in econometric analysis, as they are gaining importance in analysing time series data, particularly in financial applications. They are conditional variance models that gauge volatility in the series.

An auto-regression model (AR) uses OLS regression to establish a relationship between a time series variable and its lagged values. An expansion of the univariate AR model, the vector auto-regression model (VAR) applies autoregression to a vector of time series variables. This process aims to choose the optimal VAR model for the sample data, and the estimation error of a VAR model rises with the number of variables. Since it lowers the quantity of coefficients that require estimation, it is preferable to build a model with as few variables as is practical. The model's quantity of variables and lags determines how many coefficients exist (Ahmad et al., 2018).

The enhanced GARCH model combines many extensions of the famous and frequently used ARCH technique. It was first presented by Duan & Yeh (2011) and includes asymmetric, threshold, power, exponential, and standard (linear) GARCH processes. In this work, their work examines the asymptotic distribution of different functions of the process that arise in statistical inference issues, as well as the probabilistic structure of augmented GARCH (1, 1) sequences. By employing the independence properties of perturbed GARCH sequences to explicitly confine their asymptotic behaviour to the situation of independent random variables, we avoid the Markov structure and associated mixing characteristics of the model (Hörmann, 2008)

H_1: There is a significant ARCH effect in crude oil returns.

H_2: There is a significant GARCH effect in crude oil returns.

H_3: Crude oil returns observe Mean Reversion.

3 **Methodology**

This thesis measures crude oil volatility. Here, the daily observations of WTI and Brent crude oil from February 1, 2014, to February 1, 2024 are considered. It researched and evaluated crude oil's volatility and collected data on crude oil online through the Statista website(https://www.statista.com/). This study is based on quantitative data and attempts to determine the best way to present it. To do this, the study analysed the data in E-views using the GARCH Approach Unit-root, ARCH & GARCH models, graphical analysis, and other tables were employed in this thesis utilising SPSS, Microsoft Excel, and E-views. The data used in this research is based on daily prices. After data analysis, further drew out the Graphical Analysis of RW data and concluded the results in Unit root for checking where there is data significance and also check the Test Critical Value of both crude oil at 1%, 5%, and 10%. After, I made a table where the addition of ARCH and GARCH to find the value of Lambda (λ), the sum of ARCH and GARCH values tell about the speed of mean reversion. For further information about the mean reversion in days, find out about Half-life. Throughout the below-given formula of half-life.

$$Half\ life = 1 - \frac{log(2)}{log(\lambda)}$$

Where λ (lambda) denotes α+β, i.e., the sum of ARCH and GARCH.

3.1 Data and Variables

This thesis uses secondary data to compare the crude oil prices daily. Crude oil price data in this analysis was taken from the Statista website (https://www.statista.com/). The analysis period is from 1st Feb 2014 to 1st Feb 2024. These data describe crude prices in dollars per barrel for a mixture of two types of oil, including Brent crude (North Sea – Europe) and West Texas Cushing crude (Americas). The ten-year total observations are 2536 for both crude oil. This thesis mainly focuses on gauging the Returns and Volatility of crude oil prices.

3.2 Sample

The time focuses on the sample from 1st Feb 2014 to 1st Feb 2024.

3.3 Descriptive Analysis

Descriptive statistics, including Mean, Median, Std- Deviation, and Skewness, have been used to test the data set's attributes.

3.4 Estimations

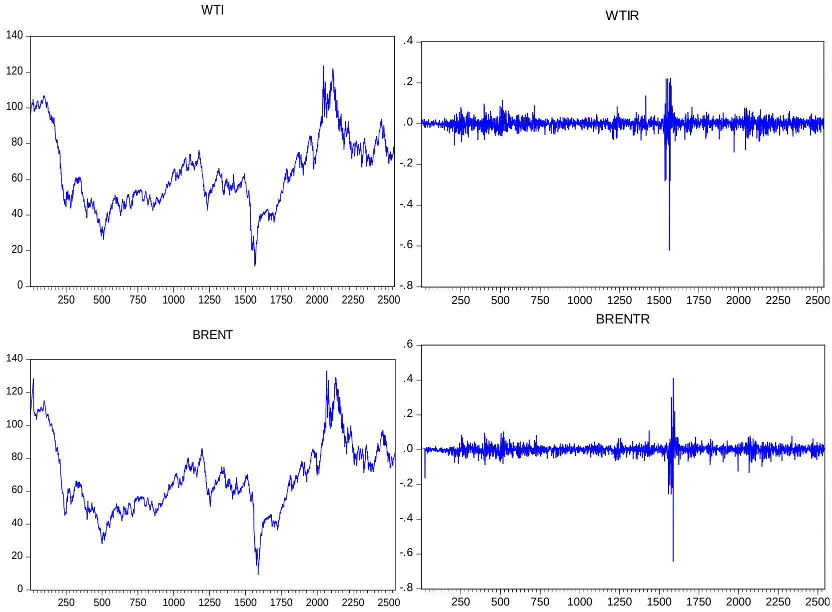
The analysis of this thesis has been defined into five parts. In 1st part, a graphical representation of daily data based on historical data is presented. The unit root test of crude oil returns is given in 2ndpart of the results.3rd, Descriptive statistics were discussed in the

4th part, finding the econometric analysis for the sum of the returns of ARCH and GARCH for finding Lemda. In the last part, find the half-life. There are four different types of crude oil, as shown below. The first graph defines the WTI, the Second defines the WTI returns, the third defines the Brent, and the last defines the Brent returns. These four graphs define the Volatility of two crude oil data in a specific period. It is graphical representation indicates that Brent oil is highly volatile. It has come to its original position after the last few days compared to WTI. The second part of my output is a numerical representation of WTI and Brent. The unit root defines that both crude oils are significant at first difference. In the 3rd stage, sum the ARCH and GARCH values to know the Lemda value (λ) for calculating the Half-life. Both ARCH and GARCH results show that Brent comes to its actual position first, and WTI comes after many days. For further checking, the days calculated in the results are used to determine how many days after it comes to its original position. Results show that Brent takes 16 days to go back to reverence. On the other hand, WTI returns after 99 days.

4 Results

This Graphical Analysis of crude oil and their returns show their daily volatility in pre-defined years from 1st February 2014 to 1st February 2024. The above-mentioned graphical representation shows that crude oil indicates that both crude oil at half of the time period has a downward trend in the prices and after the other half of the period indicates upward trends. The returns graph is zigzag after the end of the period. There is large volatility in both crude oil and crude oil.

Figure 1 Graphical Analysis



4.1 Unit Root Test

Applying the unit root test to ascertain whether a data series is stationary. The Augmented Ducker Fuller (ADF) test must be performed to ascertain the unit root test. If the distribution of the time series has a particular shape, the time series data is said to be stationary. It has little effect on alterations over time. Similarly, if a series is stationary, its mean and variance will stay the same for a predetermined amount of time (Ahmad, Nazeer, & Kaddour, 2023).

Table 1

	Level	P-value	Ist difference	P-value
WTI	-2.277	0.1794	-51.739***	0.0001
WTIR	-24.138***	0.0000		
Brent	-2.291	0.1748	-49.560***	0.0001
BrentR	-12.023***	0.0000		
Test Critical Value		1%	-3.432735	

	5%	-2.862480
	10%	-2.567315

The unit root is used in this study to determine whether the data is stationary. WTI is stationary at the first difference since the probability value is less than 0.1 on the other side. At the level that is none stationary, WTI's probability is 0.1794, which indicates that it is more than 0.1. Additionally, non-stationary at level is Brent crude, whose sig value at level is 0.1748, indicating greater than 0.1. Then, it was verified that Brent crude was stationary at the first difference, and since its pro value was 0.0220 and it showed less than one, it was stationary at the first difference, just like WTI crude. When the WTI Pro value exceeds 0.5, it indicates that the Sig is at 1%, and vice versa. The positive value of Brent crude exceeds 0.5. Brent is also significant at 1%.

Table 2 Descriptive Analysis

Statistics	WTI	WTI-return	Brent	Brent-return
Mean	63.73694	-9.47	68.06895	-9.36
Median	59.96000	0.001112	64.88000	0.001133
Maximum	123.7000	0.223940	133.1800	0.412023
Minimum	11.25800	-0.622205	9.120000	-0.643699
Std.Dev	20.11868	0.031034	21.62653	0.031183
Skewness	0.511434	-3.379878	0.483570	-2.836911
Kurtosis	2.740560	79.33642	2.894581	96.59830
Jarque-Bera	117.7134	620574.4	100.2472	930941.3
Probability	0.000000	0.000000	0.000000	0.000000

The average value of return for WTI is -9.47, and for Brent's,the return is -9.36 returns for the average value of Brent return. The Median shows the middle values of the data set for WTI.

The median is 0.001112, and Brent's median is 0.001133 these are their middle. In addition, the std. Dev value indicates that, on average, the WTI return deviates from its mean value by 20.1186, and Brent crude return deviates from its mean by 21.6265; except for mean and standard deviation, the value of skewness and kurtosis regarding the return sequence's regularity. A negative skewness score indicates that the return series' left tail is lengthy regarding crude oil returns. Additionally, WTI is 2.740560 less than Brent crude, with a kurtosis score of 2.894581 for Brent crude. Additionally, Jarque-Bera shows the return series distribution. Given that there is a chance of less than 0.05 for the two crude oil return series.

Table 3 Econometric Analysis

Variables	α	B	α+ β
R-WTI	0.121431	0.872151	0.993582
R-Brent	0.118919	0.837275	0.956194

In econometric analysis, the values of both ARCH and GARCH to the crude oil return. The return of WTI is 0.993582, and RBrent crude is 0.956194. These returns show that WTIR is closer to one. It typically indicates that it is lower volatile. The returns of Brent are further away from one, showing that Brent is a highly volatile crude oil. Large price fluctuations indicate high volatility, whereas more steady price movements indicate low volatility. For further close check, the Volatility calculates the half-life below, which gives a clear picture of which crude is highly volatile.

4.2 Half-Life

According to (Ghaffar, Aslam, & Zardari, 2023)The half-life model is used to find the speed of mean reversion, or how long it will take to revert back to its mean position.

Table 4

Index	α+ β	Half-life
R WTI	0.993	99
R Brent	0.956	16

After determining that the returns show mean reversion through the ARCH and GARCH models, as previously stated, the next stage will be to determine the pace of mean reversion, which will be accomplished by using the half-life technique. The half-life technique can calculate the time it takes for returns to move half the distance of the long-term average values of Brent and WTI crude oil. To find out which crude oil exhibits faster mean reversion than the other, one can compare the numerical numbers that indicate the speed of mean reversion of these two crudes. Mean reversion is the tendency for prices to return to their long-term average over time. A shorter mean reversion period typically indicates higher volatility and quicker price adjustment. In this case, since Brent has a mean reversion period of 16 days compared to WTI, which is 99 days, Brent is more volatile than WTI crude in terms of volatility and shorter-term price movements. This shows that the price of WTI is more stable than Brent's.

Table 5 Hypotheses Assessment Summary

Hypotheses	Sig-value	Conclusion
H1: There is a significant ARCH effect in crude oil returns.	0.0001	Supported
H2: There is a significant GARCH effect in crude oil returns.	0.0001	Supported
H3: Crude oil returns observe Mean Reversion.	$\alpha+\beta < 1$	Supported

The summary of the assessment of the hypotheses shows that the two created hypotheses are statistically significant and that the effects of both GARCH and ARCH are significant, with p-values less than 0.01. Furthermore, the finding of a mean reversion process in the returns of the two crude oil indices, when the sum of the GARCH and ARCH coefficients approaches one ($\alpha+\beta<1$), supports the third hypothesis.

4.3 Discussion

The thesis paper evaluates the volatility and returns of two types of crude oil regarding the presence of mean reversion in the price of crude oil per US dollar barrel.

Additionally, to gauge and contrast the crude oil's mean reversion speed, the study's findings show that two types of crude oil exhibit a notable mean reversion process. This indicates that after a predetermined amount of time, the returns on the two crude indices return to their initial values. The study's results show that Brent crude reverted back to its Origen after 16 days. Conversely, WTI reverted back to its main position after 99 days.

According to (Palao et al., 2020) Despite WTI being the most traded futures contract, a multiple regression model finds that the Brent futures market is the most important in determining oil prices. At the same time, WTI seems to be the most sensitive. Furthermore, the data of this paper is stationary and significant at a 1% level.

According to (Tissaoui et al., 2024) at the 1% level, the BRENT return has statistical significance. Furthermore, the findings show that the long-run dynamic correlation measured by the coefficient is statistically significant at the 1% level.

This paper's findings show Brent is more stable than WTI. According to (Okoroafor & Leirvik, 2022) After examining the efficiency of the crude oil market and its response to significant developments in the global financial and commodities markets, it can be concluded that the Brent market is more efficient than the West Texas Intermediate (WTI) crude oil market.

According to (Palao et al., 2020)At the 1% level, there is a strong and positive correlation between WTI and Brent crude oil. WTI is the more sensitive market, and the only major one is the Brent futures market, whose β-value is positive and significant at the 1% level. Notably, the WTI futures markets exhibit a high degree of sensitivity.

5 Conclusion

This thesis mainly focuses on gauging the Returns and Volatility of two crude oil (Brent and WTI) for gauging the Returns and Volatility. The GARCH model determines whether the GARCH and ARCH impacts are significant in each crude oil. To determine whether this is the case, the Unit Root Test looks for two factors: the crude oil is stationary at the first difference and its sig at 5%. Additionally, it may be prepared to determine the returns for that by adding the values of the GARCH and ARCH to the returns of the two crude oils. The return of WTI is 0.993582, and Brent crude is 0.956194. These returns show that WTIR is closer to one. It typically indicates that it is lower volatility. The returns of Brent are further away from one, showing that Brent is a highly volatile crude oil. Furthermore, closely checking the volatility to calculate the half-life gives a clear picture of which crude is highly volatile. Half-life clear picture in days means how many days after the price of the two crude oils return to their original mean position. For that, I determined it through the Half-life method to check which crude oil comes back to its original position first. Half-life results show that WTI reverted to its previous position after 99. On the other hand, Brent crude oil returned to its previous position after 16 days. This indicates that the WTI crude oil has the slowest speed of mean reversion compared to the Brent crude oil. On the other hand, Brent crude oil has the fastest mean reversion. A greater half-life indicates that slow mean reversion and slow mean reversion means higher volatility. This study hypothesis is supported because the sig-value is less than 0.01.

5.1 Limitations

This thesis chooses the benchmark of two crude oil, Brent and WTI, from 1st Feb 2014 to 1st Feb 2024, and chooses the data in daily crude oil prices; here, the crude prices are in $ per barrel. This paper is based on secondary data. The others may choose other time periods, another benchmark of crude oil like Dubai, Omani, Canadian crude oil, etc., and different time durations. This thesis aims to gauge the Returns and Volatility of two crude oils using the GARRCH approach. Others may use another approach to gauge the returns and volatility of crude oil.

5.2 Recommendations

This study's finding is vital for policymakers, Investors, and future researchers. Crude oil is essential for policymakers because they need to develop strategies to secure reliable long-term sources of oil. Policymakers also control the oil price volatility to control inflation. It is vital for them. Investors can use this information to decide whether to invest in these crudes. If investors want to invest in the short term, they invest in Brent because its return period is 16 days. If they want to invest in long-term investment, it goes towards the WTI because the return period is 99 days and also for another future researcher. The literature survey clarifies that many research papers have used the ADF model for stationary and the ARCH & GARCH models for testing mean reversion. As a result, both models have been used in this study to identify mean reversion. The rate of mean reversion has also been ascertained using the Half-life model (Palwasha et al., 2018)

References

Agnolucci, P. (2009). Volatility in crude oil futures: A comparison of the predictive ability of GARCH and implied volatility models. *Energy Economics*, *31*(2), 316-321, https://doi.org/10.1016/j.eneco.2008.11.001

Ahmad, W., Rais, S., & Shaik, A. R. (2018). Modelling the directional spillovers from DJIM Index to conventional benchmarks: Different this time? *Quarterly Review of Economics and Finance*, *67*, 14-27, https://doi.org/10.1016/j.qref.2017.04.012

Alizadeh, A. H., Kavussanos, M. G., & Menachof, D. A. (2004). Hedging against bunker price fluctuations using petroleum futures contracts: Constant versus time-varying hedge ratios. *Applied Economics*, *36*(12), 1337-1353. https://doi.org/10.1080/0003684042000176801

Behera, C., Priyadarsini, B. T., & Patnaik, D. (2024). Impact of geopolitical risk and crude oil prices on stock return. *Buletin Ekonomi Moneter Dan Perbankan*, *27*, 45-58. https://doi.org/10.59091/2460-9196.2158

Bouri, E., Kachacha, I., Lien, D., & Roubaud, D. (2017). Short- and long-run causality across the implied volatility of crude oil and agricultural commodities. *Economics Bulletin*, *37*(2), 1077-1088.

Christoffersen, P., & Pan, X. (Nick). (2018). Oil volatility risk and expected stock returns. *Journal of Banking and Finance*, *95,* 5-26. https://doi.org/10.1016/j.jbankfin.2017.07.004

Dutta, A., Bouri, E., & Roubaud, D. (2021). Modelling the volatility of crude oil returns: Jumps and volatility forecasts. *International Journal of Finance and Economics*, *26*(1).889-897. https://doi.org/10.1002/ijfe.1826

Floros, C., & Galyfianakis, G. (2020). Bubbles in crude oil and commodity energy index: New evidence. *Energies*, *13*(24), 6648. https://doi.org/10.3390/en13246648

Foroutan, P., & Lahmiri, S. (2024). Deep learning-based spatial-temporal graph neural networks for price movement classification in crude oil and precious metal markets. Machine Learning with Applications, 16, 100552.

Ghaffar, A., Aslam, U., & Zardari, Z. (2023). Gauging the Fuel Price Volatility using GARCH Models. International Journal of Emerging Business and Economic Trends, 2(2), 115-121.

Gong, X., Wen, F., Xia, X. H., Huang, J., & Pan, B. (2017). Investigating the risk-return trade-off for crude oil futures using high-frequency data. *Applied Energy*, *196*, 152-161. https://doi.org/10.1016/j.apenergy.2016.11.112

Gong, Z., & Kappi, J. (2019). Measuring Risks in WTI Crude Oil Market: Application of Value at Risk Models. *SSRN Electronic Journal*, *13*(6), 3156-3171. https://doi.org/10.2139/ssrn.3480780

Hörmann, S. (2008). Augmented GARCH sequences: Dependence structure and asymptotics. *Bernoulli*, *14*(2) , 543-561. https://doi.org/10.3150/07-BEJ120

Kang, S. H., Kang, S. M., & Yoon, S. M. (2009). Forecasting volatility of crude oil markets. *Energy Economics*, *31*(1), 119-125. https://doi.org/10.1016/j.eneco.2008.09.006

Kristoufek, L. (2019). Are the crude oil markets really becoming more efficient over time? Some new evidence. Energy Economics, *82*, 253-263.

Le, T. H., Boubaker, S., Bui, M. T., & Park, D. (2023). On the volatility of WTI crude oil prices: A time-varying approach with stochastic volatility. *Energy Economics*, *117*, 106474. https://doi.org/10.1016/j.eneco.2022.106474

Liang, C., Wei, Y., Li, X., Zhang, X., & Zhang, Y. (2020). Uncertainty and crude oil market volatility: new evidence. *Applied Economics*, *52*(27), 2945-2959. https://doi.org/10.1080/00036846.2019.1696943

Liu, Z., Ding, Z., Zhai, P., Lv, T., Wu, J. S., & Zhang, K. (2019). Revisiting the Integration of China Into the World Crude Oil Market: The Role of Structural Breaks. *Frontiers in Energy Research*, *7*, 146. https://doi.org/10.3389/fenrg.2019.00146

Lu, W., & Huang, Z. (2024). Crude Oil Prices Forecast Based on Mixed-Frequency Deep Learning Approach and Intelligent Optimization Algorithm. Entropy, *26*(5), 358.

Ma, R., Zhou, C., Cai, H., & Deng, C. (2019). The forecasting power of EPU for crude oil return volatility. *Energy Reports*, *5*, 866-873. https://doi.org/10.1016/j.egyr.2019.07.002

Odu, A. T., Abubakar, B., Sulaimon, A., & Momoh, C. (2022). Modelling oil price volatility with structural break: A re-examination. West African Financial and Economic Review (WAFER), *22*(2).

Okoroafor, U. C., & Leirvik, T. (2022). Time varying market efficiency in the Brent and WTI crude market. *Finance Research Letters*, *45*, 102191. https://doi.org/10.1016/j.frl.2021.102191

Oyuna, D., & Yaobin, L. (2021). Forecasting the Crude Oil Prices Volatility With Stochastic Volatility Models. *SAGE Open*, *11*(3), 21582440211026269. https://doi.org/10.1177/21582440211026269

Palao, F., Pardo, Á., & Roig, M. (2020). Is the leadership of the Brent-WTI threatened by China's new crude oil futures market? *Journal of Asian Economics*, *70*, 101237. https://doi.org/10.1016/j.asieco.2020.101237

Palwasha, R. I., Ahmad, N., Ahmed, R. R., Vveinhardt, J., & Štreimikienė, D. (2018). Speed of mean reversion: An empirical analysis of kse, lse and ise indices. *Technological and Economic Development of Economy*, *24*(4), 1435-1452. https://doi.org/10.3846/20294913.2017.1342286

Pandit, S., & Luo, X. (2024). A novel prediction model to evaluate the dynamic interrelationship between gold and crude oil. *International Journal of Data Science and Analytics* ,1-22. https://doi.org/10.1007/s41060-024-00519-8

Qadan, M., & Cohen, G. (2024). Uncertainty about interest rates and crude oil prices. *Financial Innovation*, *10*(1), 9. https://doi.org/10.1186/s40854-023-00551-w

Raheem Ahmed, R., Vveinhardt, J., Štreimikienė, D., Ghauri, S. P., & Ahmad, N. (2017). Estimation of long-run relationship of inflation (CPI & WPI), and oil prices with KSE-100 index: evidence from Johansen multivariate cointegration approach. *Technological and Economic Development of Economy*, *23*(4), 567-588. https://doi.org/10.3846/20294913.2017.1289422

Ryspaeva, S., Kerimkulova, A., Rafikova, K., Naurizova, S., Islam, S., Aydemir, M. (2024). Deep Eutectic Solvents for Sustainable Management of Asphaltene Deposition in Oil Production. *Engineered Science* , *27*, 1-14.

Salisu, A. A., & Fasanya, I. O. (2012). Comparative performance of volatility models for oil price. *International Journal of Energy Economics and Policy*, *2*(3), 167-183.

Salman, B. H. (2024). Managing foreign reserves and its impact on avoiding economic crises resulting from the decline in global oil prices for the period (2008-2020). Iraqi Journal For Economic Sciences, *22*(80. S).

Sikandar, S., & Ahmad, N. Assessing Bitcoin Volatility using GARCH Model: A Comparative Study in the Pakistani Context.

Su, R., Du, J., Shahzad, F., & Long, X. (2020). Unveiling the effect of mean and volatility spillover between the United States economic policy uncertainty and WTI crude oil price. *Sustainability (Switzerland)*, *12*(16), 6662. https://doi.org/10.3390/su12166662

Tissaoui, K., Abidi, I., Azibi, N., & Nsaibi, M. (2024). Spillover Effects between Crude Oil Returns and Uncertainty: New Evidence from Time-Frequency Domain Approaches. *Energies*, *17*(2), 340. https://doi.org/10.3390/en17020340

Zhang, C., & Zhou, X. (2024). Forecasting value-at-risk of crude oil futures using a hybrid ARIMA-SVR-POT model. Heliyon, *10*(1). https://doi.org/10.1016/j.heliyon.2023.e23358

Zhang, Q., Hu, Y., Jiao, J., & Wang, S. (2024). The impact of Russia–Ukraine war on crude oil prices: an EMC framework. Humanities and Social Sciences Communications, *11*(1). https://doi.org/10.1057/s41599-023-02526-9

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