Anticipating Volatility: The Impact of OPEC Announcements on Oil Market Dynamics

Ilsin Su Sahin
UNIVERSITY OF GLASGOW | STUDENT ID: 2838393S

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ABSTRACT

With an emphasis on market expectations and response swings, this dissertation provides a detailed analysis of how OPEC decisions influence crude oil spot prices. It examines the daily price returns of Brent and West Texas Intermediate (WTI) oil starting in 2002. The three primary goals of the study were to determine how OPEC announcements affect spot prices, assess the asymmetry of market fluctuations during these announcements, and investigate the effects of various announcement types on market reactions, such as cut, maintain, or hike.

The methodological approach timed OPEC announcements using certain variables and sophisticated econometric techniques like the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model. To provide precise market forecasting and tactical decision-making, this method tried to unravel the complex market reactions and provide in-depth insights into price dynamics.

The empirical results revealed that predictions and volatility of oil prices are strongly impacted by OPEC announcements. In particular, an apparent asymmetry in fluctuations was present, with effects that were more prominent prior to the announcements. The model had a high degree of predictive power before the OPEC decisions were made public, suggesting that the market had backward-looking anticipation. An in-depth analysis of volatility reactions revealed that market players may be adjusting in anticipation of upcoming OPEC announcements.

The study evaluated long-term memory effects in the market data by looking at Hurst exponents and Lo's modified R/S tests. It highlighted persistent volatility shocks, particularly in squared returns. This emphasised the need for a modelling strategy that could capture these long memory effects, which is why FIGARCH and EGARCH models were used. The asymmetric effects of OPEC decisions on market volatility were particularly well-represented by the EGARCH model, which also demonstrated a higher market response to positive news, such as production increases.

The robustness of the models was verified by comparing regression models with and without appropriately updated dummy variables; lower Akaike Information Criterion (AIC) values indicated a better model fit. The updated dummy variables highlighted how the market responded to expected actions, impacting volatility prior to OPEC announcements.

Value at Risk (VaR) models for WTI and Brent crude oil underwent rigorous evaluation, successfully passing both unconditional and conditional coverage tests at the 95% and 99% confidence levels, highlighting their resilience in forecasting potential losses up to specified thresholds. It is noteworthy that the Expected Shortfall (ES) evaluations contributed to a more nuanced comprehension: the adapted models exhibited a heightened responsiveness to more severe losses, particularly at the more stringent 99% threshold. This increased sensitivity is specifically noticeable in the adjusted models for short positions, signifying a heightened perception of risk. Conversely, the adjusted model for long positions in WTI indicated a more cautious risk evaluation.

The research concluded with a performance analysis of forecast accuracy, where the modified dummy models exhibited slightly higher Mean Error (ME) for WTI, implying the integration of additional volatility factors post-modification. However, this increase in ME was balanced by minimal changes in Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for Brent, indicating that the model adjustments did not significantly improve predictive precision.

In conclusion, it can be affirmed that the thesis provides evidence to support the notion that the production decisions made by OPEC play a crucial role in shaping the dynamics of crude oil pricing. These decisions, along with the specific nature and timing of their announcements, lead to distinct anticipatory and responsive behaviours within the market. Through the use of econometric models, the intricate relationship between expectations and reactions has been effectively unravelled. This accomplishment lays a solid groundwork for future research endeavours to expand upon, especially within the domain of proactive market analyses and strategies for risk assessment.

1 INTRODUCTION

The global crude oil market possesses immense economic importance, functioning as a fundamental energy source and exerting influence over macroeconomic and financial markets (Council on Foreign Relations, 2016). It occupies a central position within the transportation sector and is subject to the fluctuating demands for petroleum products, fertilizers, and petrochemicals (World Economic Forum, 2022). The rise in active oil-producing regions reflects the escalating global reliance on this valuable resource. From the oil embargo of the 1970s to the extraordinary surge past $100-a-barrel, the crude oil market has been a theatre of dramatic volatility, mirroring the profound economic shifts felt across the globe. Yet, it's the inherent unpredictability of this market—shaped by geopolitical tensions, the ebb and flow of supply and demand, and seismic economic events like the 2020 pandemic's historic crash, where prices tumbled into negative territory for the first time—that truly captures its essence. This volatility has consequences, as: it shapes government fiscal strategies, has a significant impact on global economies, and is essential in geopolitical manoeuvring. It also highlights the intricate interplay that characterises the global oil market (Council on Foreign Relations, 2016; World Economic Forum, 2022).

The Organization of the Petroleum Exporting Countries (OPEC), which was founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela as a response to oil price reductions driven by multinational companies and import limitations imposed by the United States, plays a crucial role in directing global oil prices through its production decisions. With its production accounting for approximately 40% of the world's oil output, OPEC's biannual meetings along with extraordinary meetings serve as a platform for aligning production strategies among member states. The intricate task of balancing market stability with the diverse economic requirements of its members presents OPEC with a challenging yet indispensable role. The market closely monitors decisions regarding production cuts or increases, as they have implications for expectations, volatility, and subsequently influence investment and pricing strategies. Acknowledging the intricacies of such decisions, experts emphasize the need to consider long-term trends and potential market shifts when analysing OPEC's impact on oil volatility (Horn, 2004; Pindyck, 1978; Salant, 1976; Aggarwal et al., 1999; Arouri et al., 2012a; Arouri et al., 2012b; Ewing and Malik, 2013; Kang et al., 2009, 2011; Lamoureux and Lastrapes, 1990; Lastrapes, 1989).

The role of OPEC's announcements is indeed paramount, with each declaration closely scrutinized for its potential impact on oil returns and market stability. These decisions have asymmetric effects; a decision to cut production typically precedes negative expectations, while decisions to maintain or increase production can signal positive market reactions. Yet, alongside its central market role, OPEC faces scrutiny and speculation. Analysts and the media, such as the Financial Times, have occasionally questioned the efficacy of OPEC's policies, debating whether they mitigate or exacerbate market volatility (Financial Times, 2008).

Empirical research on crude oil price movements around OPEC meetings presents a diverse picture, reflecting the contentious nature of the organization's influence on oil markets (Pindyck, 1978; Salant, 1976). Such studies highlight the need for sophisticated analytical approaches that can parse through the data and discern the real impacts of OPEC's decisions. This thesis, therefore, takes on the mantle of investigating the nexus between OPEC's strategies and the ensuing fluctuations in benchmark oil prices.

By integrating advanced econometric analyses and volatility modelling techniques, this study will delve into the quantitative assessment of OPEC's production choices and their repercussions on the oil market. Recognizing the importance of long-range dependencies in volatility, as emphasized by researchers such as Kang et al. (2009, 2011) and Choi and Zivot (2007), the analysis here is poised to offer nuanced insights into the forces shaping oil price movements.

The goal of the thesis is to identify the predictive effects on market volatility that various OPEC decision types have. This project will use advanced econometric tools to monitor market expectations prior to OPEC output adjustments, therefore tailoring OPEC's policies. Precisely measuring the pre-announcement effects on oil prices is the aim, as is comprehending how expectations held by investors and officials coincide with future market moves.

A crucial element of this study involves identifying the optimal GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which plays a vital role in comprehending how market volatility reacts to new information over time. The GARCH model excels in uncovering the persistence of volatility shocks, enabling the ability to track the market's recollection of previous occurrences. Through contrasting the initial decision-based model with an adjusted version that integrates anticipatory impacts, it becomes possible to deconstruct and compare the diverse depictions of OPEC's choices on volatility predictions and risk evaluations.

This comparative examination will be enhanced by thorough forecasting and assessments of Value at Risk (VaR). Employing a dual-model strategy will enhance the comprehension of the market's ability to anticipate OPEC's decisions and offer a strong evaluation of the anticipatory consequences on oil price volatility.

1.1 LITERATURE REVIEW

The crude oil markets, as a cornerstone of the global economic infrastructure, play a pivotal role in influencing the stability and growth of various sectors, including energy and manufacturing. Given that price fluctuations can significantly affect raw material costs and the economic health of nations, a comprehensive understanding of market volatility is indispensable for effective economic planning and forecasting. Recognizing this, scholars have delved into the unique characteristics of oil price time series—namely volatility clustering, fat-tailed distributions, asymmetry, and mean reversion—to better model price movements and their implications. Morana (2001) and Bina & Vo (2007) underscore that empirical studies consistently highlight these features as defining elements of crude oil prices. Furthering this exploration, Askari and Krichene (2008) observe that oil price dynamics, especially during periods of market turmoil, exhibit pronounced volatility, frequent intensity jumps, and a strong upward trend. They link these dynamics to the core fundamentals of oil markets and the global economy, suggesting that oil prices are not only a reflection of immediate market conditions but also of the broader economic environment.

To assess this volatility of the market conditions associated with oil prices, econometric tools like the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and ARCH models have significantly helped in understanding the market volatility. The ARCH model, pioneered by Engle (1982), and subsequently extended by Bollerslev (1986) with the GARCH model, can be used as an approach for a Value-at-risk estimation. Value-at-Risk (VaR) is a critical metric in financial risk management, quantifying the potential maximum loss of a portfolio over a specified period with a given confidence level. Among the various approaches for VaR estimation, GARCH models are prevalently utilized due to their ability to capture the complex volatility patterns observed in financial markets, particularly in the crude oil sector.

Fan et al. (2008) applied GARCH models using the Generalized Error Distribution to estimate the VaR of crude oil prices, uncovering substantial risk spillover effects between Brent and WTI markets. Concurrently, Hung et al. (2008) explored the impact of fat-tailed distributions on the performance of one-day-ahead VaR estimates for energy commodities, emphasizing the necessity of accurately modelling the volatility of crude oil prices, which is often characterized by heteroscedasticity. This comprehensive modelling is integral, not only for capturing the immediate financial risks but also for reflecting the broader economic repercussions of oil price fluctuations, thereby informing market dynamics and policy decision-making.

Within this framework of market dynamics and volatility modelling, the role of OPEC is pivotal. As the linchpin in oil price determination, OPEC’s production announcements carry significant weight, influencing market expectations and guiding oil price trajectories (Lin, 2018; Perifanis, 2017; Adelman, 2019). The influence of global macroeconomic news, particularly OPEC announcements, on market volatility has received considerable academic attention. Such pronouncements shape market sentiment and can have a profound effect on global oil prices and, by extension, the economy (Demirer and Kutan, 2010; Jiang et al., 2012; Marshall et al., 2012; Rangel, 2011; Schmidbauer and Rösch, 2012). The volatility observed after the second Gulf War, for example, exemplifies the market's sensitivity to geopolitical and economic shifts.

Literature on the subject has examined OPEC’s influence from theoretical and empirical perspectives. Both theoretical models (Aguiar-Conraria and Wen, 2012; Cairns and Calfucura, 2012) and empirical studies (Bremond et al., 2012; Horan et al., 2004; Wirl and Kujundzic, 2004) have detailed how OPEC’s decisions can lead to increased market volatility. This body of work underscores the importance of OPEC’s strategic communication in market dynamics and highlights the need for careful analysis in this area.

Draper's (1984) pioneering work employed an event study methodology on heating oil futures, revealing a marked reaction in market returns pre- and post-OPEC announcements. This early exploration found that investors were, in fact, anticipating OPEC's production decisions, although the period studied was brief and narrowly focused on a subset of the oil contracts. Later, Deaves and Krinsky (1992) extended this analysis, discerning a significant difference in returns tied to favourable news from OPEC, which indicated economic gains for traders positioned accordingly. Their findings cast doubt on the efficient market hypothesis, positing that information dissemination and market response might not be as synchronous as previously assumed.

Demirer and Kutan (2010) furthered this line of inquiry, scrutinizing the impact of OPEC and U.S. Strategic Petroleum Reserve announcements from 1983 to 2008, using a similar event study framework. They discovered an asymmetrical impact where only announcements of production cuts by OPEC had a significant influence, suggesting that market participants assign disparate weights to different types of news. This asymmetry was particularly evident as the significant market reactions to production cuts translated into substantial gains for investors, who capitalized on the information post-conference.

Hanabusa's (2012) contribution to the field leveraged the Exponential GARCH (EGARCH) model to investigate the immediate effects of OPEC meetings on oil price volatility, identifying a pronounced increase in both price levels and volatility after these events. His findings are in harmony with the broader literature acknowledging OPEC's sway over global oil prices. Furthermore, the research highlights the differentiated response of oil price benchmarks to OPEC announcements, with WTI and Brent crude demonstrating nuanced behaviours, as detailed by Lin and Tamvakis (2010), suggesting that market reactions are also dependent on the specific characteristics of the oil grade in question and the prevailing market conditions at the time of the announcements. Nonetheless, the study did not account for the long memory aspect of volatility, a feature that has significant implications for forecasting and risk management and is suggested by other research to potentially affect market expectations over the long term.

Long memory in financial markets refers to the persistence of volatility shocks over time. In the context of crude oil markets, this long memory signifies that past market events can influence future volatility for extended periods. Studies have identified long memory features in crude oil markets, suggesting that price movements are not only a product of recent events but also of historical volatility (Belkhouja and Boutahary, 2011; Arouri et al., 2012a). This characteristic affects the accuracy of forecasts and the calibration of models used for hedging and trading strategies in oil markets.

Incorporating the concept of long memory and structural breaks into the econometric modelling of oil markets allows for a more nuanced understanding of the market's behaviour. Structural breaks, which are drastic changes in volatility regimes, can often be traced back to significant economic events or policy announcements. It helps to explain why certain periods are characterized by more pronounced volatility and why some shocks have lasting effects. For example, Arouri et al. (2012a; 2012b) highlighted that ignoring structural breaks could lead to the misestimation of volatility persistence and misinterpretation of information flows between the crude oil markets. Their work suggests that accurately accounting for these breaks is critical in understanding market dynamics and in enhancing the robustness of predictive models. This comprehensive approach to analysing oil market dynamics offers significant insights for investors, regulators, and policymakers who seek to navigate the complex and often turbulent landscape of global crude oil markets.

Furthermore, Demirer and Kutan (2010) offer a comprehensive review of the market's efficiency in reacting to OPEC and SPR announcements. Their investigation, utilizing the event study method, elucidates the short-term reactions of oil spot and futures markets to these announcements. Particularly in the case of OPEC's production cuts, the study provides evidence of statistically significant market reactions, with pronounced excess returns for investors who acted swiftly after the announcements. This suggests that while the market may generally be efficient, it does exhibit periods of inefficiency where informed investors can reap benefits. Conversely, their findings indicate that SPR announcements incite a swift, albeit temporary, market response, reinforcing the role of strategic reserves in market stabilization.

Lin and Tamvakis (2010) extend this analysis by conducting a comparative examination of the impacts of OPEC announcements under varied market conditions and price regimes. By applying an event study approach across different oil grades and benchmark prices, they demonstrate that market reactions to OPEC's quota decisions are far from homogeneous and are influenced by existing price trends. Their research suggests that the impact of these decisions, including production increases, cuts, or maintenance, is mediated by the type of crude—be it light or heavy—as well as the OPEC and non-OPEC categorization.

Adding to this nuanced understanding of oil market volatility, Schmidbauer and Rösch's (2009) study employs a combination of regression and GARCH models to explore the effects of OPEC announcements on oil price expectations and volatility. By introducing modified dummy variables to capture the timing of these announcements, they reveal that pre-announcement periods are marked by heightened volatility, while post-announcement periods significantly influence price expectations. This asymmetry in the market's response—particularly following production cuts compared to other outcomes—underscores the critical role of OPEC's communication in market sentiment and demonstrates the value of event studies in energy economics research.

Building upon the foundational research by Schmidbauer and Rösch (2009), this thesis aims to explore the asymmetrical effects of OPEC announcements on oil price volatility further. The EGARCH model is employed to account for the different impacts of positive and negative shocks, owing to its design that allows for a differential response to such events. Complementing this, the Fractionally Integrated GARCH (FIGARCH) model will be utilized, which is adept at capturing long memory characteristics in volatility data. This dual application of EGARCH and FIGARCH models will provide a comprehensive analysis of the immediate and persistent effects of OPEC announcements on market volatility.

1.2 RESEARCH QUESTION

This study intends to comprehensively assess the impact of OPEC decision on the prices of crude oil in spot markets, specifically concentrating on anticipations and fluctuations, through an examination of daily price returns of WTI and Brent oils from the year 2002 onwards. The subsequent hypotheses are to be empirically tested:

- The spot prices of crude oil are significantly influenced by OPEC announcements, affecting both market anticipations and fluctuations.
- The influence on fluctuations displays asymmetry, with more pronounced impacts observed before the announcements.
- The scale of the influence fluctuates based on the type of announcement, whether it involves a reduction, maintenance, or escalation in production.

The study strives to clarify the effects of OPEC decisions on crude oil prices utilizing a three-pronged methodology: evaluating the presence of long memory in market data, investigating the informative implications of OPEC decisions on WTI and Brent returns with a specific emphasis on asymmetric impacts, and examining the effects of different OPEC production decisions on market expectations and volatility by employing GARCH-type models.

2 DATA AND DESCRIPTIVE STATISTICS

To conduct the empirical analysis, we will examine the daily closing spot prices of two prominent crude oil benchmarks: specifically, Europe Brent, which serves as the reference crude oil for the North Sea, and West Texas Intermediate (WTI), which functions as the reference crude oil for the United States. The data utilized in this analysis has been sourced from Bloomberg and encompasses the time spanning from January 1, 2002, to November 8, 2023.

Our empirical analysis computes continuously compounded daily returns by taking the logarithmic difference of consecutive oil prices, following the methodology outlined by Lux et al. (2015):

$$r_t = \mu_t + \sigma_t \epsilon_t$$

where $r_t = 100 \times \ln\left(\frac{p_t}{p_{t-1}}\right)$, $\ln(p_t)$ is the log asset price,

$\mu_t = E_{t-1}[r_t]$ is the return series conditional mean,

σ_t is the volatility process and

$\epsilon_t \sim N(0,1)$

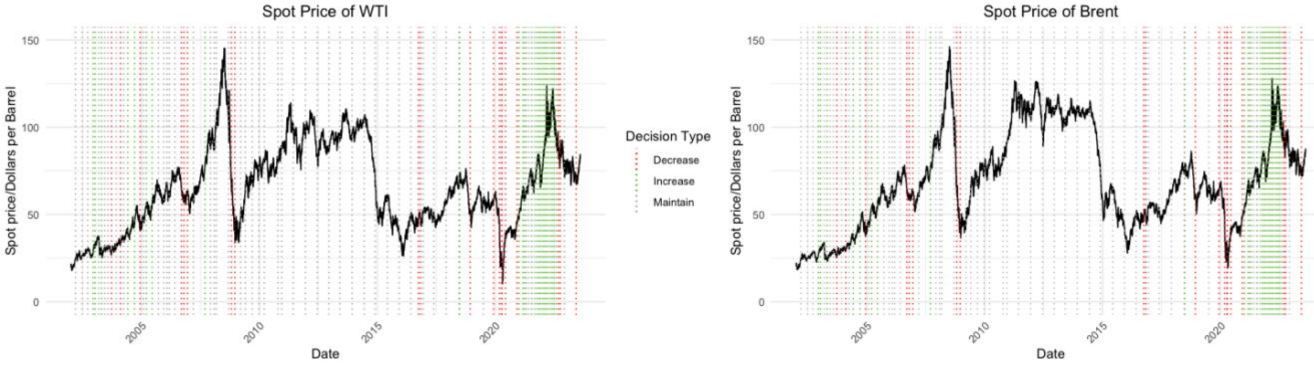
The data concerning OPEC meetings were meticulously gathered from press releases issued by the OPEC Secretariat and a compiled list of official announcements on production decisions. The analysis differentiates between production cut decisions, decisions to maintain production levels, and production increases. Schmidbauer and Rösch (2012) note that such announcements can have an immediate impact—that is, affecting both the expected level of prices (first moment) and the volatility (second moment)—on the very day the announcement is made and in the surrounding period. Furthermore, to capture the nuances of the OPEC meetings within the analysis, additional dummy variables are employed. These variables are designed to denote an immediate effect of an announcement.

TABLE 1: OPEC Production Decisions and Meeting Types

	Announcements	**Ordinary**	**Extraordinary**
OPEC production cut	20	11	9
OPEC production maintain	46	33	13
OPEC production hike	24	20	4
Total OPEC meetings	90	64	26

Table 1 describes the different kinds of OPEC's decisions from Jan 2002 to Aug 2023. During this period, OPEC has set 90 decisions broken down as follows: 20 cuts, 46 maintains, and 24 hikes in the production level. With 64 ordinary meetings versus 26 extraordinary ones, the data implies that ordinary meetings often result in maintaining or increasing production. The higher proportion of cuts during extraordinary meetings may point to their convening under more pressing market conditions.

FIGURE 1: Spot Price Trends of WTI and Brent Crude with OPEC Decision Annotations



Oil is the most volatile commodity. Fig. 1 presents the time- variations of the WTI and Brent prices, according to the plots of the prices and returns for both WTI and Brent indexes, we clearly observe similar evolution, showing a co-movement over the sample period spanning 2002 to 2023, suggesting that they are highly correlated.

Table 2 provides a thorough analysis of the statistical characteristics of crude oil returns for WTI and Brent, offering valuable insights into market dynamics. The average return for WTI slightly surpasses that of Brent, indicating a marginally higher mean return during the observation period. Moreover, the standard deviation, which measures market risk and volatility, is also greater for WTI, suggesting more pronounced price fluctuations. The skewness in both datasets highlights distributional asymmetries, with WTI displaying near symmetry and Brent showing a leftward skew, implying more frequent negative returns. Additionally, the kurtosis values point to a leptokurtic distribution for both, indicating a higher probability of extreme price movements compared to a normal distribution. The Jarque-Bera test confirms that neither return series adheres to a normal distribution, underscoring the implications for modelling, given that many traditional financial models assume normality in price returns (Jarque & Bera, 1980).

TABLE 2: Statistical properties of crude oil returns.

	WTI	**Brent**
Panel A: Descriptive Statistics		
Mean	0.0356	0.0255
Standard Deviation	2.5955	2.3029
Skewness	0.0666	-0.6095
Kurtosis	17.6970	11.6286
Jarque-Bera	72528 ***	31688 ***
Ljung–Box (15)	49.5520 ***	30.0710 ***
Panel B: unit root and stationary tests		
ADF	-15.5660 ***	-16.9210 ***
PP	-75.8188 ***	-76.3417 ***
KPSS	0.0875 ***	0.1377 ***
Panel C: heteroskedasticity test		
ARCH LM test	733.88 ***	279.56 ***

Notes: *** indicates significance level at 1%.

Various tests such as the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are utilized to assess the stationarity of the time series. The ADF and PP tests reject the existence of a unit root, while the KPSS test refutes the null hypothesis of stationarity, all at the 1% significance level, indicating the stability of price series over time without enduring trends or seasonal patterns (Dickey & Fuller, 1979; Phillips & Perron, 1988; Kwiatkowski et al., 1992).

The presence of conditional heteroskedasticity in the series is identified through the Autoregressive Conditional Heteroskedasticity (ARCH) Lagrange Multiplier (LM) test, which detects varying volatility over time—a common characteristic in financial time series. The significant ARCH effects suggest that periods of heightened and reduced volatility cluster over time, justifying the adoption of a GARCH model to address this volatility clustering (Engle, 1982).

In summary, these statistical assessments suggest that a GARCH model is well-suited for modelling crude oil returns, given its ability to address the non-normality, autocorrelation, and heteroskedasticity observed in the data. This sets the stage for more sophisticated risk evaluation and modelling techniques, essential for stakeholders and policymakers involved in energy markets.

2.1 SAMPLE HORIZONS

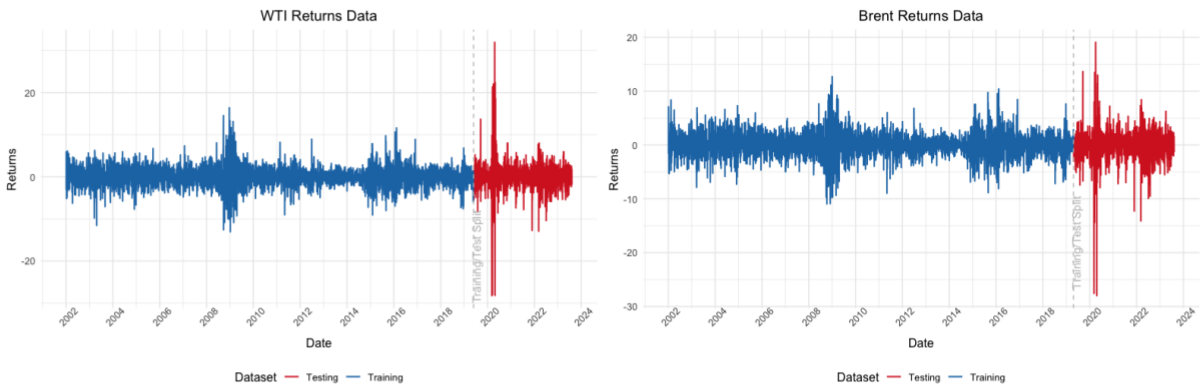
The research defines the time frames selected for WTI and Brent crude oil returns, encompassing intervals marked by significant economic occurrences, as evidenced by the spikes in volatility in Plot 2. These spikes correspond to the 2008 financial crisis and the exceptional market responses observed during the COVID-19 pandemic, which are pivotal periods for comprehending reactions to market shocks.

TABLE 3: Distribution of Data for WTI and Brent Crude Oil Analysis

	Train Set	Test Set	Total Observations
WTI	4444	1112	5556
BRENT	4448	1111	5559

When partitioning the data into training and testing sets, approximately 80% is allocated for training to capture the fundamental market dynamics, while the remaining 20%, which covers the COVID-19 period, is set aside for testing purposes. This delineation in Fig. 2 ensures that our models are trained on past data while being assessed against recent and highly unstable market conditions.

FIGURE 2: WTI and Brent Crude Oil Returns with Training and Testing Periods Indicated



The discrepancy in the number of observations between WTI and Brent, as illustrated in Table 3, originates from different trading days resulting from regional market closures and holidays. Such variations are common in financial datasets and have negligible impact on the analytical soundness.

By including the COVID-19 timeframe in the testing set, our models undergo a rigorous evaluation of their predictive capabilities during a period of global upheaval. This methodology evaluates the robustness of our GARCH models, detailed in Table 3, in adapting to market conditions characterized by significant fluctuations in volatility—an indication of their practical utility in real-world contexts.

3 METHODOLOGY

The methodology presented entails a comprehensive analysis with multiple layers, commencing with an investigation into the enduring memory traits within the fluctuations of crude oil prices. Through the utilization of various tests, distinct persistence patterns are identified, shaping the utilization of GARCH-type models crucial for capturing the phenomena of volatility clustering and leverage effects.

To scrutinize the intricate aspects of the impact of OPEC, the incorporation of dummy variables is enhanced to track not only the immediate repercussions but also the anticipatory and subsequent consequences of production determinations on the volatility of the market. This intricate adaptation of variables facilitates a thorough exploration of how markets react prior to and post OPEC declarations, providing a more comprehensive insight into the dynamics of prices.

The validation of our Value at Risk (VaR) evaluations is rigorously conducted through backtesting using, while the selection of models is guided by criteria such as AIC and log-likelihood. Subsequently, the accuracy of forecasting is gauged through metrics to assess and ensure the strength of our modelling decisions.

3.1 LONG MEMORY TESTS

Long memory, also referred to as long-range dependence, pertains to the characteristic of a time series where disturbances to the system exhibit a persistent impact that diminishes at a slower rate than an exponential decay, often conforming to a power-law. To examine the long memory properties in these series, we utilize three distinct statistical measures: The Hurst–Mandelbrot Rescaled Range (R/S) statistics; Lo (1991) Rescaled Range R/S; and the Geweke and Porter-Hudak (1983) (GPH) Each of these statistical methods for long memory is elaborated upon below. When investigating long memory in crude oils, we adopt the absolute returns and squared returns as proxies for daily volatility, following the approach of Arouri et al. (2012).

3.1.1 HURST – MANDELBROT R/S TEST

The metric known as R/S, derived from the rescaled range statistic, was initially introduced by Hurst (1951) to analyse time series data. Subsequently, Mandelbrot and Wallis (1969) further developed this metric with the main goal of identifying long-term memory within time series data. This metric provides a numerical indication that assists in discerning the characteristics of a time series, particularly in determining whether it displays mean-reverting, random walk, or trending behaviour.

The computation of the rescaled range statistic involves calculating the span of cumulative deviations of a time series from its mean, normalized by the standard deviation, as emphasized by Zivot and Wang (2003). The Hurst exponent, denoted as H, quantifies the scaling behaviour of this range by reflecting the cumulative deviations of a time series from its mean over a specific period. The determination of the range of R of a time series $\{x_t, t = 1, \dots, T\}$ is as follows:

$$R_T = \max_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) - \min_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}),$$

where $\bar{x}$ is the sample mean estimate. The R/S statistic can be defined as:

$$R/S = \frac{1}{\hat{\sigma}} \left[\max_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) - \min_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) \right], \hat{\sigma}^2 = \frac{1}{T} \sum_{t=1}^{T} (x_t - \bar{x})^2$$

Therefore, a time series can then be characterized as following:

- $H < 0.5$: The time series is mean reverting.
- $H = 0.5$: The time series is a random process.
- $H > 0.5$: The time series is trending, which shows long memory effects.

The Hurst Exponent not only plays a role in characterizing time series but also offers insights into the extent to which a series displays certain behaviours. A value close to 0 indicates a series with a high degree of mean reversion, while a value close to 1 suggests a series with a strong trend.

3.1.2 LO'S MODIFIED R/S TEST

The Hurst exponent is well-known for its resilience against deviations from normality in data distributions. However, estimates may be biased in the presence of autocorrelation in the dataset. To address this issue, Lo (1991) introduced a modification to the conventional rescaled range statistic, known as $\mathrm{Q_T}$, which considers short-term dependencies in the data. This adjustment involves replacing the standard sample deviation, S, with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) estimator. By employing this estimator, the calculation of $\mathrm{Q_T}$ is modified, thereby improving the accuracy of the Hurst exponent when autocorrelated observations are present.

$$\mathrm{Q_T} = \frac{1}{S_T}\left[\max_{1\le t\le T}\sum_{t=1}^{T}(x_t-\bar{x}) - \min_{1\le t\le T}\sum_{t=1}^{T}(x_t-\bar{x})\right]$$

$$S_T^2 = S^2 + \frac{2}{T}\sum_{j=1}^{\tau}\omega_j(\tau)\left\{\sum_{i=j+1}^{T}(x_t-\bar{x})(x_{t-j}-\bar{x})\right\},\ \omega_j(\tau) = 1-\frac{j}{\tau+1}$$

where j is the lag order in the autocovariance estimation and $\omega_j(\tau)$ is the weights in the Newey-West estimator, which decrease as the lag j increases. It is a function of τ, which represents a lag truncation parameter.

The statistical significance of the estimated Hurst exponent H is evaluated using the t-test. Lo's hypothesis posits the null hypothesis $\mathrm{H_0}$: H = 0.5, indicating no long-term dependence or random walk. Conversely, the alternative hypothesis $\mathrm{H_1}$: H ≠ 0.5 suggests the presence of long-term dependence. In contrast, Mandelbrot's hypothesis assumes the absence of long-term dependence by asserting the non-existence of autocorrelation in the data.

3.1.3 GEWEKE AND PORTER-HUDAK (GPH) TEST

Geweke and Porter-Hudak (1983) introduced the GPH estimator, a semi-parametric approach, to detect long-term memory in time series data. This method relies on frequency domain characteristics and utilizes the periodogram to depict the spectral density of a series. Focusing on the long memory parameter, denoted as d, the GPH estimator conducts regression analysis on the logarithm of the periodogram, emphasizing the slope of the log-periodogram regression as a distinguishing feature from other techniques like the GSP test, which estimates parameter d using a different statistical framework. The effectiveness of the GPH method lies in its ability to capture the intrinsic nature of long-term dependencies by transforming the time series into the frequency domain through Fourier transformation.

Let $\mathrm{r_t}$ be the return series. The GPH estimator of the long memory parameter d for $\mathrm{r_t}$ can be then determined using the following periodogram:

$$\log[I(w_j)] = \beta_0 + \beta_1\log\left[4\sin^2\left(\frac{w_j}{2}\right)\right] + \varepsilon_j,$$

where $w_j = 2\pi\frac{j}{T}, j = 1, \dots, n$: ε_j is the residual term and represents the $n = \sqrt{T}$ Fourier frequencies. $I(w_j)$ stands for the sample periodogram expressed as:

$$I(w_j) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} r_{te^{-wjt}}\right|^2$$

GPH is assumes that the $\mathrm{r_t}$ is covariance stationarity. The primary focus of the test lies in the estimation of the fractional differencing parameter, denoted by d, which plays a crucial role in determining the presence of long memory within the time series. The null hypothesis of the GPH test posits the non-existence of long memory, expressed as $\mathrm{H_0}$: $d = 0$.

3.2 GARCH MODELS

The research methodology utilizes the GARCH (1,1) framework to examine the impact of OPEC announcements on crude oil returns and volatility. This framework, crucial in financial time series analysis, was first introduced by Bollerslev in 1986 and is adept at capturing the dynamic nature of volatility, often characterized by clustering and persistence phenomena.

The GARCH (1,1) model defines the conditional variance h_t to account for the behaviour of volatility over time. It considers past squared residuals to reflect immediate market movement effects and the lagged conditional variance to show volatility persistence across periods. The model is formally expressed through specific equations:

1. The return equation, which models the daily returns r_t on crude oil prices as:

$$r_t = \mu + \sum_{k=1}^{m} \psi_k r_{t-k} + \sum_{h=1}^{n} \theta_h \epsilon_{t-h} + \epsilon_t$$

Here, μ serves as the constant term, setting the baseline for the average return. The autoregressive coefficients, ψ_k **,** quantify the influence of returns from preceding days on the current return, establishing a link across time. The moving average coefficients, θ_h, address the impact that previous unexpected shocks (ϵ_{t-h}) have on today's return. Lastly, the error term $\epsilon_t$represents the unpredicted elements of the return at any given time tt, capturing the random variations that the historical values and past shocks cannot explain.

2. The error term equation, which defines the relationship between the error term $\epsilon_t$and the conditional variance h_t:

$$\epsilon_t = v_t \,.\sqrt{h_t}$$

In this context, v_t is a Gaussian white noise term with a mean of zero and variance of one, providing the stochastic component of the model.

3. The conditional variance equation, which captures the evolving variance of returns:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1} + \sum_i \gamma_i d_{it},$$

This equation models h_t, the conditional variance at time *t*, as a function of the intercept α_0 the impact of the lagged squared residuals $\alpha_1 \epsilon_{t-1}^2$, indicating the effect of previous day's volatility shocks, the lagged conditional variance βh_{t-1}, which provides the measure of volatility persistence and d_{it} is the OPEC's is the series of dummy variables for announcements of kind i. Each OPEC's conference is considered as an event represented by a dummy variable, coded one or zero for each event. We define that the dummy variables in terms of the kind of production decisions are undertaken as follows:

$$d_{cut,t} = \begin{cases} 1 \text{ production cut" announced on day t} \\ 0 \text{ no such OPEC annoucement on day t} \end{cases}$$

$$d_{maintain,t} = \begin{cases} 1 \text{ production maintain" announced on day t} \\ 0 \text{ no such OPEC annoucement on day t} \end{cases}$$

$$d_{hike,t} = \begin{cases} 1 \text{ production hike" announced on day t} \\ 0 \text{ no such OPEC annoucement on day t} \end{cases}$$

3.2.1 EGARCH MODEL

The EGARCH model, a ground-breaking advancement in econometrics introduced by Nelson (1991), is notably applied in analysing the dynamic and often unpredictable oil market volatility. This model provides significant advantages over the traditional GARCH model, particularly in its approach to ensuring positivity in forecasted conditional variance without the need for nonnegative constraints on parameters such as α, β, and γ.

An essential characteristic of the EGARCH model is its method of maintaining forecasted conditional variance positivity by using logarithmic terms in the variance specification, thus naturally constraining the variance to positive values. Additionally, the model effectively captures the asymmetric response of volatility to shocks, as demonstrated by the presence of the γ term in the variance equation. This feature enables the model to differentiate between the impacts of positive and negative shocks, where a positive γ parameter signifies a greater impact of positive shocks on future volatility compared to negative shocks of the same magnitude.

Furthermore, the EGARCH model's ability to distinguish between the directional effects of shocks is particularly valuable in financial markets, where negative news often triggers stronger responses from investors. The model's stationarity is determined by the sum of the absolute values of autoregressive parameters being less than one, allowing for the assessment of shock longevity and influence over time. Notably, the β parameter plays a crucial role in this evaluation, with higher values indicating a longer period for volatility to dissipate post-shock.

The conditional variance equation of the EGARCH model is expressed as:

$$\log(h_t) = \omega + \alpha\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\epsilon_{t-1}|}{h_{t-1}}\right)\right] + \gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta\log(h_{t-1})\sum_i \delta_i d_{it,}$$

Here the term $\alpha\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\epsilon_{t-1}|}{h_{t-1}}\right)\right]$ represents the model's capability to account for the magnitude of shocks, while the term $+\gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right)$ signifies the leverage effect, acknowledging that volatility is not only a consequence of past fluctuations but also the sentiment and reactions of market participants. The addition of dummy variables $\delta_i d_{it,}$ allows for the quantification of the impact of scheduled events, such as OPEC meeting decisions, on volatility.

3.2.2 FIGARCH MODEL

Most of the time, high-frequency financial data tends to exhibit a pattern resulting in a sum of α_1 and β_1 that approximates one, where α_1 is relatively small and β_1 is relatively large. Consequently, the impact of shocks on the conditional variance experiences a gradual reduction. In such scenarios, Baillie et al. (1996) propose the utilization of Fractionally Integrated GARCH (FIGARCH) models. These models are designed to capture the slowly diminishing volatility while accounting for both the long memory and short memory characteristics of conditional variance (Chkili et al. 2014). Fractionally integrated processes stand out due to their distinctiveness from stationary and unit-root processes, showcasing features of persistence and mean reversion.

Formally, the FIGARCH (1, d, 1) model can be precisely characterized using the lag operator denoted as "L" in the following manner:

$$h_t = \omega + \beta h_{t-1} + [1 - (1 - \beta L^{-1})(1 - \lambda L)(1 - L)^d]\varepsilon_t^2,$$

where $\omega > 0$, $\beta \prec 1$ and $\lambda < 1$. The FIGARCH model revolves around the fractional integration parameter d, which measures the extent of long memory or the endurance of shocks in the conditional variance. This parameter is constrained within the interval $0 \leq d \leq 1$. A non-zero dd ranging from 0 to 1 signifies a notable long memory impact, indicating that volatility shocks will decay at a hyperbolic pace rather than an exponential one, as seen in short-memory models. In situations where d equals zero, the FIGARCH model reduces to the conventional GARCH (1,1) model, signifying short memory. Conversely, if d reaches one, the model transforms into an Integrated GARCH (IGARCH) model, suggesting a variance process that does not revert to the mean and persists indefinitely (Chkili et al., 2014).

3.3 VARIABLE CONSTRUCTION AND MODIFICATION

The unaltered dummy variables, as specified, only reflect the immediate effect of an OPEC announcement, meaning they influence expectations and volatility solely on the day the announcement is made. To represent the impact of these announcements, the dummy variables are adjusted to encapsulate (i) how an OPEC announcement is anticipated, and (ii) the aftermath of an announcement more accurately. For the latter, three operations, informed by the work of Harald Schmidbauer and Angi Rösch (2009), are employed, labelled A1, A2, and A3 ("A" standing for aftereffect):

A1: Shifting of 1s: For a given sequence $d = (d_t)$, we define a new sequence where the position of 1s is shifted forward by s_1 days, using the lag operator L. This can be expressed as:

$$d^{(1)} = L^{+s_1} d, \qquad \text{where } s_1 \in \mathbb{N}$$

Example: Let $d = (0,0,1,0,0,0,0,0,0,0)$ and $s_1 = 1$. Then $d^{(1)} = (0,0,0,1,0,0,0,0,0,0)$.

A2: Extension of 1s: Starting from the sequence $d^{(1)} = \left(d_t^{(1)}\right)$ this sequence is further modified to replace each single occurrence of 1 with a consecutive run of s_2 ones directly following it. This can be described as:

$$d^{(2)} = \sum_{i=1}^{s_2} L^{i-1} d^{(1)}, \text{where } s_2 \in \mathbb{N}$$

The summation is performed element-wise. It's assumed that s_2 is less than the minimum spacing between consecutive ones in the initial sequence to ensure no overlap. If $s_2 = 1$, the operation does not modify the sequence, resulting in $d^{(2)} = d^{(1)}$.
Example: Given $d^{(1)}$ as previously described, with $s_2 = 2$, then $d^{(2)}$ would appear as: (0,0,0,1,1,0,0,0,0,0).

A3: Attaching a Geometric Sequence: For each occurrence of 1 followed by 0 in $d^{(2)}$, a finite geometric sequence with a ratio of s_3 is used to replace subsequent zeros. This can be expressed as:

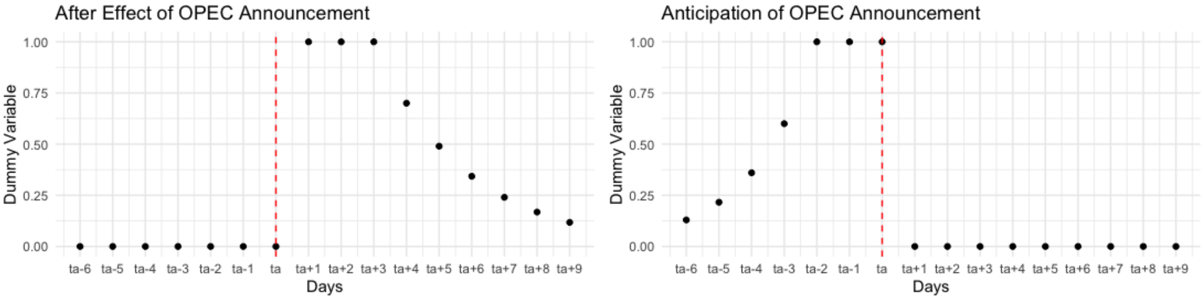
$$d^{(3)} = d^{(2)} + \sum_{i=1}^{k} s_3^i L^{s_2-1+i} d^{(1)},$$
$$\text{where } s_3 \in (0,1), \qquad k \text{ is the smallest intiger for which } s_3^{m+1} < 0.1.$$

The summation is defined element-wise, allowing for the decay effect after an event.

Example: If $d^{(2)}$ is as previously specified, and with $s_3 = \frac{1}{2}$, then $d^{(3)}$ could be represented as: $\left(0,0,0,1,1,\frac{1}{2},\frac{1}{4},\frac{1}{8},0,0\right)$.

These modifications are collectively referred to by the notation $sc_{after} = (s_1, s_2, s_3)$, defining a scenario of effect following an event. For instance, if there was an OPEC announcement on day t_a (i.e., $d_{t_a} = 1$ in the original sequence), the plot would illustrate the modified variable with $s_1 = 1$, $s_2 = 1$ and $s_3 = 0.8$. Similarly, the sequence $d = (d_t)$ can be altered to reflect the anticipation of an announcement, with duplication of 1s in the reverse direction and the geometric sequence attached in reverse. This anticipation scenario is denoted as $sc_{before} = (s_1, s_2, s_3)$.An example scenario with $s_1 = 0$, $s_2 = 3$ and $s_3 = 0.6$ is visualized on the right-hand side of Figure 2.

FIGURE 3: Visualisation of Dummy Variables Adjusted for After Effects and Anticipation of Announcements



Given the high computational demand of this task, particularly when handling data with high frequencies, parallel computing methodologies are utilized. To handle the computational burden and enhance the process of selecting parameters, a randomized approach to parameter selection is deployed across various cores or computing nodes. This method facilitates the completion of 1500 iterations, guaranteeing thorough exploration of potential parameter settings while remaining within computational limits.

3.4 BACKTESTING VAR (VALUE AT RISK)

Value at Risk (VaR) is a key instrument in risk management, offering a quantified estimate of the potential maximum loss that a portfolio might incur within a specific time frame, contingent on a chosen confidence level. Commonly calibrated at a 1% significance level for robust risk evaluation, VaR establishes a threshold beyond which the likelihood of a more substantial loss is represented by the variable α. This provides a measure for the gravest loss expected during ordinary market behaviour. The efficacy of VaR lies in its dual capacity to assess the level of risk and its sensitivity concurrently, rendering it a universally beneficial tool capable of encapsulating a spectrum of risk types, as discussed Alexander (2009). The VaR calculation employs the following formula:

$$VaR_t = \mu_t + Z_\alpha \sigma_t,$$

where μ_t represents the projected mean return, σ_t is the estimated standard deviation of returns, and Z_α is the corresponding quantile from the standard normal distribution for the specified confidence level.

While VaR is a valuable tool for capturing the risk of loss up to a certain threshold, it falls short in its non-sub-additive nature and does not always effectively measure the risk present in the tail end of the distribution. To address this gap, the Expected Shortfall (ES) has been introduced, which calculates the average loss expected when the loss exceeds the VaR threshold. (Scaillet 2000) ES complements VaR by providing insight into the magnitude of losses during the most adverse market conditions, as reflected by the equation:

$$ESF_t = E(|L_t| > |VaR_t|),$$

where L_t is the expected value of loss if a VaR_t violation occurs. Hendricks (1996) interpreted the ESF1 as the excess value of the losses over the VaR, the ESF2 as expected value of loss exceeding the VaR level, divided by the associated VaR values.

In this study, both long and short trading positions were used to estimate the relevant $VaRs$ for the GARCH-type models under the skewed student-t distribution. The daily VaR for long and short trading positions at time t can be calculated as:

$$VaR_{L,t} = \hat{\mu}_t + skst_{\alpha}\hat{\sigma}_t$$

$$VaR_{S,t} = \hat{\mu}_t + skst_{1-\alpha}\hat{\sigma}_t$$

This study also integrates the Expected Shortfall Test to verify whether the ES accurately captures the conditional shortfall, testing the null hypothesis that the mean excess shortfall is zero against the alternative that it is positive, indicating a systematic underestimation of risk. This additional layer of risk assessment is crucial for a complete understanding of the market risks involved.

3.4.1 KUPIEC'S PROBABILITY OF FAILURE (POF)

To assess the precision of a Value at Risk (VaR) model, the practice of backtesting is employed, entailing a juxtaposition of the past financial setbacks (or advancements) with the VaR predictions to pinpoint occurrences of surpassing, termed as failures. The predominant technique utilized for such examination is Kupiec's Proportion of Failures (POF) test, which was first introduced in 1995.

The POF test assesses whether the empirical frequency of exceedances in a sample matches the frequency predicted by the VaR model. For a set of observations T, the number of exceedances N is defined as $N = \sum_{t=1}^{T} I_t$, where $I_t$is an indicator function that equals 1 if the loss on day t exceeds the VaR threshold and 0 otherwise.

Kupiec's (POF) test proposes the null hypothesis H_0: $\alpha = \alpha_0$ which posits that the failure rate of the model equals the expected rate, denoted as α_0, determined by the model's level of confidence. The anticipated occurrences of surpassing this rate, denoted as α, can be computed by dividing the total number of observed exceptions N by the overall number of observations T.

The test statistic for the POF test, denoted as LR_{POF}, is calculated using the following formula:

$$LR_{POF} = -2\log\left(\frac{(1-\alpha_0)^{T-N}{\alpha_0}^{N}}{\left(1-\frac{N}{T}\right)^{T-N}\left(\frac{N}{T}\right)^{N}}\right),$$

where the symbol α_0 is used to represent the specified VaR level, while T and N stand for the total number of observations and the count of failures, respectively. The test statistic associated with this scenario conforms to a chi-squared distribution with a single degree of freedom $\left(\chi^2(1)\right)$.In the event that the hypothesis test does not lead to the rejection of H_0, it indicates that the anticipated risk level of the model aligns with the actual occurrence of failures. This, in turn, confirms the accuracy of the model's forecasts and signifies dependable risk coverage at the chosen significance level α_0.

3.4.2 CHRISTOFFERSEN’S TEST OF INDEPENDENCE

Christoffersen's Test of Independence provides a thorough assessment of the distribution of exceedances within Value at Risk (VaR) predictions to ascertain whether violations manifest in isolation or clusters. The test devised by Christoffersen (1998) aimed to overcome the limitations of Kupiec's test, which is unable to differentiate between conditional violation patterns. An effective VaR model needs to anticipate exceedances - instances where actual losses exceed the VaR threshold - occurring randomly over time without clustering, indicating the truly stochastic nature of risk.

To perform the Test of Independence, a sequence of binary results is generated based on the dataset, where '1' indicates instances of loss surpassing the VaR (exceedance) and '0' represents days without such occurrences. By analysing these binary results, one can observe shifts from '0' to '1' (non-exceedance to exceedance), '1' to '0' (exceedance to non-exceedance), and other transitions. The evaluation process then entails the computation of the probabilities associated with these transitions:

- π_0: The probability of observing a non-exceedance today, given there was no exceedance on the previous day.
- π_1: The probability of observing an exceedance today, given there was an exceedance on the previous day.

These probabilities are used to form the likelihood ratio test statistic:

$$LR_{CCI} = -2\log\left(\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1^{n_{11}}}\right),$$

In this context, n_{00} , n_{01} , n_{10} and n_{11} denote the frequency of transitions between periods of exceedances and non-exceedances. By comparing the likelihood ratio statistic with a chi-squared distribution, it is possible to determine whether the pattern of violations is independent of time. If the statistic significantly surpasses the critical chi-squared value, it indicates a lack of independence, suggesting potential issues with the VaR model's risk assessments during periods characterized by market stress and heightened volatility.

3.5 MODEL SELECTION CRITERIA

When enhancing our approach to selecting the most suitable forecasting model, we utilize the Akaike Information Criterion (AIC) established by Hirotugu Akaike (1973). AIC serves as a penalized-likelihood criterion that measures the adequacy of a model's fit while accounting for the number of parameters to prevent overfitting. A lower AIC value indicates a more favourable trade-off between model intricacy and alignment with the observed data.

Moreover, the loglikelihood function plays a crucial role in model choice, where higher values indicate greater effectiveness of a model. Models characterized by the highest loglikelihood or the lowest information criteria, including Akaike, Bayes, Shibata, and Hannan-Quinn, are deemed optimal choices.

In evaluating forecasting performance, we gauge model accuracy by comparing predicted returns with actual realized returns. Various metrics are employed to quantify forecast accuracy:

- Mean Error (ME) calculated as $ME = \frac{1}{n}\sum_{j=1}^{n}(y_i - y_j^*)$, captures the average deviation of the forecasted values from the actual values.
- Mean Absolute Error (MAE), given by $MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_i - y_j^*\right|$, reflects the average magnitude of errors in the forecast without considering the direction.
- Root Mean Square Error (RMSE) computed as $RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_i - y_j^*\right)^2}$, provides a measure of the average magnitude of the forecast error squared, penalizing larger errors more severely.

Here y^* are the forecasted values and y the realized values.

This thorough research finds the most predictive model and assesses if our adjustments to dummy variables, which represent OPEC's production choices, improve forecasting performance, and produce a more accurate picture of market movements. These analyses are crucial for supporting the changes made to the dummy variables and determining if the updated model does a better job of capturing the anticipated impacts of market reactions to OPEC statements.

4 EMPRICAL RESULTS

This section delineates the empirical results derived from our examination of the crude oil markets, focusing specifically on the long memory traits and market reactions to OPEC declarations. By employing an extensive dataset, we scrutinize the complexities of WTI and Brent crude oil yields utilizing advanced statistical methodologies and econometric frameworks.

Initially, we assess the persistence of disturbances in market prices through long memory examinations, offering insights into the informational effectiveness of the market. After this, we investigate the influence of OPEC resolutions on oil prices by utilizing regression models featuring both conventional and adjusted dummy variables.

Through the integration of GARCH models, we subsequently scrutinize market volatility and evaluate the prognostic precision of our models via Value at Risk (VaR) backtesting at varying confidence intervals. Finally, we juxtapose the forecast performance utilizing loss functions, evaluating the supplementary value of adjustments made to dummy variables in our models.

4.1 RESULTS OF LONG MEMORY TESTS

Long memory test results for crude oil returns are displayed in Table 4. Both the WTI and Brent crude oil returns' Hurst exponents are found to be below the crucial value of 0.5, suggesting a propensity for mean reversion as opposed to a long-lasting long memory effect. The statistical findings are quite substantial and offer compelling evidence that the null hypothesis—that there is no long memory—is rejected. Interestingly, both WTI and Brent crude have Hurst exponents for squared returns that are much larger, indicating a persistent behaviour and suggesting that volatility exhibits long memory features.

The results of Lo's modified R/S test, which greatly exceed the threshold value for both WTI and Brent delays, further support the existence of long memory in the squared returns. This confirms the existence of persistent volatility shocks and is consistent with Panel A's results.

TABLE 4: Analysis of Long Memory in WTI and Brent Crude Oil Returns

	WTI Returns	**Brent Returns**	**WTI Squared Returns**	**Brent Squared Returns**
Panel A: Hurst-Mandelbrot R/S test				
Hurst Exponent	0.5874 (0.0058)	0.5889 (0.0057)	0.7767 (0.0316)	0.7661 (0.0320)
Test statistic	104.904 ***	103.261 ***	24.56 ***	23.911 ***
Panel B: Lo's modified R/S test				
Test statistic (q=1)	1.0741 ***	1.0754 ***	1.2408 ***	1.2372 ***
Test statistic (q=5)	1.0438 ***	1.0359 ***	1.1513 ***	1.1604 ***
Panel C: GPH test				
$\boldsymbol{d(\alpha = 0.45)}$	-0.0859 (0.0779)	-0.0061 (0.1107)	0.0795 (0.0478)	0.1423 (0.0659) ***
$\boldsymbol{d(\alpha = 0.50)}$	-0.0300 (0.0637)	0.0452 (0.0881)	0.2238 (0.0411) ***	0.3413 (0.0627) ***
$\boldsymbol{d(\alpha = 0.55)}$	0.0378 (0.0585)	0.1212 (0.0745)	0.5165 (0.0563) ***	0.5803 (0.0644) ***

Notes: The numbers in parentheses are the standard deviations of the estimates. "q" in Lo's modified R/S test is the number of lag of autocorrelations. *** indicates significance level at 1%.

The GPH test presents an interesting contrast. For actual returns, the estimated d values at $\alpha = 0.45$ and $\alpha = 0.50$ are either negative or minimal for both WTI and Brent, indicating an absence of long memory. However, at $\alpha = 0.55$, the d values increase significantly, particularly for Brent returns, hinting at long memory effects becoming more pronounced at higher levels of significance. In the case of squared returns, the d values are substantially positive and significant at the 1% level, confirming that the volatility of both WTI and Brent prices indeed follows a long memory process.

4.2 PURE REGRESSION

Models of crude oil price returns are constructed by methodically defining how OPEC statements impact market dynamics. The previous section's insights guide the creation of dummy variables that represent the complex time impacts of these announcements. The model is refined iteratively by carefully minimising the AIC before and after adjusting these variables to determine the best modelling scenarios. The scenarios with the lowest AIC values are considered optimal as they provide a model that effectively explains the relationship between the comments made by OPEC and the volatility and expectations that follow in the movements of crude oil prices. In parallel, a choice of other regressors is made that have been shown to have a major impact on crude oil prices. Notably, the S&P 500 (SP500_r) returns and Dollar Index returns (dxy_r) are included in the model and show up as a prominent regressor, improving the forecast accuracy of the model. The approach and reasoning behind this choice of variables are explained in detail in a separate exposition.

These are only anticipated return models; volatility is not considered.

A. Regression with unmodified dummy variables

When examining the WTI crude oil series of returns, considerable autocorrelation is found at lags 2, 3, and 4. Thus, the model is modified to consider these findings when all three dummy variables are included in the regression model, regardless of their relative importance. In the same way, the regression model for Brent crude oil is adjusted to account for the notable autocorrelation that exists at lag 4.

For WTI, the regression model is represented by:

$$r_t = c + a_2.r_{t-2} + a_3.r_{t-3} + a_4.r_{t-4} + b_{cut}.d_{cut,t} + b_{hike}.d_{hike,t} + b_{maintain}.d_{maintain,t} + b_{SP500\_r}.d_{SP500\_r,t} + b_{dxy\_r}.d_{dxy\_r,t} + \varepsilon_t$$

For Brent, the regression model is represented by:

$$r_t = c + a_4.r_{t-4} + b_{cut}.d_{cut,t} + b_{hike}.d_{hike,t} + b_{maintain}.d_{maintain,t} + d_{maintain,t} + b_{dxy\_r}.d_{dxy\_r,t} + \varepsilon_t$$

TABLE 5: Regression Analysis with Unmodified Dummy Variables for WTI and Brent Crude Oil Returns

WTI	estimate	std.error	t value	$\mathbf{Pr}(>\lvert\mathbf{t}\rvert)$	**Brent**	estimate	std.error	t value	$\mathbf{Pr}(>\lvert\mathbf{t}\rvert)$
$\boldsymbol{c}$	0.02399	0.03368	0.712	0.47630	c	0.008921	0.029689	0.300	0.7638
$\boldsymbol{a_2}$	-0.04012	0.01285	-3.121	0.00181 ***	a_4	0.024634	0.012792	1.926	0.0542 *
$\boldsymbol{a_3}$	-0.04564	0.01288	-3.542	0.00040 ***	b_{cut}	0.122306	0.491761	0.249	0.8036
$\boldsymbol{a_4}$	0.03259	0.01286	2.534	0.01129 *	b_{hike}	0.729163	0.448851	1.625	0.1043
$\boldsymbol{b_{cut}}$	-1.06955	0.55818	-1.916	0.05540 *	$b_{maintain}$	-0.415028	0.324854	-1.278	0.2015
$\boldsymbol{b_{hike}}$	0.40371	0.50894	0.793	0.42768	b_{SP500_r}	0.443721	0.024310	18.252	<2e-16 ***
$\boldsymbol{b_{maintain}}$	-0.17119	0.36837	-0.465	0.64216	b_{dxy_r}	-0.768429	0.061197	-12.557	<2e-16 ***
$\boldsymbol{b_{SP500\_r}}$	0.47122	0.02763	17.058	< 2e-16 ***					
$\boldsymbol{b_{dxy\_r}}$	-0.81797	0.06913	-11.832	< 2e-16 ***					
AIC				25886.45	**AIC**				24502.68

Note: The asterisks represent significance levels: *** for 1%, ** for 5%, and * for 10%.

Table 5 presents the results of a regression analysis for WTI and Brent crude oil returns with unmodified dummy variables. In the WTI model, the negative coefficients for lags 2 and 3 suggest that returns from two and three days prior negatively influence current returns, indicating a potential mean-reverting behaviour. For the dummy variables, 'cut' has a negative coefficient, implying that an OPEC decision to reduce output generally leads to a decrease in WTI returns on that day. However, 'hike' and 'maintain' decision does not seem to have a significant effect on returns, as shown by the larger p-value. Brent's model is simpler, with only lag 4 being significant, suggesting that past returns have a lingering impact. The coefficients for the dummy variables in the Brent model have higher p-values, indicating less certainty about their influence.

B. Regression with optimally modified dummy variables

This is again a regression model with daily returns as independent variable, but the dummy variables were modified in such a way that the AIC is minimized:

For WTI, the regression model is represented by:

$$r_t = c + a_2.r_{t-2} + a_3.r_{t-3} + a_4.r_{t-4} + b_{cut}.d^*{}_{cut,t} + b_{hike}.d^*{}_{hike,t} + b_{maintain}.d^*{}_{maintain,t} + b_{SP500\_r}.d_{SP500\_r,t} + b_{dxy\_r}.d_{dxy\_r,t} + \varepsilon_t$$

For Brent, the regression model is represented by:

$$r_t = c + a_4.r_{t-4} + b_{cut}.d^*{}_{cut,t} + b_{hike}.d^*{}_{hike,t} + b_{maintain}.d^*{}_{maintain,t} + b_{SP500\_r}.d_{SP500\_r,t} + b_{dxy\_r}.d_{dxy\_r,t} + \varepsilon_t$$

Table 6, detailing the regression analysis for WTI and Brent with modified dummy variables, illustrates the statistical significance of OPEC's 'cut' and 'hike' decisions on oil returns. The WTI crude model's coefficients for 'cut' and 'hike' decisions are significantly negative and positive, respectively, at the 1% significance level. This implies that market expectations are such that an announcement of a production cut is associated with a subsequent decrease in price returns, while an announcement of an increase, or 'hike', is linked to higher returns. For Brent crude, similarly significant effects were observed for 'cut' and 'hike' decisions, but the 'maintain' decisions did not show a significant impact post-optimization of dummy variables.

TABLE 6: Regression Analysis with Modified Dummy Variables for WTI and Brent Crude Oil Returns

WTI	estimate	std.error	t value	$\Pr(>\lvert t\rvert)$	Brent	estimate	std.error	t value	$\Pr(>\lvert t\rvert)$
c	0.01541	0.03475	0.444	0.657391	c	0.01628	0.03016	0.540	0.589303
a_2	-0.04127	0.01283	-3.217	0.001305 ***	a_4	0.02338	0.01277	1.831	0.067160 *
a_3	-0.04448	0.01285	-3.463	0.000539 ***	b_{cut}	-1.35372	0.35147	-3.852	0.000119
a_4	0.03071	0.01284	2.392	0.016794 ***	b_{hike}	1.23136	0.44621	2.760	0.005806 ***
b_{cut}	-1.52622	0.39857	-3.829	0.000130 ***	$b_{maintain}$	-0.09252	0.18046	-0.513	0.608175
b_{hike}	1.42862	0.46802	3.052	0.002280 ***	b_{SP500_r}	0.44043	0.02427	18.148	<2e-16 ***
$b_{maintain}$	0.17900	0.22793	0.785	0.432308	b_{dxy_r}	-0.77133	0.06111	-12.623	<2e-16 ***
b_{SP500_r}	0.46906	0.02757	17.011	< 2e-16 ***					
b_{dxy_r}	-0.82181	0.06904	-11.904	< 2e-16 ***					
AIC				25866.17	**AIC**				24484.29

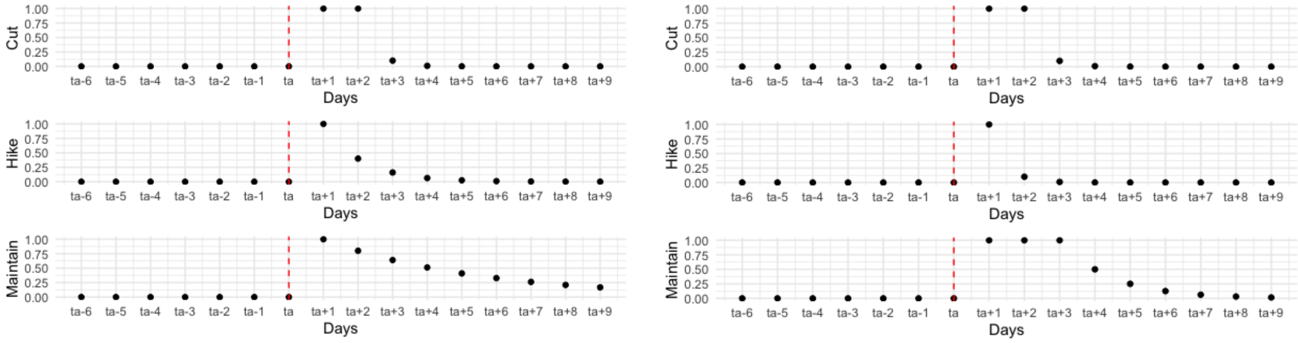
Note: The asterisks represent significance levels: *** for 1%, ** for 5%, and * for 10%.

The refinement of dummy variables is also evident in the lowered AIC scores, signifying a better fit for models that consider the temporal dynamics associated with OPEC's announcements. This method captures not only immediate impacts but also the subsequent market responses to the announcements, as depicted visually in Fig 4. This visualization offers a graphical representation of how the aftermath and expectations surrounding OPEC decisions influence oil price returns across a defined timeframe.

The optimal scenarios are:

WTI		**BRENT**	
For $d_{cut,t}$:	$sc_{after} = (1, 2, 0.1)$	For $d_{cut,t}$:	$sc_{after} = (1, 2, 0.1)$
For $d_{hike,t}$:	$sc_{after} = (2, 1, 0.4)$	For $d_{hike,t}$:	$sc_{after} = (2, 1, 0.1)$
For $d_{maintain,t}$:	$sc_{after} = (4, 1, 0.8)$	For $d_{maintain,t}$:	$sc_{after} = (1, 3, 0.5)$

FIGURE 4: Optimally Modified Dummy Variables in the Regression Model for WTI and Brent respectively



4.3 AUGMENTING THE MODEL WITH A GARCH PROCESS

To represent the volatility seen in the time series (ϵ_t), a GARCH process is incorporated into the econometric model refinement. In this section, two separate models for comparison are outlined: a GARCH model with dummies in their original form; and a GARCH model with dummies that have been optimally modified to improve model effectiveness. After a thorough analysis of the economic predictors, it was found that only the S&P 500 returns were significantly relevant in describing the volatility. As a result, the dollar index returns were eliminated from later models. The ARMA (2,2) model was selected for WTI, while the ARMA (2,1) model was chosen for Brent, based on the lowest AIC values derived from the covariates, as reported in Appendices 1 and 2. This suggests that these configurations provide the best fit for the individual data series.

4.3.1 FIGARCH MODEL

An effective model to represent the long memory characteristic in oil price returns, as demonstrated by Hurst exponents and other long memory tests, was thought to be a Fractionally Integrated Generalised Autoregressive Conditional Heteroskedasticity (FIGARCH) model. The studies indicated that shocks to volatility were persistent, which made it necessary to investigate FIGARCH—a programme built to handle long memory processes in time series data.

The FIGARCH $(1, d, 1)$ model was specified to incorporate unmodified dummy variables for 'cut', 'hike', and 'maintain' decisions, intending to capture the immediate impact of OPEC announcements on oil price volatility. The model, expressed as:

$$h_t = \omega + \beta h_{t-1} + [1 - (1 - \beta L^{-1})(1 - \lambda L)(1 - L)^d]\varepsilon_t^2 + \gamma_{cut} d_{cut,t} + \gamma_{hike} d_{hike,t} + \gamma_{maintain} d_{maintain,t}$$

After being estimated, the WTI and Brent crude oil FIGARCH models produced an insignificant pattern across the dummy variable coefficients. The calculations were accompanied by diagnostic tests that indicated the intricacy of the volatility structure that the FIGARCH models were unable to adequately capture.

The outcomes of the model within the dataset, which demonstrate similar attributes as those delineated in Table 7, are elaborated in Appendix 3. More specifically, the analysis of in-sample ARFIMA-FIGARCH for WTI and Brent crude oil returns also indicates that the dummy variables lack statistical significance. This is consistent with the results from Table 7, where the absence of notable coefficients for the dummy variables implies that the FIGARCH models might not fully capture the nuances of OPEC's influence on crude oil markets. Despite the FIGARCH model's ability to address long-term memory effects, its limited response to event-induced volatility changes, particularly those stemming from OPEC's determinations, highlights a potential area for enhancing the model.

TABLE 7: Out-Sample ARFIMA-FIGARCH Model Estimates with Unmodified OPEC Dummy Variables

	WTI			BRENT		
Models	(norm)	(std)	(sstd)	(norm)	(std)	(sstd)
$\boldsymbol{\mu}$	0.024157 (0.001157) ***	0.021423 (0.002874) ***	0.026853 (0.000169) ***	-0.072512 (0.032755) ***	0.044346 (0.002741) ***	-0.045704 (0.000811) ***
$\boldsymbol{\psi_1}$	-0.150875 (0.000077) ***	-0.143823 (0.000071) ***	-0.185174 (0.000031) ***	-0.672017 (0.000400) ***	-1.077374 (0.000258) ***	-1.065693 (0.000831) ***
$\boldsymbol{\psi_2}$	-0.735850 (0.000041) ***	-0.704411 (0.000181) ***	-0.698543 (0.000106) ***	0.086231 (0.005470) ***	-0.128207 (0.000007) ***	-0.198309 (0.000275) ***
$\boldsymbol{\theta_1}$	0.103577 (0.000030) ***	0.091841 (0.000024) ***	0.137704 (0.000595) ***	0.705577 (0.000019) ***	0.921527 (0.000420) ***	0.919570 (0.001068) ***
$\boldsymbol{\theta_2}$	0.718570 (0.000033) ***	0.676843 (0.001131) ***	0.667281 (0.000270) ***	-	-	-
d	0.019964 (0.000079) ***	0.026423 (0.001102) ***	0.023185 (0.000311) ***	0.065051 (0.004656) ***	0.042878 (0.000881) ***	0.030480 (0.000682) ***
$\boldsymbol{\omega}$	0.001368 (0.000027) ***	0.007513 (0.000581) ***	0.007467 (0.000275) ***	0.026066 (0.002290) ***	0.006016 (0.000235) ***	0.015573 (0.000408) ***
$\boldsymbol{\alpha_1}$	0.053971 (0.000086) ***	0.026906 (0.000516) ***	0.032189 (0.000578) ***	0.008491 (0.000398) ***	0.052575 (0.000812) ***	0.062469 (0.000258) ***
$\boldsymbol{\beta_1}$	0.900249 (0.000067) ***	0.901642 (0.002118) ***	0.901106 (0.000220) ***	0.928413 (0.000158) ***	0.900376 (0.000456) ***	0.869658 (0.000476) ***
$\boldsymbol{\gamma}$	0.400232 (0.000010) ***	0.406652 (0.000596) ***	0.405580 (0.000389) ***	0.841295 (0.000018) ***	0.400744 (0.000110) ***	0.555975 (0.001303) ***
$\boldsymbol{d_{cut,t}}$	0.000000 (0.006046)	0.000000 (0.015898)	0.000000 (0.049263)	0.000000 (0.269904)	0.000000 (0.006407)	0.000000 (0.151195)
$\boldsymbol{d_{hike,t}}$	0.000000 (0.002837)	0.077538 (0.090346)	0.000000 (0.065330)	0.000000 (0.458135)	0.000000 (0.003740)	0.000000 (0.148769)
$\boldsymbol{d_{maintain,t}}$	0.000000 (0.004271)	0.000000 (0.014200)	0.000000 (0.002556)	0.000000 (0.142543)	0.000000 (0.009848)	0.000000 (0.143844)
$\boldsymbol{d_{SP500\_r,t}}$	0.000000 (0.000787)	0.000000 (0.001227)	0.000000 (0.001084)	0.000000 (0.001897)	0.000000 (0.001163)	0.000000 (0.001419)
skew	-	-	0.964602 (0.014377) ***	-	-	0.943742 (0.015385) ***
shape	-	3.962874 (0.119536) ***	3.967070 (0.109055) ***	-	4.087400 (0.122767) ***	4.824097 (0.190170) ***
$\boldsymbol{AIC}$	5.3186	4.5762	**4.5755**	**4.2275**	4.3820	4.2834
$\boldsymbol{logL}$	-11806.59	-10155.68	**-10152.98**	**-9386.837**	-9729.455	-9509.08

4.3.2 EGARCH MODEL

Given the limitations highlighted by FIGARCH estimations, the EGARCH model was used. The unique benefit of EGARCH is its capacity to represent asymmetric effects and its resistance to the constraints that frequently impose limitations on conventional GARCH models. With this change, we want to give a more thorough knowledge of how OPEC statements asymmetrically affect market volatility as well as a more comprehensive framework for analysing the behaviour of the oil market. In the sections that follow, we will examine how EGARCH is applied to our volatility research, reassessing how OPEC actions fit into this sophisticated modelling framework and looking for more statistically sound explanations of market dynamics.

A. EGARCH with dummy variables

Including the unmodified dummy variables in the conditional variance specification leads to:

$$\log(h_t) = \omega + \alpha\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\epsilon_{t-1}|}{h_{t-1}}\right)\right] + \gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta\log(h_{t-1}) + \delta_{SP500\_r}\cdot SP500_{\mathrm{r,t}} + \delta_{cut}\cdot cut_t + \delta_{hike}\cdot hike_t + \delta_{maintain}\cdot maintain_t$$

The in-sample EGARCH model for both types of crude oil show patterns like those observed in the out-of-sample models (see Appendix 4). The out- sample EGARCH model estimations for both crude oils with unaltered OPEC announcements with varying distributions are shown in Table 8. The variable representing a hike displays a noteworthy positive coefficient for WTI, indicating that notifications of a production increase stimulate an escalation in market volatility. This illustrates the market's apprehension regarding possible excess supply. Conversely, the dummy variable for a cut does not exhibit equivalent statistical importance, which may imply a pre-emptive response from the market to these notifications or a perceived sufficiency of the measures taken, consequently mitigating the impact without substantial volatility. The maintenance coefficient is also not significant, indicating that the market mostly expected these announcements or saw them as a continuation of the current policy, which made them less effective on volatility.

Hike and maintain decisions have significance in the Brent model because they show how the market responds to the possibility of higher supply as well as the current situation. This may be because Brent is a worldwide benchmark and is sensitive to both sustained production levels and changes in supply. The fact that reduction announcements for WTI are less significant than for Brent is interesting and might suggest that the two benchmarks' markets have differing views of or sensitivity to supply changes.

TABLE 8: Out-Sample EGARCH Model Estimates with Unmodified OPEC Dummy Variables

	WTI			**BRENT**		
Models	(norm)	(std)	(sstd)	(norm)	(std)	(sstd)
$\boldsymbol{\mu}$	0.015217 (0.027556)	0.036363 (0.018192) **	0.009906 (0.023014)	0.033072 (0.025477)	0.046641 (0.019240) **	0.030333 (0.022337)
$\boldsymbol{\psi_1}$	-0.751008 (0.025589) ***	-0.058321 (0.006226) ***	0.127271 (0.004905) ***	-0.986828 (0.007160) ***	-0.977378 (0.010047) ***	-0.981876 (0.013006) ***
$\boldsymbol{\psi_2}$	0.175187 (0.022449) ***	-0.969936 (0.003747) ***	-0.980727 (0.002849) ***	-0.042941 (0.013097) ***	-0.048009 (0.011198) ***	-0.050479 (0.016840) ***
$\boldsymbol{\theta_1}$	0.722969 (0.024917) ***	0.050339 (0.006923) ***	-0.133373 (0.003179) ***	0.932810 (0.005178) ***	0.915032 (0.014952) ***	0.917249 (0.009277) ***
$\boldsymbol{\theta_2}$	-0.194950 (0.023386) ***	0.962881 (0.001268) ***	0.991166 (0.000010) ***	-	-	-
$\boldsymbol{\omega}$	0.013957 (0.001470) ***	0.009291 (0.001390) ***	0.009313 (0.001444) ***	0.012525 (0.001460) ***	0.006942 (0.001488) ***	0.006699 (0.001498) ***
$\boldsymbol{\alpha_1}$	-0.052421 (0.006619) ***	-0.046809 (0.007017) ***	-0.049252 (0.006997) ***	-0.039907 (0.006088) ***	-0.036164 (0.006666) ***	-0.036945 (0.006625) ***
$\boldsymbol{\beta_1}$	0.989879 (0.000056) ***	0.991842 (0.000058) ***	0.992284 (0.000062) ***	0.989683 (0.000110) ***	0.992480 (0.000110) ***	0.992934 (0.000100) ***
$\boldsymbol{\gamma_1}$	0.080592 (0.010526) ***	0.075885 (0.007103) ***	0.076799 (0.005721) ***	0.091078 (0.008976) ***	0.087225 (0.010623) ***	0.086064 (0.009691) ***
$\boldsymbol{\delta_{cut,t}}$	0.150003 (0.120459)	0.170787 (0.125664)	0.163128 (0.124775)	0.275179 (0.124691) **	0.214122 (0.134570)	0.208576 (0.132740)
$\boldsymbol{\delta_{hike,t}}$	0.296474 (0.156819) **	0.301923 (0.139806) **	0.315857 (0.135278) **	0.208531 (0.145191)	0.263928 (0.152771) *	0.275263 (0.148769) *
$\boldsymbol{\delta_{maintain,t}}$	0.166317 (0.101639) **	0.118295 (0.083436)	0.113495 (0.081934)	0.233806 (0.078735) ***	0.181953 (0.089527)	0.175473 (0.088315) **
$\boldsymbol{\delta_{SP500\_r,t}}$	-0.033696 (0.007431) ***	-0.033867 (0.006509) ***	-0.030190 (0.006544) ***	-0.037696 (0.006217) ***	-0.036334 (0.006801) ***	-0.032929 (0.006866) ***
skew	-	-	0.911687 (0.019584) ***	-	-	0.948097 (0.020010) ***
shape	-	11.567453 (1.820168) ***	12.115637 (1.132925) ***	-	9.173503 (1.188761) ***	9.236319 (1.150834) ***
$\boldsymbol{AIC}$	4.2303	4.2153	**4.2100**	4.0759	4.0565	**4.0555**
$\boldsymbol{logL}$	-9388.909	-9354.504	**-9341.631**	-9050.847	-9006.632	**-9003.49**

The importance of the γ parameter in the EGARCH model for both WTI and Brent shows how asymmetrically the market responds to news. A positive coefficient of γ denotes more market volatility after positive news, such output increases, indicating a more robust response to positive events relative to negative ones of same scale. This observation—which indicates a bias in market behaviour towards positive economic indicators—is crucial for risk management.

For both crudes, the skewed Student's t-distribution (sstd) provides a better model fit, which is consistent with the non-normal properties of the return distributions, namely the skewness and leptokurtosis. The sstd model is more appropriate, according to AIC and log-likelihood ratios where the improved fit with the inclusion of dummy variables indicate a more sophisticated understanding of volatility dynamics.

B. EGARCH with Optimally Modified Dummy Variables

To do a thorough examination of the expected versus consequential effects of OPEC statements on oil price volatility, the research now moves on to the change of dummy variables. To make this analysis easier, the research outlines:

$$\delta_{any,t} = \delta_{cut,t} + \delta_{hike,t} + \delta_{maintain,t}$$

As a result, the variable $d_{any,t}$ is assigned to represent any day of an OPEC announcement, regardless of the type of announcement. After this designation, $\delta_{any,t}$ is changed to represent two different scenarios: the first, referred to be "forward-looking" ($sc_{after} = (0,3,0)$), suggests that oil price volatility will be influenced starting on the day of the announcement and continuing for the next two days. In contrast, the 'backward-looking' scenario ($sc_{before} = (0,3,0)$) postulates a relationship between the volatility of oil prices and events that begins two days before the announcement and ends on the day of the announcement. The empirical results obtained from fitting the model under these two conditions will shed light on how different the effects of proactive vs reactive market actions in reaction to OPEC statements are:

$$\log(h_t) = \omega + \alpha\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\epsilon_{t-1}|}{h_{t-1}}\right)\right] + \gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta\log(h_{t-1})\ \ \delta_{any}\cdot\ any,t$$

TABLE 9: Out-Sample OPEC Announcement Effects in EGARCH Models

	sc_{after}		sc_{before}	
Models	**WTI**	**BRENT**	**WTI**	**BRENT**
$\boldsymbol{\mu}$	-0.014232 (0.017761)	0.006530 (0.024194)	-0.000256 (0.026417)	0.013988 (0.017285)
$\boldsymbol{\psi_1}$	1.120496 (0.011429) ***	-0.736473 (0.028923) ***	-1.167879 (0.013161) ***	-1.057640 (0.021796) ***
$\boldsymbol{\psi_2}$	-0.153811 (0.010879) ***	-0.011497 (0.013218)	-0.206637 (0.000013) ***	-0.065503 (0.022225) ***
$\boldsymbol{\theta_1}$	-1.154932 (0.046473)	0.677573 (0.029618) ***	1.134024 (0.000001) ***	0.992747 (0.000001) ***
$\boldsymbol{\theta_2}$	0.193232 (0.000396) ***	-	0.178641 (0.001064) ***	-
$\boldsymbol{\omega}$	0.008567 (0.001526) ***	0.006066 (0.001666) ***	0.008475 (0.001695) ***	0.005413 (0.001582)
$\boldsymbol{\alpha_1}$	-0.060262 (0.008097) ***	-0.045761 (0.006662) ***	-0.054673 (0.006875) ***	-0.044518 (0.006560) ***
$\boldsymbol{\beta_1}$	0.992914 (0.000099) ***	0.993610 (0.000119) ***	0.992381 (0.000113) ***	0.993500 (0.000119) ***
$\boldsymbol{\gamma_1}$	0.089202 (0.009072) ***	0.094876 (0.011060) ***	0.091653 (0.010298) ***	0.095126 (0.011105) ***
$\boldsymbol{\delta_{any,t}}$	0.044656 (0.024643) *	0.055008 (0.026007) **	0.062928 (0.024906) *	0.069316 (0.025834) ***
skew	0.899099 (0.018782) ***	0.932185 (0.019420) ***	0.901210 (0.019086) ***	0.931850 (0.019041) ***
shape	10.977624 (1.614474) ***	8.516284 (1.020901)	10.848115 (1.555928) ***	8.837310 (0.186988) ***
$\boldsymbol{AIC}$	4.2163	4.0609	**4.2159**	**4.0597**
$\boldsymbol{logL}$	-9358.719	-9018.393	**-9357.89**	**-9015.686**

The results in Table 9 consistently indicate a superior fit of the model for the retrospective scenario in relation to both WTI and Brent crude oils, as indicated by the lower values of AIC. For WTI, the adjustments looking back on $\delta_{any,t}$ imply that traders might be incorporating OPEC-related information before it is made public. A similar yet more pronounced impact is observed for Brent, where expectations regarding OPEC decisions appear to have a more significant effect on volatility. This is especially intriguing as it underscores the global benchmark status of Brent, where even the anticipation of continuity or change in supply can have a significant influence.

The GARCH model effectively conveys the previous influence all the way through to the post-announcement stage, proving that expectations leading up to the actual event impact the market's reaction to OPEC pronouncements. Given that both crude model's residuals continue to favour the backward-looking scenario, this indicates that there are strong anticipatory effects in this market.

These findings point to a compelling market dynamic in which the volatility of crude oil prices is partly explained by anticipatory effects that precede and responses that follow OPEC statements. The wilderness of the announcements—cuts, hikes, or maintenance—which all influence the market's anticipatory stance, helps to further define this interaction between expectation and reaction. The next stage is to present the relevant model.

For WTI no modification of $\delta_{cut,t}$ and $\delta_{maintain,t}$was found significant. Therefore, the model for WTI is:

$$\log(h_t) = \omega + \alpha\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\epsilon_{t-1}|}{h_{t-1}}\right)\right] + \gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta\log(h_{t-1}) + \delta_{SP500\_r}SP500_{\mathrm{r,t}} + \delta_{hike}hike_t{}^{*}$$

TABLE 10: EGARCH Model Estimations with Optimal Modifications for WTI

WTI	**In- Sample**				**Out-Sample**			
Model	estimate	std.error	t value	$\mathbf{Pr}(>\lvert\mathbf{t}\rvert)$	estimate	std.error	t value	$\mathbf{Pr}(>\lvert\mathbf{t}\rvert)$
$\boldsymbol{\mu}$	0.009924	0.029577	0.33554	0.737214	0.010395	0.025845	0.40221	0.687526
$\boldsymbol{\psi_1}$	0.127396	0.005441	23.41448	0.000000	0.127385	0.005182	24.58131	0.000000
$\boldsymbol{\psi_2}$	-0.980986	0.002880	-340.59209	0.000000	-0.980806	0.002842	-345.11145	0.000000
$\boldsymbol{\theta_1}$	-0.133567	0.003576	-37.34956	0.000000	-0.133572	0.003325	-40.17143	0.000000
$\boldsymbol{\theta_2}$	0.991195	0.000010	97220.39145	0.000000	0.991205	0.000011	92022.36478	0.000000
$\boldsymbol{\omega}$	0.009716	0.001217	7.98700	0.000000	0.009692	0.001154	8.39490	0.000000
$\boldsymbol{\alpha_1}$	-0.051199	0.006765	-7.56837	0.000000	-0.051323	0.006778	-7.57181	0.000000
$\boldsymbol{\beta_1}$	0.992816	0.000047	21323.25133	0.000000	0.992847	0.000046	21754.97162	0.000000
$\boldsymbol{\gamma_1}$	0.074443	0.004536	16.41014	0.000000	0.074463	0.004415	16.86398	0.000000
$\boldsymbol{\delta_{hike^*,t}}$	0.143821	0.042390	3.39281	0.000692	0.143569	0.042512	3.37715	0.000732
$\boldsymbol{\delta_{SP500_R,t}}$	-0.029729	0.006488	-4.58224	0.000005	-0.029728	0.006479	-4.58833	0.000004
skew	0.911502	0.019775	46.09363	0.000000	0.911111	0.019672	46.31404	0.000000
shape	12.128835	1.151268	10.53520	0.000000	11.603701	1.098475	10.56346	0.000000
AIC				4.2075				4.2083
LogLik				-9336.122				-9339.958

The model for Brent is:

$$\log(h_t) = \omega + \alpha\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\epsilon_{t-1}|}{h_{t-1}}\right)\right] + \gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta\log(h_{t-1})\, \delta_1 SP500_{\mathrm{r,t}} + \delta_2 hike_t{}^{*} + \delta_3 maintain_t{}^{*} + \delta_4 cut_t$$

Upon examining the results obtained from the changed dummy model, which are presented in Tables 11 for Brent and Table 10 for WTI, we find that the modified dummies differ significantly from the original models in terms of significance and coefficient values. Notably, the hike dummy variable for WTI starts to take on more significance, indicating that market reaction to news of production increases has grown more acute. According to Brent, the finding indicates that traders in oil exhibit a greater degree of sensitivity to OPEC's choices about supply schedules. This is clear from the fact that changing the 'cut' dummy variable is not required. Additionally, there is a noticeable degree of focus among traders on discussions concerning the increase in oil output, as seen by the modifications made to the 'hike' dummy variable.

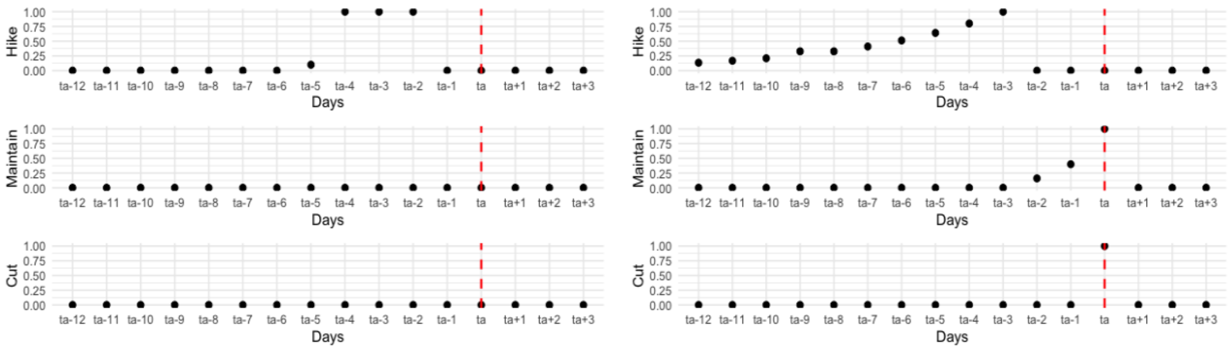
TABLE 11: EGARCH Model Estimations with Optimal Modifications for Brent

BRENT	**In- Sample**				**Out-Sample**			
Model	estimate	std.error	t value	**Pr**(> |**t**|)	estimate	std.error	t value	**Pr**(> |**t**|)
$\boldsymbol{\mu}$	0.021305	0.015110	1.4100	0.158538	0.029696	0.023783	1.24862	0.211803
$\boldsymbol{\psi_1}$	0.789562	0.069257	11.4005	0.000000	-0.063584	0.042811	-22.88038	0.000018
$\boldsymbol{\psi_2}$	0.087877	0.013066	6.7257	0.000000	-0.979540	0.056518	-0.87836	0.379747
$\boldsymbol{\theta_1}$	-0.869383	0.070432	-12.3436	0.000000	-0.049644	0.007604	120.43019	0.000000
$\boldsymbol{\omega}$	0.006261	0.001442	4.3430	0.000014	0.915788	0.001520	4.17829	0.000029
$\boldsymbol{\alpha_1}$	-0.042291	0.007528	-5.6181	0.000000	0.006351	0.007041	-5.34821	0.000000
$\boldsymbol{\beta_1}$	0.993111	0.000084	11776.5676	0.000000	-0.037658	0.000095	10463.72213	0.000000
$\boldsymbol{\gamma_1}$	0.082418	0.008089	10.1884	0.000000	0.992830	0.009171	9.16542	0.000000
$\boldsymbol{\delta_{hike^*,t}}$	0.097379	0.032924	2.9577	0.003100	0.084054	0.033372	2.90121	0.003717
$\boldsymbol{\delta_{maintain^*,t}}$	0.111235	0.057169	1.9457	0.051688	0.096820	0.057638	2.08143	0.037394
$\boldsymbol{\delta_{cut,t}}$	0.219893	0.130303	1.6876	0.091497	0.119970	0.131837	1.67009	0.094902
$\boldsymbol{d_{SP500_R,t}}$	-0.033082	0.006761	-4.8933	0.000001	0.220179	0.006841	-4.88516	0.000001
skew	0.946359	0.019293	49.0532	0.000000	0.947711	0.020402	46.45285	0.000000
shape	8.894977	1.127047	7.8923	0.000000	9.278463	1.254535	7.39594	0.000000
AIC				4.0541				4.0545
LogLik				-9002.22				-9001.282

The optimal scenarios are:

WTI		**BRENT**	
For $d_{hike,t}$:	$sc_{before} = (2, 3, 0.1)$	For $d_{cut,t}$:	$sc_{before} = (0, 1, 0.0)$
		For $d_{hike,t}$:	$sc_{before} = (3, 1, 0.8)$
		For $d_{maintain,t}$:	$sc_{before} = (0, 1, 0.4)$

FIGURE 5: Optimally Modified Dummy Variables in the EGARCH Model for WTI and Brent respectively



The improved dummy model provides a better fit, according to a comparison analysis utilising the log-likelihood values and AIC. Improved log-likelihood statistics support the higher explanatory power shown by the updated model's reduced AIC for both WTI and Brent. This suggests that the updated model better represents the complex volatility patterns associated with OPEC pronouncements.

Most importantly, the updated dummies highlight a backward-looking market trend. In advance of formal releases, traders and investors may set expectations and modify their positions, according to the statistically significant sc_{before} scenarios across the dummies. Furthermore, the dynamic character of the EGARCH model demonstrates that these anticipatory actions not only take place but also have a long-lasting effect that modifies the post-announcement volatility.

A thorough set of diagnostics was carried out to assess the models' suitability and robustness for WTI and Brent crude oil prices which can be found in Table 12. The goal was to verify that the residuals of the fitted models were normally distributed, did not display any ARCH effects, and did not show serial correlation—all of which are necessary for reliable findings and forecasts.

TABLE 12: Modified Model Diagnostics

	WTI Model	Brent Model
Panel A: Descriptive Statistics		
Jarque-Bera	2736 ***	1591.1 ***
Panel B: Tests for Serial Correlation		
Ljung–Box Test on Residuals	37.752 ***	37.736 ***
Ljung–Box Test on Squared Residuals	3991.6 ***	3324.7 ***
Panel C: Tests for Stationarity		
ADF Test on Residuals	-15.198 ***	-14.586 ***
ADF Test on Squared Residuals	-7.2678 ***	-7.5547 ***
Panel D: Tests for ARCH Effects		
ARCH LM Test on Squared Residuals	156.2 ***	54.576 ***

Notes: *** indicates significance level at 1%.

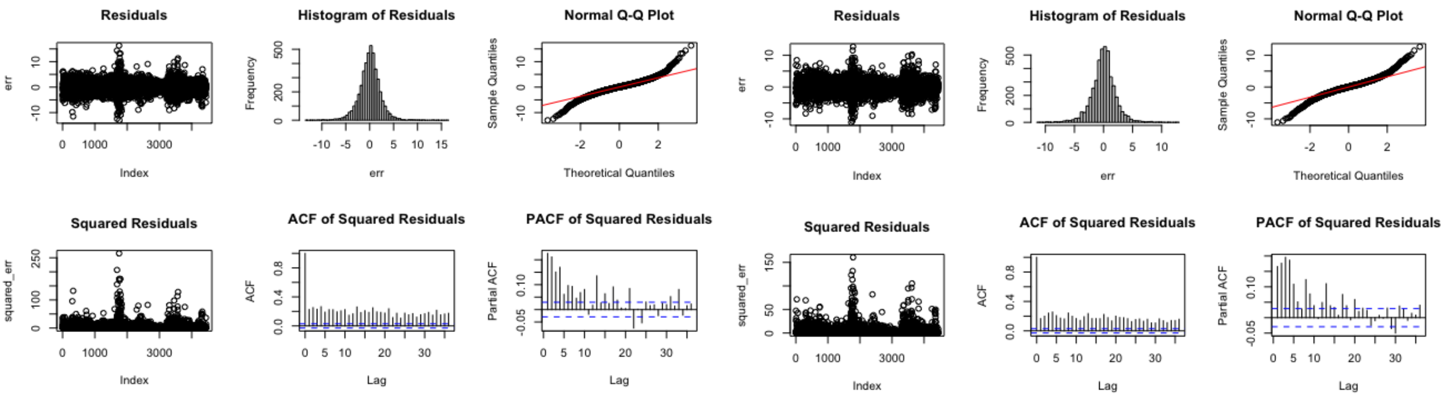
Jarque-Bera test implies that both models' residuals show non-normality, which is typical of financial time series data because of skewness and fat tails which can also be seen in Fig1 and 2.

For WTI and Brent, the Ljung–Box tests on the residuals and squared residuals produced significant results. These findings imply that serial correlation exists in the residuals of both models, which is undesirable as it suggests that the models aren't fully capturing the predictive structure in the data.

The residuals from both models revealed stationarity, as indicated by the significant negative values found in the ADF tests conducted on the residuals and squared residuals. This suggests that the time series data does not have a unit root, which satisfies a crucial condition for the model's validity.

Both models had ARCH effects, according to the ARCH LM tests on the squared residuals, with the WTI model showing a larger effect than the Brent model. This result indicates that the models do not fully explain volatility clustering, and it points to a possible direction for future work, such as incorporating more complex GARCH-type components or considering different distributions for the error terms.

FIGURE 6: Diagnostic Plots for Modified WTI and Brent Model Respectively



These diagnostics highlight areas for improvement in the WTI and Brent crude oil price EGARCH models. The assumption of normally distributed residuals is broken, according to the significant Jarque-Bera statistics for both models. This might have an impact on the kinds of statistical tests and confidence ranges that are employed. When serial correlation and ARCH effects are present, the model parameters should be reviewed. To better capture the autocorrelation and volatility dynamics, this may involve looking at the lag structure or adding extra explanatory variables.

4.4 VAR BACKTESTING

The Unconditional Coverage (Kupiec) and Conditional Coverage (Christoffersen) tests used in the Value at probability (VaR) backtesting findings for the WTI and Brent crude oil models provide a thorough understanding of the models' effectiveness in forecasting the probability of excessive losses. The models were evaluated at two confidence levels, 95% and 99%, for both kinds of crude oil.

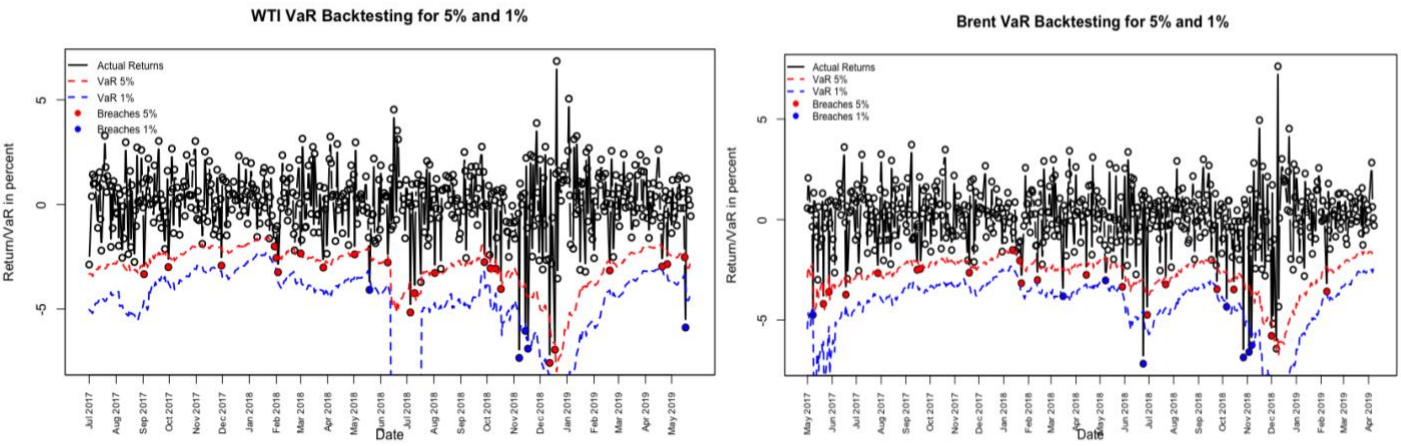
When assessing the Value at Risk (VaR) backtesting results for WTI and Brent crude oil, showcased in Table 12, a comparison between unmodified and modified dummy models offers a more comprehensive insight into market dynamics and the effectiveness of these models.

TABLE 13: Evaluation of VaR Model Predictions Using Unconditional and Conditional Coverage

Panel A: Unconditional Coverage (Kupiec)								
	Unmodified dummy models				**Modified dummy models**			
	WTI		**Brent**		**WTI**		**Brent**	
alpha	5%	1%	5%	1%	5%	1%	5%	1%
Backtest length	500	500	500	500	500	500	500	500
Expected Exeed	25	5	25	5	25	5	25	5
Actual VaR Exceed	34	6	30	9	28	5	27	8
Actual %	6.8%	1.2%	6%	1.8%	5.6%	1%	5.4%	1.6%
Null- Hypothesis	Correct Exceedances							
LR uc Statistic	3.081	0.19	0.992	2.613	0.365	0	0.164	1.538
LR uc Critical	3.841	3.841	3.841	3.841	3.841	3.841	3.841	3.841
LR uc p-value	0.079	0.663	0.319	0.106	0.546	1	0.685	0.215
Reject Null	NO	NO	NO	NO	NO	NO	NO	NO
Panel B: Conditional Coverage (Christoffersen)								
Null- Hypothesis	Correct Exceedances & Independence of Failures							
LR uc Statistic	3.133	0.336	4.833	2.943	0.629	0.101	3.255	1.799
LR uc Critical	5.991	5.991	5.991	5.991	5.991	5.991	5.991	5.991
LR uc p-value	0.209	0.845	0.089	0.23	0.73	0.951	0.196	0.407
Reject Null	NO	NO	NO	NO	NO	NO	NO	NO

For WTI, the VaR exceedances of the unmodified dummy model at the 95% confidence level were slightly higher than expected. Nevertheless, with a high p-value, there was no statistically significant difference between the model's forecasts and the actual results. This indicates a reasonable fit, though not flawless. The modified dummy model displayed some enhancement, reducing the exceedances and demonstrating a closer alignment with anticipated risk levels.

FIGURE 7: VaR Backtesting Comparisons for Optimally Modified WTI and Brent Crude Oil Models



For Brent, the results were much more noteworthy. With a lower p-value at the 95% confidence level, the unmodified dummy model performed less accurately, indicating that the model's fit may be strengthened. After the modifications, the updated dummy model did show some improvement, but not enough to refute the theory of accurate exceedances.

The models performed admirably in both scenarios, with WTI's exceedances exactly matching predictions and Brent's falling within a reasonable margin of error, at the 99% confidence level. At this risk level, the higher p-values provide even more evidence to support the models' predictive ability.

With no rejection of the null hypothesis in any test for either the WTI or Brent models, the Conditional Coverage test results, as shown in Figure 6, mainly support the preliminary results of the Unconditional test. This supports the claim that exceedances are efficiently predicted, and independent failures are suitably considered.

The research suggests that there should be more faith placed in the models at the 99% confidence level from the standpoint of risk management. Regarding 95% confidence level risk assessments, specifically for Brent, analysts may want to consider closely examining the model's robustness or carefully modifying risk estimates to avoid underestimating.

4.5 VALUE-AT-RISK (VAR) EXPECTED SHORTFALLS

Critical insights into the market risks connected with various trading positions are revealed by comparing the Expected Shortfall (ES) between the WTI and Brent crude oil models. Table 14 presents a comparison of the ES for short and long positions at different quantile levels between the unmodified and modified dummy models.

In the case of WTI, a slight rise in ES at the 95% quantile in the modified model suggests an enhanced risk perception, indicating the need for the model to readjust to acknowledge previously unaddressed market vulnerabilities. This trend becomes more pronounced at the 99% quantile, emphasizing the model’s increased sensitivity to significant market downturns. Conversely, concerning long positions in WTI, the reduction in ES under the modified model reflects a more cautious risk assessment approach, signalling a proactive stance against less severe loss probabilities.

TABLE 14: In-Sample Value-at-Risk (VAR) Backtesting for crude oil models

Panel A: Expected Shortfalls for WTI				
	Unmodified dummy model		Modified dummy model	
α quantile	**EFS1**	**EFS2**	**EFS1**	**EFS2**
Short Positions				
0.95	4.5741	1.0702	4.6563	1.0722
0.99	6.4352	1.0010	6.5025	1.0110
Long Positions				
0.05	2.3911	0.4247	2.0542	0.3745
0.01	3.6690	0.3593	3.0029	0.3014
Panel B: Expected Shortfall for Brent				
	Unmodified dummy model		Modified dummy model	
α quantile	**EFS1**	**EFS2**	**EFS1**	**EFS2**
Short Positions				
0.95	4.2982	1.0547	4.3408	1.0537
0.99	6.2375	1.0091	6.3187	1.0083
Long Positions				
0.05	1.6298	0.3825	1.5745	0.3860
0.01	2.0299	0.3296	2.3961	0.3818

Shifting focus to Brent crude, a notably distinct pattern emerges. The modified model shows a slight increase in ES at the 95% quantile for short positions, coupled with a minor decline in the relative ES measure, signalling a nuanced change in the risk profile without a significant shift in the expected severity of tail losses. At the 99% quantile, the rise in both absolute and relative ES values indicates a corresponding increase in risk preparedness for extreme scenarios. For long positions, the modified model presents a more intricate risk framework, particularly at the 1% quantile, where the ES values rise, suggesting a readiness for more substantial adverse outcomes than initially anticipated by the unmodified model.

This comprehensive comparison highlights the complexities of model adjustments and their potential to enhance risk assessments for trading positions. The modifications in both WTI and Brent models not only signify a refinement in overall risk sensitivity but also underscore the significance of model accuracy in capturing the nuances of market risks at varying confidence levels.

The notion that the average of excess breaches of VaR exceeds zero is contested by the ESF Test in Table 15. The null hypothesis is rejected at both the 95% and 99% quantiles for both models and crude types since actual breaches exceed predicted ones and the p-values are large enough to support the rejection of the null hypothesis. This result suggests that risk is continuously underestimated at these levels in both adjusted and unmodified dummy models.

Ultimately, the modified dummy models for WTI and Brent seem to provide a more complex understanding of the market, highlighting a possible undervaluation of risk in some market circumstances, especially during extreme fluctuations in markets.

TABLE 15: EFS Test for crude oil models

ESF TEST H_1: Mean of Excess Violations of VaR is greater than zero					
		Unmodified Dummy Models		Modified Dummy Models	
α quantile		**WTI**	**Brent**	**WTI**	**Brent**
0.95	Expected	55	55	55	55
	Actual	62	62	57	57
	p-value	0.02407317	0.01825963	0.01168646	0.01619789
	Decision	Reject H_0	Reject H_0	Reject H_0	Reject H_0
0.99	Expected	11	11	11	11
	Actual	14	18	14	18
	p-value	0.004368412	0.012561	0.003236818	0.0197804
	Decision	Reject H_0	Reject H_0	Reject H_0	Reject H_0

4.6 FORECASTING

Table 15 evaluates the unmodified and modified dummy models' predicting performance for 500 observations of WTI and Brent crude oils. Three common measures serve as the foundation for the evaluation: Mean Error (ME), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

TABLE 16: Forecast Performance Metrics

	Unmodified Dummy Models		Modified Dummy Models	
	WTI	**Brent**	**WTI**	**Brent**
ME	0.05784803	-0.01769776	0.1123719	-0.01701763
RMSE	3.58518	2.989176	3.710437	2.988722
MAE	2.181288	1.92856	2.25242	1.92837

When compared to the unmodified model, the modified dummy model for WTI crude shows a greater Mean Error (ME), suggesting a tendency towards stronger average overestimations after the alteration. This phenomenon could be caused by the model's capacity to account for previously unaccounted-for extra volatility related to OPEC pronouncements. However, this modification is linked to an increase in RMSE, suggesting that although the model's central tendency has changed, its predictive accuracy has only slightly declined over the spectrum of forecast errors. In both models, the Mean Error (ME) for Brent stays close to zero, indicating that the projections do not regularly overestimate or underestimate the actual values on average. The RMSE and MAE show little variation between the unmodified and changed dummy models for Brent, suggesting that the prediction accuracy for this specific kind of crude oil has not been significantly impacted by the modifications made to the dummy variables.

The results indicate that while the higher ME for WTI indicates that the modified dummy variables may better represent the market's reaction to OPEC announcements, the overall forecast accuracy for both types of crude oil may not necessarily increase because of this improvement. Concerns regarding possible overfitting, in which the model becomes unduly adapted to the characteristics of the sample data, are also raised by the minor increase in RMSE for WTI post-modification. This might make the model less relevant for out-of-sample predictions.

5 DISCUSSION

The research within this thesis has meticulously investigated the complexities of the crude oil markets, with a particular focus on the predictive power of OPEC announcements over market volatility for both West Texas Intermediate (WTI) and Brent oils. Utilizing a variety of econometric models, including GARCH variants like EGARCH and FIGARCH, the study parsed through a wealth of data to illuminate the effects of these strategic decisions. The integration of advanced statistical techniques has led to an improved understanding of how pre-announcement and post-announcement behaviours shape market movements.

The discussion within the thesis has highlighted that markets react not just to the content of announcements, but also to the anticipation of them. This insight underscores the market's sensitivity to OPEC's influence and its ability to integrate expectations into pricing mechanisms. The comprehensive approach adopted by this thesis, which accounted for long memory and volatility clustering in oil price returns, has demonstrated that market dynamics around OPEC announcements are more intricate than previously understood.

5.1 LIMITATIONS AND FUTURE DIRECTION

Despite its extensive scope, this research acknowledges multiple constraints, each paving the way for future academic exploration:

The utilization of GARCH-type models might have limited the comprehensive understanding of market volatility dynamics, especially during the unprecedented circumstances brought about by the pandemic. This necessitates diversifying the range of models used, potentially through the exploration of hybrid approaches that combine the strengths of current methodologies to better address the intricate nature of markets.

This research might also have overlooked the wider geopolitical environment affecting oil markets, including global policies, trade agreements, and regional tensions. Recognizing and integrating these elements could offer a more thorough and holistic analysis of the market.

Most importantly, model diagnostics showed room for improvement in both models. The statistical conclusions are affected by the non-normality of residuals, as indicated by the substantial Jarque-Bera statistics. The models' serial correlation and ARCH effects point to the need for improved specifications to better manage the complexities of autocorrelation and volatility in the dynamics of oil prices, such as modified lag structures or additional variables.

With regards to the long-term memory feature present in market data, the underperformance of the FIGARCH model highlights the necessity for alternative strategies that can bridge the theoretical gap and practicalities of financial markets. Non-linear models, such as neural network frameworks, may provide improved predictive capabilities for capturing long-term memory patterns in financial time series.

Moreover, the thesis failed to distinguish between OPEC's routine and extraordinary meetings, potentially overlooking their varying effects on market volatility. A nuanced classification of these meetings in future studies could unveil distinct market reactions, thus enriching risk management tactics and market forecasts.

Looking ahead, the research establishes the framework for several research opportunities:

By applying an event study methodology and focusing on OPEC statements by considering a 5-day window—two days before and two days after an OPEC announcement, it may be possible to better understand market reactions by examining the market's pre- and post-announcement readjustment and forecasting behaviour. This more accurate approach could aid in distinguishing the announcement's influence from other concurrent market activity, enhancing the model's resistance against such rare events.

Incorporating structural breaks within the modelling process has the potential to greatly enhance the level of accuracy achieved. These models demonstrate a heightened ability to adjust to and predict shifts in market volatility triggered by significant geopolitical or economic occurrences, thus potentially providing a more accurate projection of long-term volatility. Nevertheless, the time constraints faced in this study prevented the integration of structural breaks, despite the recognition that their incorporation could improve the model's performance and present a promising direction for future investigation.

Fig 10 in the Appendix 5 depicts the impact of extraordinary OPEC meetings on crude oil production, offering a compelling opportunity for future research. These meetings, often called during crucial moments or to implement significant policy changes, have the potential to significantly influence market sentiment and behaviours. The analysis illustrated in Figure 10 suggests that extraordinary meetings can be decisive in shaping market volatility. To expand on this notion, it is advisable for further research to explore in detail the effects of OPEC's meetings. By comparing the outcomes of regular and extraordinary sessions, scholars could reveal unique patterns of impact on market volatility, enhancing our understanding of OPEC's role.

Lastly, sophisticated models for extended dependency, like Recurrent Neural Networks (RNNs) encompassing LSTM and GRU variations, represent a promising frontier. These models, recognized for their proficiency in learning from time series data, could be optimized to capture and forecast the enduring long memory in crude oil markets, conceivably addressing the constraints identified with FIGARCH models.

5.2 CONCLUSION

With a focus on market expectations and volatility, the research conducted a thorough investigation to clarify the complex effects of OPEC decisions on the current prices of crude oil. Specifically, we looked at the price patterns of WTI and Brent oil going back to 2002. The goals included assessing the degree to which OPEC statements had an immediate impact on values, identifying the asymmetry of these effects, particularly in relation to earlier announcements, and quantifying the influence variation in relation to the type of announcement.

The research's empirical findings have successfully met these goals. First, the research demonstrated that OPEC decisions do, in fact, significantly influence market expectations and movements. Using advanced statistical techniques like GARCH models, our analysis confirmed the presence of long memory in market data and revealed complex asymmetric effect patterns in reaction to OPEC resolutions.

The study's conclusions also indicated asymmetry in market reactions, highlighting the fact that the anticipatory impacts were stronger before OPEC pronouncements. This finding was reflected in the regression models' adjusted dummy variables, which led to a minimised AIC and a better model fit. In response to OPEC's conclusions, the EGARCH models shed more light on the asymmetric nature of market volatility.

Furthermore, it was shown that the degree of effect varied according on the kind of OPEC decision. The finding that market dynamics were more responsive to announcements of production increases but less responsive to choices about maintenance or reduction is noteworthy. This distinction is important for traders because it sheds light on how various OPEC decisions are incorporated into trading plans.

The practical implications of our results for market players' risk management and strategic planning are significant. Our extensive VAR backtesting confirmed the models' reliability in forecasting possible hazards, but it also showed that market risks related to OPEC announcements may be overestimated, particularly in times of increased market volatility.

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APPENDIX

APPENDIX 1: ARMA Model coefficients for Brent

Models	Arma (2,0)	Arma (0,2)	Arma (2,1)	Arma (1,2)
$\boldsymbol{\mu}$	0.0288 (0.0298)	0.0281 (0.0300)	0.0280 (0.0298)	0.0284 (0.0310)
$\boldsymbol{\psi_1}$	-0.070 (0.015)	-	-0.9962 (0.0340)	0.5243 (0.2409)
$\boldsymbol{\psi_2}$	0.008 (0.015)	-	-0.0518 (0.0158)	-
$\boldsymbol{\theta_1}$	-	-0.0709 (0.0151)	0.9277 (0.0303)	-0.5959 (0.2406)
$\boldsymbol{\theta_2}$	-	0.0164 (0.0149)	-	0.0614 (0.0202)
$\boldsymbol{d_{cut,t}}$	0.0386 (0.6322)	0.0423 (0.6321)	0.0808 (0.6314)	0.0425 (0.6315)
$\boldsymbol{d_{hike,t}}$	1.0892 (0.7003)	1.0779 (0.7001)	1.0716 (0.6978)	1.0538 (0.6991)
$\boldsymbol{d_{maintain,t}}$	-0.2533 (0.3286)	-0.2509 (0.3285)	-0.2848 (0.3285)	-0.2430 (0.3282)
AIC	19227.17	19226.77	**19223.64**	19226.4
LogLik	-9606.59	-9606.39	**-9603.82**	-9605.2

APPENDIX 2: Model coefficients for WTI

Models	Arma (2,0)	Arma (1,2)	Arma (2,1)	Arma (2,2)
$\boldsymbol{\mu}$	0.0247 (0.0324)	0.0236 (0.0325)	0.0239 (0.0324)	0.0235 (0.0341)
$\boldsymbol{\psi_1}$	-0.0489 (0.0150)	-0.3350 (0.2709)	-0.3361 (0.2470)	0.0453 (0.0273)
$\boldsymbol{\psi_2}$	-0.0239 (0.0151)	-	-0.0414 (0.0179)	-0.9406 (0.0236)
$\boldsymbol{\theta_1}$	-	0.2874 (0.2704)	0.9277 (0.0303)	-0.0743 (0.0244)
$\boldsymbol{\theta_2}$	-	-0.0385 (0.0182)	-	0.9409 (0.0271)
$\boldsymbol{d_{cut,t}}$	-1.0282 (0.6930)	-1.0298 (0.6929)	-1.0370 (0.6929)	-0.9453 (0.6903)
$\boldsymbol{d_{hike,t}}$	1.0230 (0.7677)	1.0421 (0.7676)	1.0461 (0.7675)	0.9446 (0.7624)
$\boldsymbol{d_{maintain,t}}$	-0.0401 (0.3600)	-0.0345 (0.3600)	-0.2848 (0.3285)	-0.0195 (0.3582)
AIC	20012.44	20013.92	20013.27	**19996.94**
LogLik	-9999.22	-9998.96	-9998.63	**-9989.47**

APPENDIX 3: In-Sample ARFIMA-FIGARCH Model with Unmodified Dummy variable for WTI and Brent

	WTI			BRENT		
Models	(norm)	(std)	(sstd)	(norm)	(std)	(sstd)
$\boldsymbol{\mu}$	0.023336 (0.000007) ***	0.016106 (0.001193) ***	0.018400 (0.001892) ***	0.030765 (0.000009) ***	0.106913 (0.002105) ***	0.040647 (0.000130) ***
$\boldsymbol{\psi_1}$	-0.173766 0.000096) ***	-0.211390 (0.000686) ***	-0.189603 (0.001008) ***	-0.989778 (0.000183) ***	-1.074564 (0.001372) ***	-0.463639 (0.001488) ***
$\boldsymbol{\psi_2}$	-0.702021 (0.000046) ***	-0.683712 (0.000108) ***	-0.708916 (0.000078) ***	-0.039061 (0.000011) ***	-0.135990 (0.000226) ***	-0.071926 (0.000221) ***
$\boldsymbol{\theta_1}$	0.125409 (0.000046) ***	0.166236 (0.000245) ***	0.144643 (0.001295) ***	0.928301 (0.000082) ***	0.917859 (0.000989) ***	0.371098 (0.001255) ***
$\boldsymbol{\theta_2}$	0.672459 (0.000334) ***	0.650108 (0.000672) ***	0.678635 (0.000539) ***	-	-	-
d	0.023218 (0.000011) ***	0.021431 (0.000719) ***	0.021707 (0.000356) ***	0.041362 (0.000012) ***	0.048771 (0.000043) ***	0.007770 (0.000030) ***
$\boldsymbol{\omega}$	0.005042 (0.000002) ***	0.007496 (0.000299) ***	0.009313 (0.000402) ***	0.002065 (0.000001) ***	0.004557 (0.000152) ***	0.068322 (0.000207) ***
$\boldsymbol{\alpha_1}$	0.044207 (0.000017) ***	0.029959 (0.000332) ***	0.037783 (0.000207) ***	0.063373 (0.000020) ***	0.046964 (0.000284) ***	0.166443 (0.002337) ***
$\boldsymbol{\beta_1}$	0.899680 (0.000139) ***	0.900697 (0.000101) ***	0.900311 (0.000301) ***	0.899345 (0.000050) ***	0.903969 (0.000028) ***	0.772088 (0.006332) ***
$\boldsymbol{\gamma}$	0.401111 (0.000205) ***	0.405816 (0.000329) ***	0.403164 (0.000428) ***	0.396989 (0.000058) ***	0.409809 (0.000124) ***	0.521517 (0.004961) ***
$\boldsymbol{d_{cut,t}}$	0.000000 (0.003599)	0.000000 (0.001572)	0.000000 (0.002042)	0.000000 (0.000000)	0.000000 (0.006722)	0.000000 (0.865115)
$\boldsymbol{d_{hike,t}}$	0.000000 (0.004940)	0.077538 (0.139806)	0.000000 (0.071774)	0.000000 (0.001490)	0.000000 (0.027515)	0.000000 (0.861834)
$\boldsymbol{d_{maintain,t}}$	0.000000 (0.000000)	0.000000 (0.004571)	0.000000 (0.023272)	0.000000 (0.001523)	0.000000 (0.019649)	0.000000 (0.000160)
$\boldsymbol{d_{SP500\_r,t}}$	0.000000 (0.000000)	0.000000 (0.001630)	0.000000 (0.001244)	0.000000 (0.000000)	0.000000 (0.000095)	0.000000 (0.000011)
skew	-	-	0.962507 (0.014298) ***	-	-	0.937528 (0.017430) ***
shape	-	3.978489 (0.110477) ***	3.976273 (0.108294) ***	-	4.057151 (0.120625) ***	5.791396 (0.348805) ***
$\boldsymbol{AIC}$	5.3554	**4.5740**	4.5752	5.1449	4.3818	**4.1199**
$\boldsymbol{logL}$	-11885.61	**-10148.48**	-10150.2	-11429.19	-9731.075	**-9147.76**

APPENDIX 4: In-Sample EGARCH Model with Unmodified Dummy variable for WTI and Brent

	WTI			BRENT		
Models	(norm)	(std)	(sstd)	(norm)	(std)	(sstd)
$\boldsymbol{\mu}$	-0.010528 (0.036111)	0.037798 (0.034702) ***	0.001381 (0.031809)	0.032925 (0.026186)	0.038697 (0.026648)	0.025068 (0.022025)
$\boldsymbol{\psi_1}$	0.038381 (0.006258) ***	-1.989519 (0.002182) ***	0.868837 (0.014723) ***	-0.986689 (0.011899) ***	0.911538 (0.011153) ***	-0.973748 (0.015098) ***
$\boldsymbol{\psi_2}$	0.929094 (0.005568) ***	-0.994646 (0.001854) ***	0.093518 (0.014613) ***	-0.042930 (0.016049) ***	0.019457 (0.016216)	-0.036196 (0.020031) *
$\boldsymbol{\theta_1}$	-0.043870 (0.004986) ***	1.988304 (0.002144) ***	-0.903551 (0.000012) ***	0.932672 (0.008336) ***	-0.974573 (0.000353) ***	0.916980 (0.009582) ***
$\boldsymbol{\theta_2}$	-0.918901 (0.000002) ***	0.993674 (0.000004) ***	-0.053495 (0.000848) ***	-	-	-
$\boldsymbol{\omega}$	0.014057 (0.001489) ***	0.009186 (0.003753) ***	0.008881 (0.001498) ***	0.012505 (0.001465) ***	0.006732 (0.001504) ***	0.006888 (0.001505) ***
$\boldsymbol{\alpha_1}$	-0.056739 (0.007732) ***	-0.046876 (0.007607) ***	-0.052211 (0.008267) ***	-0.040028 (0.006132) ***	-0.040737 (0.007605) ***	-0.037835 (0.006747) ***
$\boldsymbol{\beta_1}$	0.990076 (0.000104) ***	0.991809 (0.000543) ***	0.992590 (0.000045) ***	0.989690 (0.000110) ***	0.992785 (0.000102) ***	0.992824 (0.000103) ***
$\boldsymbol{\Gamma_1}$	0.079820 (0.008728) ***	0.076870 (0.020375) ***	0.074190 (0.004778) ***	0.091182 (0.008962) ***	0.085611 (0.009831) ***	0.086700 (0.009989) ***
$\boldsymbol{\delta_{\mathrm{cut},t}}$	0.147525 (0.119620)	0.175826 (0.142957)	0.170974 (0.122283)	0.275136 (0.124743) **	0.216977 (0.132701) *	0.206349 (0.133323)
$\boldsymbol{\delta_{hike,t}}$	0.296263 (0.131073) **	0.299886 (0.161740) *	0.324258 (0.132995) ***	0.209247 (0.145256)	0.265207 (0.150230)	0.279325 (0.149307) *
$\boldsymbol{\delta_{maintain,t}}$	0.167330 (0.075729) **	0.125627 (0.083960)	0.115354 (0.081353)	0.234739 (0.078750)	0.171807 (0.088941) **	0.179852 (0.088479) **
$\boldsymbol{\delta_{SP500\_r,t}}$	-0.032956 (0.006139) ***	-0.034208 (0.007667) ***	-0.029478 (0.006486) ***	-0.037723 (0.006223) ***	-0.035976 (0.006790) ***	-0.032776 (0.006888) ***
skew	-	-	0.911278 (0.019543) ***	-	-	0.947697 (0.019988) ***
shape	-	11.731526 (0.333229) ***	11.623161 (1.785831) ***	-	9.053392 (0.017394) ***	9.273805 (1.176697) ***
$\boldsymbol{AIC}$	4.2300	4.2149	**4.2114**	4.0755	4.0562	**4.0555**
$\boldsymbol{logL}$	-9386.091	-9351.529	**-9342.824**	-9051.815	-9006.94	**-9005.367**

APPENDIX 5: In-Sample OPEC Announcement Effects

	sc_{after}		sc_{before}	
Models	**WTI**	**BRENT**	**WTI**	**BRENT**
$\boldsymbol{\mu}$	0.017115	0.013204	0.015679	0.005667
	(0.025692)	(0.024872)	(0.022413)	(0.023705)
$\boldsymbol{\psi_1}$	-0.481018	-0.980297	-1.508783	-1.017713
	(0.062090) ***	(0.004915) ***	(0.010522) ***	(0.024786) ***
$\boldsymbol{\psi_2}$	-0.180464	-0.050149	-0.537947	-0.056915
	(0.222306)	(0.015994) ***	(0.015032) ***	(0.009493) ***
$\boldsymbol{\theta_1}$	0.445324	0.915642	1.471581	0.951146
	(0.062424) ***	(0.011890) ***	(0.000000)	(0.027838) ***
$\boldsymbol{\theta_2}$	0.161358	-	0.484647	-
	(0.216749)		(0.016759) ***	
$\boldsymbol{\omega}$	0.009458	0.005785	0.009208	0.005768
	(0.001518) ***	(0.001670) ***	(0.001477) ***	(0.001668)
$\boldsymbol{\alpha_1}$	-0.045545	-0.044842	-0.037618	-0.045108
	(0.006663) ***	(0.006560) ***	(0.006650) ***	(0.006494) ***
$\boldsymbol{\beta_1}$	0.992121	0.993657	0.992091	0.993357
	(0.000076) ***	(0.000119) ***	(0.000076) ***	(0.000120) ***
$\boldsymbol{\gamma_1}$	0.079750	0.094839	0.079719	0.095274
	(0.007139) ***	(0.011034) ***	(0.007151) ***	(0.011129) ***
$\boldsymbol{\delta_{any,t}}$	0.076694	0.055687	0.088740	0.070835
	(0.035114) **	(0.025952) **	(0.035103) ***	(0.025843) ***
skew	0.912915	0.931976	0.913907	0.929990
	(0.019621) ***	(0.019461) ***	(0.019495) ***	(0.019380) ***
shape	12.409640	8.747890	11.801480	8.831893
	(2.087608) ***	(1.082924) ***	(1.834407) ***	(1.108205) ***
$\boldsymbol{AIC}$	4.2100	4.0593	4.2115	**4.0589**
$\boldsymbol{logL}$	-9345.516	-9016.976	-9343.952	**-9015.961**

APPENDIX 6: Spot Price of crude oils - Extraordinary OPEC Conference Decisions