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Forecasting WTI Crude Oil Futures Prices during the COVID-19 Pandemic: Application of GARCH Model

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Abstract:

This study attempts to focus on forecasting West Texas Intermediate (WTI) crude oil futures price changes under the effect of external shocks, namely the COVID-19 pandemic; whose quick and widespread spread has affected global demand, by utilizing time series data. This paper used the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to measure the volatility and the asymmetric effects of these shocks.

The analysis found that the optimum model for forecasting WTI crude oil futures prices is the TGARCH (1.1) with student distribution. The findings of the out-of-sample forecast revealed that Crude Oil Futures prices are steady with tiny deviations; however, the variance forecast series showed important variations during the out of the sample period.

Keywords: Crude Oil; WTI; Futures; Prices; Forecasting; GARCH.

Jel Classification Codes: C53, C58, Q47

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1. INTRODUCTION

Since its discovery, crude oil has become an indispensable source of energy all over the world because it serves numerous needs that are essential to human survival.

Oil price fluctuations have actually become a source of concern for many countries, whether they are exporters or importers, particularly in light of recent price variations.

The sharp drop in oil prices during 2014, after which they fell from an average of $110 per barrel between January 2011 and June 2014 to $29 in January 2016 and only $50 since 2015, shook the whole world. This decline was a logical result of several interconnected factors: On the one hand, geopolitical tension; more specifically, political instability in Libya reduced domestic oil production to near-zero levels in 2011 and again in 2013, and on the other hand, the Western embargo on Iranian oil exports since 2012 reduced Iranian oil production by about a third. More recently, there has been the ISIS invasion of northern Iraq, as well as the geopolitical uncertainties that have arisen because of it. This is in addition to other considerations (ECB, 2014).

Arezki and Blanchard (2015) contented that, in addition to citing Libya, Iraq, and the United States as examples, OPEC's announcement in late November 2014 that it would maintain current production levels despite increases in oil production in some non-OPEC countries was a major shock to oil price collapse expectations (Kilian, 2015).

The 2014 crisis was not the only one that resulted in a drop in oil prices. The state of uncertainty because of the COVID-19 outbreak caused another collapse of crude oil prices. Both social distancing policies and quarantine restrictions have disrupted economic and commercial activities (Atil & Mahfoud, 2021, p.1). Furthermore, Coronavirus increased unemployment rates in many countries, including developed countries, for example, the unemployment rate reached 14.8% in April 2020 - its highest levels since1948. Unemployment remained in higher rates (5.4%) in July 2021 than it had been in February 2020 (3.5%) (Nyhof *et.al*, 2020).

The global COVID-19 pandemic has had an impact on both social life and community health, as well as causing disruptions in numerous economic sectors and trade around the world. The virus's quick and ongoing spread over the world has resulted in a drop in international demand. The COVID-19 has a major impact on the global economy, particularly on oil prices, which have dropped dramatically as the number of reported cases continues to grow. In this regard, oil price forecasts are required to plan for the worst-case scenario. Even though its effectiveness may be limited. It may allow for the avoidance of additional losses, particularly if it is based on techniques and effective models.

This paper is concerned with an out-of-sample forecasting study of crude oil prices using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to answer the following main question: Which of the two models, GARCH or TGARCH, can provide better results for forecasting WTI crude oil futures prices?

This central question prompts the following sub-questions:

- What are the primary variables influencing crude oil prices?
- What exactly are the TGARCH and GARCH models?

Study Hypotheses:

In order to understand the aim of this paper and answer these questions, we base the study on the hypothesis that the TGARCH model can provide satisfactory results in forecasting crude oil prices.

Study Objectives:

The purpose of this research is to describe the importance of crude oil in economic life and its relationship with current global conditions, as well as to attempt primarily to present future forecasting of WTI crude oil futures prices from January 3, 2021, to April 25, 2021. However, this relative problem is related directly to anticipating viral patterns.

Study Importance:

The importance of this study stems from the recent situations defined by uncertainty, specifically the COVID-19 pandemic which has spread all over the world and caused enormous losses. Furthermore, crude oil is a key source of energy for the entire planet. Both price increases and decreases are an issue for both countries, whether they are exporting or importing.

2. LITERATURE REVIEW

Changes in oil prices are influenced by a number of overlapping and intertwined factors, including economic factors, geopolitical changes and crises; besides, many other elements, including consumer and financial investor behavior in choosing either to buy or sell oil and gas contracts, which could affect oil price volatility (Quan, 2014,p.16442). Anticipation, speculation, and the desire to make money, and beliefs affect the direction of price movement be it up or down.

Regarding the previous factors, fluctuations in global oil prices have an impact on goods and services, either directly or indirectly, because of their tight linkages to economic growth. As low oil prices are usually an indicator of a broad economic slowdown, oil prices reflect the worldwide economic situation. As a result, changes in oil prices can cause inflationary or deflationary pressures (Atil & Mahfoud, 2021, p.2); resulting in worldwide economic crises despite the fact that many countries ignore this reality (soualem, 2021, p.447). In this context, energy producers and customers attempt to forecast oil prices and other commodities over a twenty or thirty years timeframe in order to assess strategic and investment decisions (Pindyck, 1999, p.1). Changes in demand for oil inventories are influenced by expectations of future supply relative to future demand, and therefore may be dictated by supply factors or by demand factors (Khaldi & Ziad, 2019, p.68).

In recent years, economists and financial analysts have focused on modeling and forecasting oil price volatility. The majority of them have employed improved Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Despite numerous efforts to identify the best model that provides the best out-of-sample forecasting performance, no model has consistently outperformed the others.

Dondukova Oyuna and Liu Yaobin (2021) focused on the stochastic volatility model to forecast crude oil volatility by comparing the Heston and GARCH-Type Models using data from the West Texas Intermediate (WTI) and Brent markets from January 4, 2009 to December 31, 2019, totaling 5,549 observations. They discovered that the stochastic volatility model outperforms traditional GARCH-class models in terms of fitting oil return data.

Ana Maria Herrera *et al*. (2018) used some models, including RiskMetrics, GARCH, asymmetric GARCH, Fractional Integrated GARCH, and Markov switching GARCH. They discovered that models with a Student's t innovation outperform those with a normal innovation; RiskMetrics and GARCH(1,1) had good predictive accuracy at short forecast horizons, whereas EGARCH(1,1) yelled the most accurate forecast at medium horizons, and Markov switching GARCH has superior predictive accuracy at long horizons.

3. METHODS AND MATERIALS

Volatility clustering occurs often in financial time series such as stock prices, oil prices, interest rates, foreign exchange rates, and inflation rates. That is, there are moments of turbulence in which their prices fluctuate widely, and periods of tranquility in which there is relative calm (Damodar Gujarati, 2012, p. 248).

3.1. The ARCH / GARCH Approach and Uncertainty Modeling

Risk, according to Diebold and Nason (1990), can remain in financial series: the study of these series indicated a temporal dependency of risk, which frequently fades gradually. However, these studies do not distinguish between the conditional revealing reliance of the mean and that of the variance. Then, two components are distributed. The first investigates the equation of the conditional mean using the models ARMA, ARIMA, ARFIMA... The second examined conditional variance. To characterize this variation, two kinds of nonlinear models have been created. The first class pertains to Taylor's Stochastic Volatility (SV) models (1986) (Lahiani Amine and Yousfi Ouidad, 2007, p. 2).

Engle's (1982) general principle proposes that variance is determined by the amount of information available. He proposes the ARCH(q) specification, in which the square of the perturbations follows an autoregressive process of order q. The ARCH models are hence autoregressive conditionally heteroscedastic models. Engle (1982) has so proposed these processes to compensate for the shortcomings of the ARMA representation class, particularly in the case of financial series with time-dependent volatility (measured by conditional variance) and asymmetrical adjustments (Christophe Hurlin, 2007, pp. 16-17).

The aims of ARCH model that developed by Engle is to predict the conditional variance of return series.

$$y_t = C + \varepsilon_t \qquad \mathbf{1}$$

$$\varepsilon_t = z_t \delta_t \qquad \mathbf{2}$$

Where y t is an observed data series, C is a constant value, , ε_t is the residual, z_t is the standardized residual with mean equal to zero and variance equal to one, and δ_t is the square root of the conditional variance with non-negative process. The general form of the ARCH(q) model with first q past squared innovations is as follows:

$$\sigma_t^2 = \eta + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \qquad \mathbf{3}$$

The parameter requirements are $\eta > 0$ and $\alpha_j \geq 0$ (j = 1..., q), which ensures that the conditional variance, σ_t^2 is non-negative. Although the ARCH model is a straightforward model that is commonly utilized by academics, it has flaws. When modeling volatility using ARCH, a large value of the lag q may be required, resulting in a large number of parameters to be estimated. As a result, estimating parameters may be problematic (Md Ghani and H A Rahim, 2019, p. 3).

After four years of work based on the conditional mean equation, a generalized extension of the ARCH models has been developed: the GARCH model. This latter takes into account not just the current volatility expressed by the squares of past residues, but also the past volatility: it therefore provides a more flexible specification of conditional variance (Lahiani Amine and Yousfi Ouidad, 2007, p. 2).

The GARCH model is more frugal (uses fewer parameters) than the ARCH model. The GARCH model is made up of two parts: the mean equation: $y_t = c + \sum_{i=1}^{m} \emptyset_i y_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j}$; and the variance equation σ_t^2. The general form of the GARCH (p,q) model is as follows (Md Ghani and H A Rahim, 2019, pp. 3-4):

$$\sigma_t^2 = \eta + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \qquad \mathbf{4}$$

Where η is the long-run volatility with condition η > 0, $\beta_i \geqslant 0$; i = 1,…p, and $\alpha_j \geq 0$; j= 1,…, q . If $\beta_i + \alpha_j < 1$, then GARCH (p,q) model is covariance stationary. The unconditional variance of the error terms :

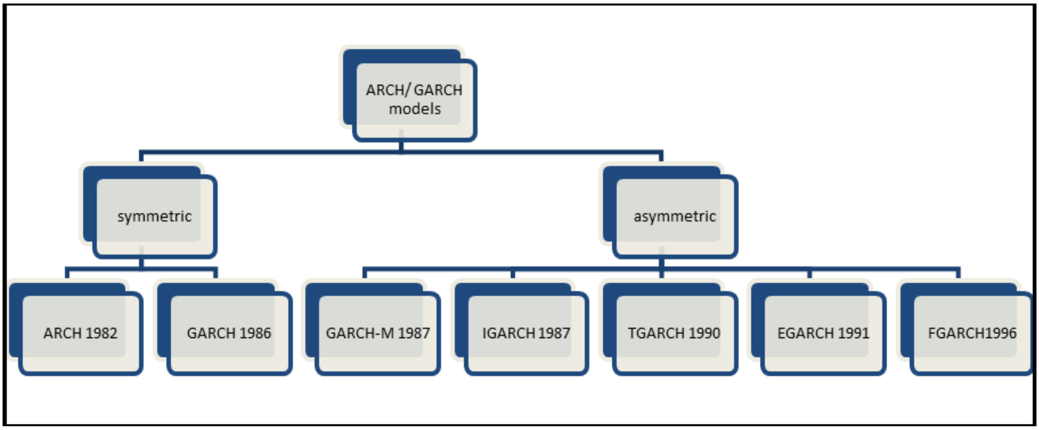
$$var(\varepsilon_t) = \frac{\eta}{1 - \beta - \alpha} \qquad \mathbf{5}$$

From the general form of GARCH (p,q) model, the GARCH(1,1) model can defined as :

$$\sigma_t^2 = \eta + \beta \sigma_{t-1}^2 + \alpha \varepsilon_{t-j}^2 \qquad \mathbf{6}$$

Furthermore, several scholars created GARCH model variations such as integrated GARCH (IGARCH), exponential GARCH (EGARCH), asymmetric power GARCH (APGARCH), and fractionally integrated GARCH (FIGARCH). The goal of these extension models is to improve the GARCH model in order to reflect the peculiarities of the return series (Dondukova Oyuna & Liu Yaobin, 2021, p. 1).

Fig. 1.ARCH/GARCH Model Classification



Source: Prepared by researchers

The enhanced GARCH-type models can capture the most essential stylistic characteristics of crude oil returns. Heavy-tailed distributions, volatility clustering, asymmetry, and extended memory volatility are among the stylized facts. These models are primarily used to describe time-varying conditional volatility as a deterministic function of lagged variance and lagged conditional squared residuals, with previous observations incorporated into future volatility. Furthermore, these models are parametric, estimating daily, weekly, or monthly volatility from data taken at the same frequency. However, these models do not always capture the fat-tail properly (Dondukova Oyuna & Liu Yaobin, 2021, p. 2).

4. RESULTS AND DISCUSSION

The data that we are studying and analyzing are the weekly WTI crude oil futures prices from 01/03/2010 to 12/27/2020. The sample size of 574 views, obtained from investing.com, and the statistical program chosen to carry out the econometric model is Eviews10.

4.1 Time Series Stability Test

The examination of the time stability of time series is a significant requirement in the modeling process. We regard a series of WTI crude oil futures prices to be stable if its arithmetic average, variance, and covariance remain consistent across time. However, by visually displaying the chain, it is possible to establish that it is unstable:

Fig.2. WTI Crude Oil Futures Prices Representation

Source: Eviews 10 outputs

The series of WTI crude oil futures prices in Fig.2 appears to be unstable because the moving average is unstable over time. The Augmented Dicky-Fuller Test (ADF) stability test can be used to guarantee this. Where the null hypothesis (H0) asserts that the unit root exists (the series is unstable).

Table 1. Unit Root Test Results on WTI Crude Oil Futures Prices Series at the 5%

Variable	Test	T- statistic	Critical-Val	prob
WTI Futures Crude Oil prices	Augmented Dicky Fuller (ADF)	-1.405652	-2.866365	0.5804

Source: Eviews 10 Outputs

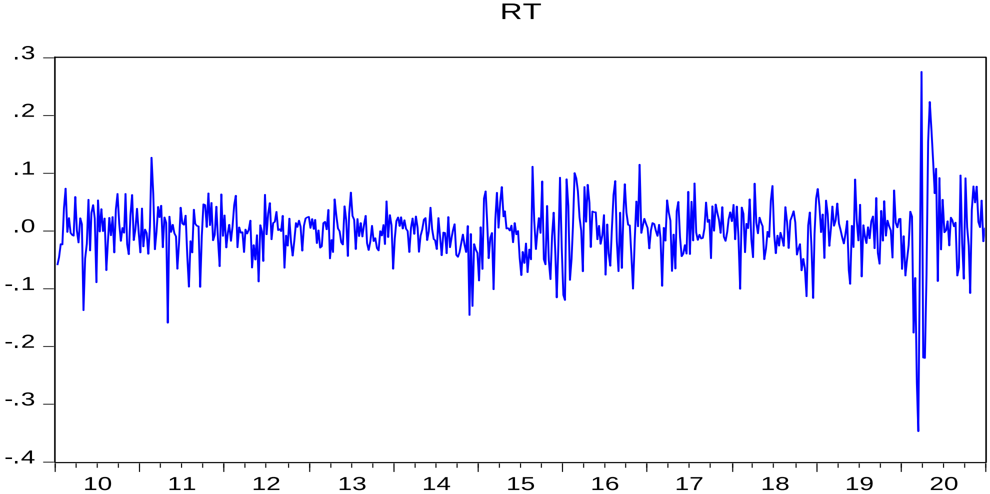
Table (1) shows that the estimated ADF test statistics in absolute value are much lower than the crucial value in absolute value at the 5% significance level. This is supported by the probability value, which is unquestionably more than 0.05. As a result, we accept the null hypothesis H0.

Because financial asset prices are not the stable data required by the time series model, they are transformed into log-returns to correct for heteroscedasticity (Lu *et.al*, 2021, p. 4)**:**

$$rt = \log(price) - \log\big(price(-1)\big) \qquad \mathbf{7}$$

The Plot of the WTI crude oil futures prices log-returns of is as follows.

Fig. 3. WTI Crude Oil Futures Log-returns



Source: Eviews 10 Outputs

Figure 2 depicts a clear volatility clustering log-return of WTI crude oil futures. That is, huge fluctuations are frequently followed by larger fluctuations, and small fluctuations are frequently followed by smaller variations. As a result, to portray the features of swings in this market, a heteroscedasticity model, such as a GARCH-type model, is required. The following are descriptive data for the log-return of WTI crude oil futures:

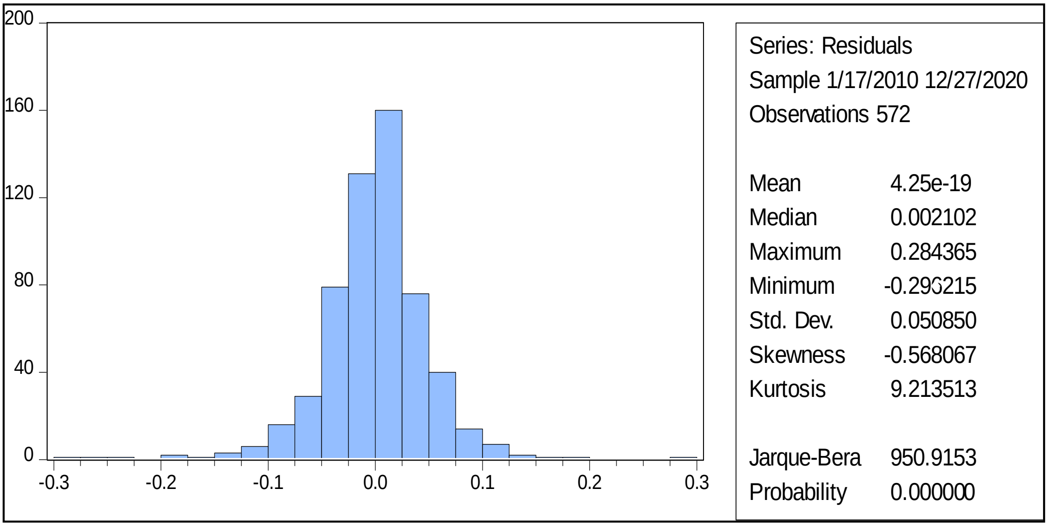
Table 2. Unit Root Test Results on log-return of WTI Crude Oil Futures Prices Series at the 5%

Variable	Test	T-statistic	Critical-Val	prob
log-return of WTI crude oil futures prices	Augmented Dicky Fuller (ADF)	-19.71912	-2.866374	0.0000

Source: Eviews 10 Outputs

Table 2 shows that the ADF test of log-returns in WTI crude oil futures prices rejects the null hypothesis of a unit root at a 5% significance level, showing that the log-returns are stationary and integrated with the same order of 0 lag.

Fig. 4. Descriptive Statistics of WTI Crude Oil Futures log-returns



Source: Eviews 10 Outputs

Figure 4 shows that the Skewness coefficient of WTI crude oil futures log-returns is negative and equal to 0.568067. (this means that the distribution is skewed to the left). The kurtosis values are more than 3, indicating that the log-returns series is leptokurtic, which suggests that it is not normally distributed. We also observe that the Jarque-Bera statistics is bigger than the chi-square distribution's critical value for a degree of freedom of 2 and a confidence level of 5%, implying that the null hypothesis of normality is rejected. Figure 4 shows that the Skewness coefficient of WTI crude oil futures log-returns is negative and equal to 0.568067. (this means that the distribution is skewed to the left). The kurtosis values are more than 3, indicating that the log-returns series is leptokurtic, which suggests that it is not normally distributed. We also observe that the Jarque-Bera statistics is bigger than the chi-square distribution's critical value for a degree of freedom of 2 and a confidence level of 5%, implying that the null hypothesis of normality is rejected.

4.2. ARCH Effect Check

Based on the ARCH-LM test, the existence of ARCH may be determined in the residual. First, we estimate the mean equation of the log-returns using the least squares method:

$$rt = \alpha + \varepsilon_t \qquad 8$$

The existence of ARCH in the estimated residues at various degrees of freedom will next be tested. The results of the ARCH-LM test on log-returns are displayed in the table below:

Table 3. ARCH-LM Test Results on the log-return Series of WTI Crude Oil Futures Prices**:**

Heteroskedasticity Test: ARCH			
F-statistic	146.7923	Prob. F(1,569)	0.0000
Obs*R-squared	117.0988	Prob. Chi-Square(1)	0.0000

Source: Eviews 10 Outputs

According to the p-value of the LM test, We reject the null hypothesis of no ARCH impact at the 5% level of significance. The data shown in table 3 below demonstrate the ARCH influence on WTI crude oil futures prices.

The presence of heteroscedasticity in residuals helps explain this.

4.3. GARCH Model Estimation and Validation

After confirming that the ARCH effect exists in the residuals, we proceed to describe the model. Six models are generated from GARCH Symmetric (GARCH) and Asymmetric (TGARCH) models. in the following error distributions: normal, Studnet, and Generalized error distribution (GED). Then we choose the best model based on the lowest Akaike Information Criteria (AIC), Hannan-Quinn Information Criterion (HQ), Schwarz Information Criterion (SC), and greatest Log-likelihood value.

Table 4. Comparison Model of Selection Criteria GARCH Models

Models	Error distribution	AIC	SC	HQ	Log-L
GARCH(1,1)	Gaussian	-3.383744	-3.346575	3.369263	1001.512
GARCH(1,1)	Student	-3.431915	-3.387314	-3.414538	1016.699
GARCH(1,1)	GED	-3.433964	-3.389362	-3.416587	1017.302
TGARCH(1,1)	Gaussian	-3.425896	-3.381294	-3.408519	1014.926
TGARCH(1,1)	Student	-3.460298	-3.408262	-3.44025	1026.058
TGARCH(1,1)	GED	-3.460079	-3.408043	-3.439806	1025.993

Source: Eviews 10 Outputs

As shown in table 4, the TGARCH (1,1) model has the lowest AIC, SC, and HQ values and the highest Log-L value with Student error distribution. As a result, we chose the TGARCH (1,1) model as the best model for the in-sample component.

Table 5 summarizes the parameter estimate of the TGARCH (1,1) model using Student error distribution:

Table 5. TGARCH (1,1) Estimation Results with Student Error Distribution

Variable	Coefficient	Std. Error	t-Statistic	Prob
Variance Equation				
$\boldsymbol{C}$	0.000198	0.00000618	3.199371	0.0014
$\boldsymbol{RESID(-1)\hat{}2}$	0.027843	0.034550	-0.805892	0.0203
(RESID(-1))^2*(RESID(-1)<0)	-0.294989	0.079707	3.700938	0.0002
$\boldsymbol{GARCH(-1)}$	0.781801	0.052858	14.79067	0.0000
$\boldsymbol{T-DIST.DOF}$	6.926974	1.871979	3.700348	0.0002

Source: Eviews 10 Outputs

From table 5, the estimated conditional variance of TGARCH (1,1) is expressed as :

$$\delta_t^2 = \alpha_0 + \alpha_1^+|\varepsilon_{t-1}^+|^2 - \alpha_1^-|\varepsilon_{t-1}^-|^2 + \delta\sigma_{t-1}^2 \qquad \mathbf{9}$$

$$\delta_t^2 = 0.000198 + 0.027843|\varepsilon_{t-1}^+|^2 - 0.294989|\varepsilon_{t-1}^-|^2 + 0.781801\delta_{t-1}^2 \qquad \mathbf{10}$$

Table 5 findings show that all parameters are statistically significant, that is, they differ substantially from zero at the threshold of 0.05. Furthermore, the coefficient is negative and statistically significant, indicating that positive shocks connected with good news produce less severe swings than negative shocks associated with bad news.

4.4. Diagnostic Checking

After determining the appropriate model for the WTI crude oil futures series, we must ensure that the Residuals series has White Noise:

Table 6. Standard Residuals ACF and PACF

Date: 10/15/21 Time: 16:29
Sample: 1/03/2010 12/27/2020
Included observations: 572

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.056	-0.056	1.8012	0.180
		2	0.015	0.012	1.9287	0.381
		3	-0.026	-0.025	2.3268	0.507
		4	-0.009	-0.012	2.3706	0.668
		5	0.000	-0.000	2.3706	0.796
		6	0.006	0.006	2.3950	0.880
		7	0.005	0.005	2.4109	0.934
		8	0.019	0.019	2.6129	0.956
		9	0.008	0.010	2.6509	0.977
		10	0.070	0.071	5.4879	0.856
		11	-0.003	0.005	5.4946	0.905
		12	0.007	0.006	5.5225	0.938
		13	0.013	0.018	5.6282	0.959
		14	0.003	0.006	5.6326	0.975
		15	0.002	0.003	5.6361	0.985
		16	-0.010	-0.011	5.6999	0.991
		17	-0.015	-0.017	5.8245	0.994
		18	-0.035	-0.039	6.5322	0.994
		19	-0.006	-0.012	6.5508	0.996
		20	0.054	0.048	8.3028	0.990
		21	-0.011	-0.008	8.3710	0.993
		22	0.013	0.009	8.4784	0.996
		23	-0.016	-0.014	8.6382	0.997
		24	-0.027	-0.028	9.0692	0.997

Source: Eviews 10 Outputs

Table (6) shows that most of the residual series coefficients (et)'s partial and autocorrelation functions are minimal. The significance level of 0.05 equals 0. The ARCH-LM test on standard residuals confirms this:

Table 7. ARCH-LM Test on Standard Residuals

Heteroskedasticity Test: ARCH

F-statistic	1.788831	Prob. F(1,569)	0.1816
Obs*R-squared	1.789493	Prob. Chi-Square(1)	0.1810

Source: Eviews 10 Outputs

This study's findings suggest that the ARCH effect does not present in residuals, because the ARCH-LM statistic is much less than the chi-square distribution's tabulated value with one degree of freedom (the P-value of the test is greater than 5%).

4.5. Forecasting the Volatility of WTI Crude Oil Futures Prices

From 01/03/2010 to 12/27/2020 WTI crude oil price data, the TGARCH(1,1) with Student distribution of errors would be the best, specified model for forecasting weekly WTI crude oil futures price data for forecasting price fluctuations and variances from 01/03/2021 to 04/25/2021.

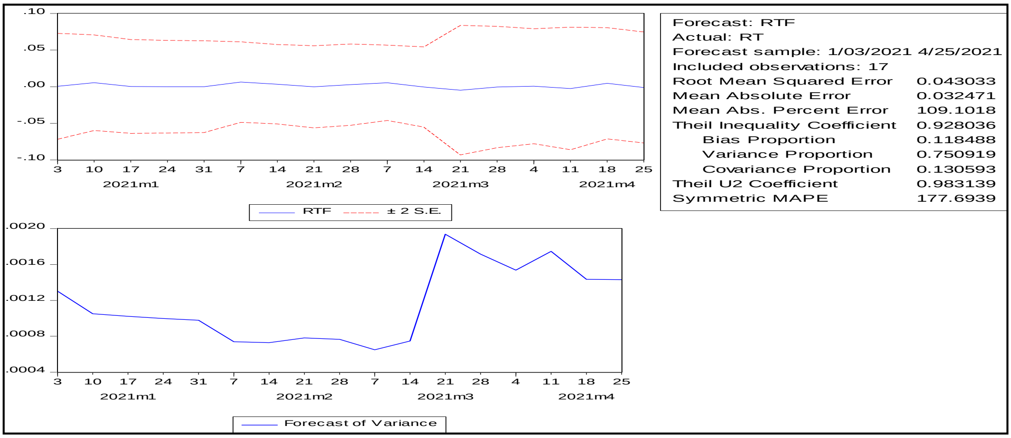
Table 8. WTI Crude Oil Futures Forecast (Prices and Variance)

Date	Price Forecast	Variance Forecast	Date	Price Forecast	Variance Forecast
01/03/2021	52.24044	0.00130	03/07/2021	52.25092	0.00065
01/10/2021	52.36537	0.00105	03/14/2021	52.25043	0.00075
01/17/2021	52.70017	0.00102	03/21/2021	52.24561	0.00194
01/24/2021	52.19981	0.00100	03/28/2021	52.24508	0.00171
01/31/2021	52.84998	0.00098	04/04/2021	52.24566	0.00154
02/07/2021	52.47623	0.00074	04/11/2021	52.24309	0.00175
02/14/2021	52.24325	0.00073	04/18/2021	52.24763	0.00143
02/21/2021	52.24297	0.00078	04/25/2021	52.24648	0.00143
02/28/2021	52.24569	0.00076			

Source: Prepared by researchers

According to the TGARCH (1.1) model findings in the table (8) above, WTI crude oil futures prices will be steady with modest fluctuations in the following weeks. While the anticipated deviations are variable.

Fig. 5. Forecasting Returns of WTI Crude Oil Futures Fluctuations and Variances over the Period from 01/03/2021 to 04/25/2021



Source: Eviews Outputs

As seen in Fig. 5, the return on assets starts out stable gradually (from 01/03/2021 to 03/14/2021), but then it increases intensely (from 03/21/2021 to 04/25/2021). The same figure shows that the forecast values of WTI crude oil futures prices are fixed in the presence of minor deviations during the studied period, while the predicted variations show that they decreased from January to March 7, 2021, then rose until March 22,2021, and then fluctuated between high and low. This can be attributed to:

- The decrease in the predicted variance values; the gradual reduction of social closure measures implemented by countries since the virus's emergence, including the return of production activity and air transport coincided with the development of an effective vaccine (the Russian and American vaccine). It instilled confidence in investors about the trading of oil company shares.
- The re-increase in predicted variance values; the high risk of fluctuations in futures prices caused by the spread of the third wave and the emergence of a new strain of Coronavirus, which will result in tough closure procedures and movement restrictions, potentially causing the market to stagnate during this period.

5. CONCLUSION

Through this study, we tried to validate the efficiency of forecasting models by comparing the two models, TGARCH and GARCH. The results demonstrated that the TGARCH model outperformed the GARCH model in forecasting future oil futures prices. On this basis, we accept the hypothesis of the study.

Each drop in the values of predicted variance reflected a decrease in the risk of fluctuations in West Texas Intermediate crude oil futures price, which occurred from the progressive reduction of the closure and social distancing measures used by many countries since the virus's debut.

The resumption of manufacturing and air travel, which coincided with the development of a viable vaccination (the Russian and American vaccines) sparked some confidence among investors dealing in oil company stocks, while the return of predicted variance values may indicate a return to the high risk of futures price fluctuations caused by the spread of waves and the emergence of a new strain of the Coronavirus; that renewed strengthening of closure procedures and movement restrictions, stagnate during that period.

Overall, variations are projected to reduce over the following several months, with a steady rise in futures prices accompanying the gradual return to regular life and more released restrictions.

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