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# Forecasting the threat of Covid-19 and Ukraine war on energy security: An empirical study using GARCH-TGARCH

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**Abstract:**
Recent developments in the oil and oil-related industries have made energy security a top priority. Concerns about immediate threats to economic growth as well as long-term energy security are sparked by high costs. To maintain the life quality for everyone in the world, there is a significant shared interest in ensuring that the globe can produce and use energy in a sustainable manner. The primary aim of the present paper is to measure the impact of the dual shock of the Covid-19 pandemic and Russia's military action in Ukraine on oil and oil-related products sus as Brent Crude oil, WTI crude oil, Heating oil, Natural Gas, UK natural gas and Gasoline. To realize our investigation daily data used for the period of 1st January 2020 to 7th October 2022, the selected period covered both of Covid-19 pandemic and Ukraine war complications. The main findings of the T-GARCH model state that there is a positive shock affect on energy prices, particularly oil prices that highly increased, followed by a notable augmentation in the rest of energy products during the Russia-Ukraine conflict. This situation can positively affect the hydrocarbon revenues for oil-exporting countries, in the counterpart the importing-countries are most suffering from the high cost.

**Keywords:** Energy security; Ukraine war; Covid-19; forecasting volatility

**JEL Classification Codes:** C53; F37; G15.

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## Introduction

Energy prices have increased at their highest rate since 1973 over the past two years. Commodity markets have experienced a significant shock as a result of the conflict in Ukraine, which has altered global trade, production, and consumption patterns in ways that will maintain prices at historically high levels through the end of 2024. The year 2022 has been particularly noteworthy for the energy industry. One example is that the price of crude oil has increased by 15% since the beginning of the year, but it is still higher than in Europe. The war that Russia is waging in Ukraine, the lingering effects of the Covid-19 pandemic, and other factors have caused natural gas prices to be eight times more volatile than we would normally expect them to trade at all. These factors are driving historical inflation, which is causing rising living costs, crises, and extraordinary levels of uncertainty.

In addition to a 50 percent increase between January 2020 and December 2021, the energy price index of the World Bank climbed by 26.3% between January and April 2022. This spike is a result of a substantial rise in the prices of coal, oil, and natural gas. Energy prices had already begun to climb prior to the crisis in Ukraine because of the Covid-19 outbreak, the effects of climate change, and other factors. One of the biggest shocks to the world's energy markets in decades occurred in the first semester of 2022. While these shocks have an effect on most nations, they have the greatest impact on disadvantaged households. The living costs crisis is being caused by the economic repercussions of Russia's invasion of Ukraine. The United Nations Development Program states that the nations suffering the most from the crisis are those with the highest levels of poverty. On the other hand, 71 million more individuals might fall into poverty.

Since the beginning of the year, the world's use of crude oil has decreased due to a combination of slowing economic growth, COVID-19 outbreaks, and the effect of rising oil prices on consumption. Oil demand decreased by 2% in 2022Q1 followed by further decline in 2022Q2 after returning to pre-pandemic levels in 2021Q4. The first quarter of 2022's demand was unaffected by the minor increase in oil prices. This is due to the extremely low-price elasticities of demand for oil products like gasoline and diesel. Additionally, several governments have implemented fuel tax cuts or introduced subsidies in response to the increase in oil prices, particularly for gasoline, which will mitigate the effects of increased oil costs on demand. On the other hand, OPEC+ continues to produce considerably below its stated objective, despite a minor increase in production. 12 of the 19 countries facing production restrictions in March 2022 fell short of their requirements. The shortage has been greater than 1 mb/d on average since the beginning of 2022, and as Russia's production fell in March, the gap grew to 1.4 mb/d.

The most recent OPEC monthly report for 2022 notes that the balance of supply and demand shows that demand has been revised down from the last MOMR by 0.2 mb/d to stand at 28.7 mb/d, which is roughly 0.6 mb/d higher than in 2021. According to secondary sources, OPEC crude output averaged 28.4 mb/d in the first quarter of this year, which is 0.3 mb/d less than OPEC crude demand. OPEC crude output averaged 28.6 mb/d in 2Q22, which is 0.1 mb/d more than what was needed. OPEC produced 29.5 mb/d of crude oil on average in 3Q22, 1.3 mb/d more than what was required.

According to what was said about OPEC, the world's oil supply is expected to tighten, escalating worries about inflation rising after the OPEC+ group, which includes Saudi Arabia and Russia, agreed its greatest supply cut since 2020. Following their first face-to-face meeting, the OPEC+ members announced an output cut beginning in November. The group claims that this decision was made in light of the ambiguity surrounding the outlooks for the global economy and oil markets; as a result, the action will help stabilize the energy markets. In comparison to the beginning of the year, when Brent prices were 79 dollars, the price of crude oil increased on the international markets after the OPEC+ statement by 1.7 percent, reaching 93.29 dollars. Global markets responded quickly to the OPEC decision, with crude oil rising by almost 1.1 percent and US West Texas Intermediate Futures rising by about 1 percent to 87.37 dollars. The decision by OPEC+ to reduce production came at a difficult time for the world economy, which was still reeling from the impact of Russia's invasion of Ukraine, especially for the import-dependent nations.

On the light of what we mentioned above concerning energy markets prices volatility, which is caused by several reasons such as Covid-19 pandemic, Ukraine war and the latest OPEC+ decisions about slashing the production about 2 million b/pd. We will investigate the energy security in the light of the accelerated economic and geopolitics events. The current paper aims to examine the impact of the different shocks on oil and oil-related prices in international markets, in addition to the forecasting volatility using suitable models based on the discussed literature review which investigate the same topic. The rest of our paper will organize as follow; section two represents the literature review, the methods will be presented in the third section, the fourth section demonstrate the discussion and finally, we have the main conclusion and future researches.

## 1. Literature review:

(Ezeaku, Asongu, & Nnanna, 2021) research examine the impact of the global demand and supply of oil prices on the commodities prices during Covid-19 pandemic. The research sot out that the covid-19 caused a dual uncertainty shock of supply and demand. According to (Demirer, Gupta, Pierdzioch, & Shahzad, 2020) the investors behaviour has a primary role on influencing oil and oil- related products volatility, whereas the results shed light on the speculation as a hedging strategy against uncertainty risks in financial assets. The spillover uncertainty for oil prices (WTI , Brent) in the G7 countries and China has been investigated by (Gupta & Pierdzioch, 2021). The main findings concluded that the US has a role on predicting oil prices volatility, as well as the G7 and China, thy also confirmed that the international spillovers and the uncertainty ha predictive value. Using GARCH-MIDAS (Salisu, Gupta, & Demirer, 2022) highlight the positive predictive relationship between the global rising in asset prices and the oil prices volatility. (Chen & Xu, 2019) used the GAS model to forecasting the volatility between WTI, Brent and gold prices. They found that the structural complexity between gold prices and Brent is large than those of WTI. (Fałdziński, Fiszeder, & Orzeszko, 2020) concluded that the GARCH models are outperform on predicting energy commodities prices such as WTI, Brent, heating oil, Gasoline and natural gas. (Hasanov, Shaiban, & Al-Freedi, 2020) confirmed that the outperforming models for forecasting volatility are the GARCH model particularly oil and oil related-products.(Hasanov et al., 2020) show oil and gas prices have a nonlinear relationship with the both of public and private information continuously. (Xu & Lien, 2022) figure out the outperforming of GARCH and EGARCH model on forecasting oil and gas volatility, because they are more vulnerable to the extraordinary shocks. (Nyga-Łukaszewska & Aruga, 2020) research investigate the impact of the Covid-19 pandemic on oil and gas prices in the US and Japan energy markets. They conclude that the oil prices got a negative shock in both of Japan and US, in contrast the gas prices affected positively during the selected period. (Adekoya, Oliyide, Yaya, & Al-Faryan, 2022) examine the spillover effect of the oil prices on the other financial assets during the Russia-Ukraine war. The study empirically confirmed the strong spillover impact of the oil fluctuations on the commodities markets and the remaining assets.(San-Akca, Sever, & Yilmaz, 2020) focused on the energy security during the Ukrainian war by specifying natural gas and fuel. The findings reveals that the Russo-Ukraine conflict encourage the independence of the exporters and importers to build an outside solutions for the security access to the resources. (Johnstone & McLeish, 2020) chose the United States and the United Kingdom as a sample to examine the impact of the wartime on oil prices behaviour. The research integrates the geopolitical and historical overview to distinguish the situation. The primary findings show that the Russia-Ukraine war put the UK and US in a big challenge on finding new solutions for the instability of energy markets particularly oil prices. (Agaton, 2022) clarified the impact of the geopolitical conflict of Russia and Ukraine on the oil prices and commodities prices especially for oil-importing countries. (Božić, Karasalihović Sedlar, Smajla, & Ivančić, 2021) presented a comparative study for the natural gas delivered from Russia to Europe via Ukraine between 2020 till 2030. The main results showed that the natural gas quantities flows in the present day less than last years, because of the green energy projects adoption in Europe. (Lambert et al., 2022) conducted more than 15 interview with academic researchers and experts on energy industries in Europe. The authors concluded that the European region by the end of 2022-2023 will unable to secure enough additional gas supplies to recompense the Russian supplies. (Kröger, Longmuir, Neuhoff, & Schütze, 2022) focus on the effect of the Natural gas prices increasing on the household's income in Germany. The primary results shows that the incomes become lower because of the natural gas bills, whereas the household pay at the median 11.70% of the total income in 2022 compared with 6.21% in 2020. (Norouzi, 2021) aim to analyse the impact of the Covid-19 pandemic on the energy industry particularly oil and natural gas. The results showed that the Covid-19 pandemic has dual impacts in the short term with 25% decrease in consumption and 30% to 40% in long-term. This augmentation of oil and natural gas caused oil project industries to decrease notably especially in the United States. (Khan et al,2020) research investigates the relationship between the crude oil (WTI) and the natural gas prices before the Ukraine war shocks. The study results can help the policymakers to adopt a mix energy industry based on the time varying field in the economic cycle. (Sohrabi, Dehghani, & Rafie, 2022) forecast the volatility of WTI crude oil, coal, natural gas prices using artificial neural network; the main results shows that there is a strong correlation between the selected variables; means the increasing of one of them push the other prices up. (Zhang & Zhao, 2021) examine the dynamic correlation between the crude oil and natural gas returns using GJR-GARCH model. (Mensi, Rehman, Hammoudeh, & Vo, 2021) the authors empirically test the systematic risk between the WTI crude oil futures, natural gas and gasoline futures in MENA region taking in consideration the period before and after 2014. The main finding shows dual evidence of positive/negative average between the selected products and for almost stock markets in MENA region. other finding shows that the oil-exporting countries in MENA region more affected in compare with importing countries in the same region.

### 1.1 Research gap

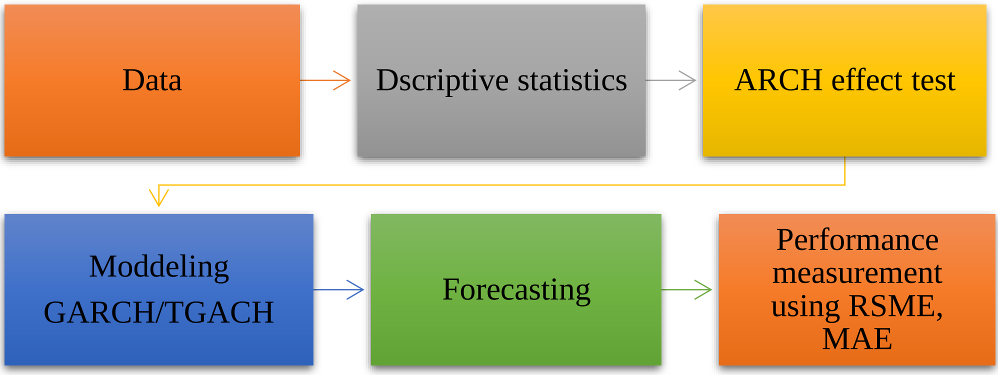
The literature review section represents the research papers that distinguished the volatility of oil prices and the related-oil products such as natural gas, gasoline, heating oil prices, under separate periods, before and during covid-19 pandemic and during the Russo-Ukrainian invasion. It is possible to note that the selected literature review aimed to show the impact of health crisis and the geopolitical instability on the energy prices in the worldwide particularly in Europe. The author’s target was only specified to analyze the energy prices shocks for each crisis separately. Furthermore, there was lack of the economic interpretation for most of the research papers, whereas, the authors used only the econometrics analysis to discuss the results. Taking in consideration these limits mentioned in the literature review, we aimed to investigate the behaviour of the energy prices during the two most difficult crises in the energy markets since 1973’s, including Covid-19 pandemic flowed by the Russia military actions against Ukraine. Therefore, the T-GARCH model will be used, since it the suitable model to examine the shocks in the time series data. The present study also will introduce an economic discussion to analyze our empirical results.

### 2.2. Hypotheses:

**H$_1$**: Positive shocks have a large impact than the negative shocks.
**H$_2$**: higher energy prices increased energy security threat.

## 2. Data and materials

**Figure number (01): Display the process used to create this research paper's work flow.**




**Source:** Author.

### 2.1 Data Description

The current paper includes daily time series data of six energy commodities prices Crude oil ICE, Natural Gas, Heating oil, Gasoline, UK Natural Gas and WTI Light sweet Crude oil. The selected sample became the most vulnerable commodities in financial markets, because of the Covid-19 pandemic and the Ukraine war consequences, when the prices of energy commodities have increased at its highest rate since the 1973 oil crisis over the past two years. The forecast for the chosen commodities shows an increase of more than 50% in 2022, followed by a decline in 2023 and 2024. Overall, because to Russia's military actions, the commodity markets especially those for energy products are facing one of the worst supply shocks in recent memory. The data collected from Thomson Reuter database covering the period of 03rd January 2020 to 07th October 2022. The sample will divide onto two panels; the first one arranges between 03rd January 22020 and 31st January 2022. Covering the time duration of Covid-19 pandemic, the second one includes the Ukraine-Russia invasion period from 01st February 2022 till 07th October 2022.

**Table number (1): data descriptive**

| Data | Description |
|---|---|
| ICE Crude Oil | A bundle of five different types of North Sea petroleum is called "waterborne crude."(Brent, Forties, Oseberg, Ekofisk and Troll) |
| WTI crude oil | is a landlocked regional crude that represents US midcontinent market dynamics. |
| Natural Gas | It is a mixture of hydrocarbon-rich gases, including methane, nitrogen, and carbon dioxide. |
| Heating Oil | After gasoline, it is the second most significant by-product of crude oil. |
| Gasoline | mixture of petroleum-derived, flammable liquid hydrocarbons that are chosen as motor vehicle fuel. |

**Source:** Author**.**

### 2.2 Methods

The current study looks at how the Covid-19 pandemic shock and the war in Ukraine affected the prices of the energy commodities that are most susceptible on the international markets. The econometric methods used in this investigation are ARCH LM, GARCH (1,1) and TGARCH models. Asymmetric approaches like the TGARCH model are used to test for the presence of asymmetry. The variations in historical returns show that future volatility will be a continuation of the past; as a result, the GARCH (1,1) model will be used in forecasting volatility.

- **ARCH model**

Engle introduced ARCH models in (1982). The model presupposes that the variance of the most recent error term is connected to the magnitude of the error terms from the prior period. Considering that an asset's return is provided by:

$$r_t = \mu + \sigma_t \varepsilon_t$$

Where $\varepsilon_t$ is a sequence of N(0,1)i.d.d random variables. The residual term at time t, $rt - \mu$ can be defined as follow:

$$at = \sigma_t \varepsilon_t$$

Wherein in ARCH model,

$$a_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2$$

Where $\alpha_0 \succ 0$ and $\alpha_1 \geq 0$ to guarantee a positive variance and $\alpha \prec 1$ to guarantee the model's stationary. The results are predicated on the assumption that all data up to time t-1 is uncorrelated but not i.i.d.

- **GARCH(1,1) model:**

Bollerslev and Taylor presented the GARCH model (1986). The conditional variance can be dependent on prior lags in the model.

In GARCH model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where $\alpha_0 > 0, \alpha_1 > 0, \beta_1 > 0,$ and $\alpha_1 + \beta_1 < 1$

An ARCH(1,1) is an ARMA(1,1) model on squared residuals by substituting $vt = a_t^2 - \sigma_t^2$ in previous equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$a_t^2 - v_t = \alpha + \alpha_1 a_{t-1}^2 - 1 + \beta_1 (a_{t-1}^2 - v_{t-1})$$

$$a_t^2 = \alpha_0 + (\alpha_1 + \beta_1) a_{t-1}^2 + v_t - \beta_1 v_{t-1}$$

Which is an ARMA(1,1) process on the squared residuals.

A GARCH (1,1) model can be writen as an ARCH $\infty$.

$$\begin{aligned}
\sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\
&= \alpha^0 + \alpha_1 a_{t-1}^2 + \beta(\alpha_0 + \alpha_1 a_{t-2}^2 + \beta_1 \sigma_{t-2}^2) \\
&= \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_0 \beta_1 + \alpha_1 \beta_1 a_{t-2}^2 + \beta_1^2 \sigma_{t-2}^2 \\
&= \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_0 \beta_1 + \alpha_1 \beta_1 a_{t-2}^2 + \beta_1^2 (\alpha_0 + \alpha_1 a_{t-3}^2 + \beta_1 \sigma_{t-3}^2) \\
&= \frac{\alpha_0}{\beta_1} + \alpha_1 \sum_{i=0}^{\infty} a_{t-1-i}^2 \beta_1^i
\end{aligned}$$

- **T-GARCH model:**

Financial investors' decisions are greatly influenced by news, events, and incidents. Therefore, have an unequal impact on global financial markets as a result.

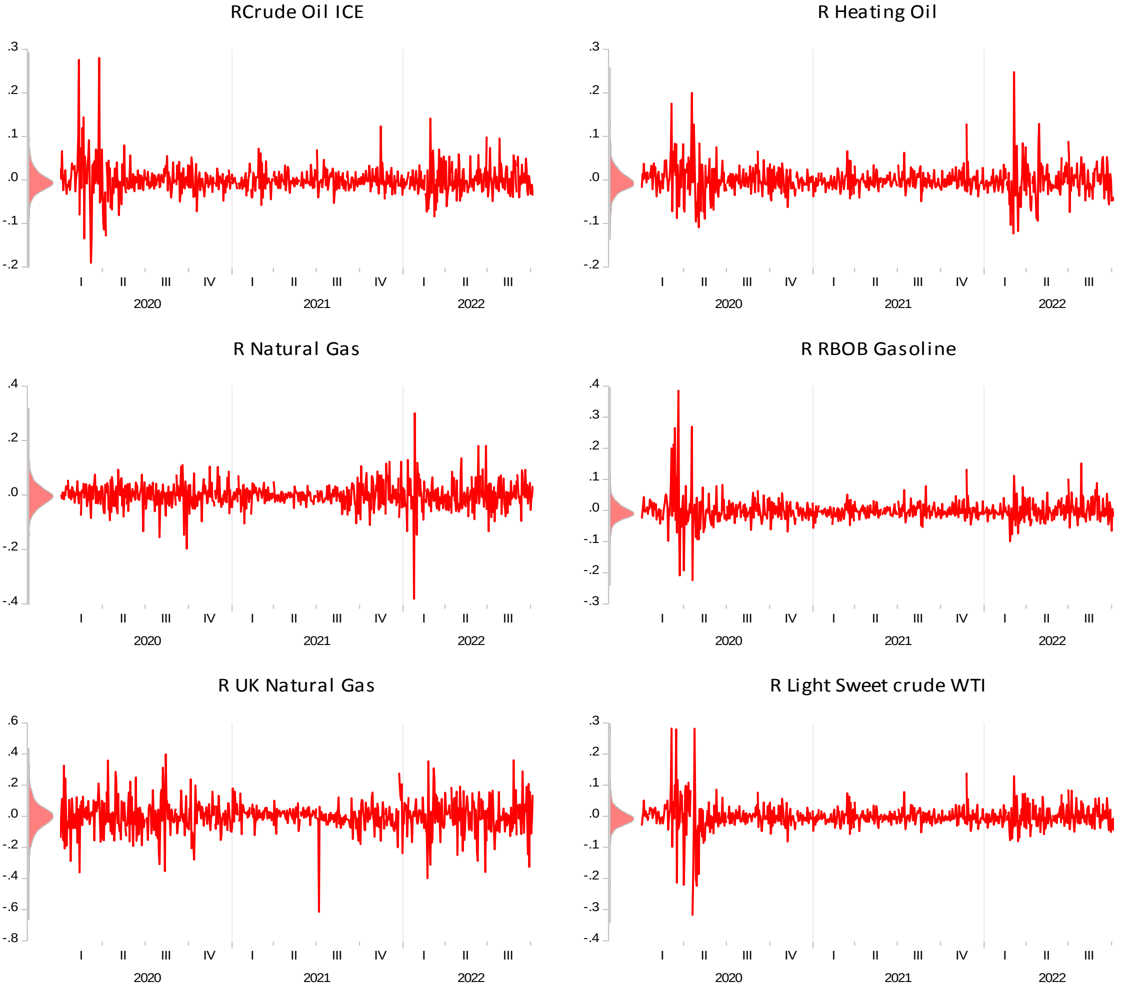
A standard ARCH and GARCH model treat bad news (negative shock ) and good news (positive shock ) symmetrically. There is impact on asset volatility ht is the same. A significant positive or negative shock will have exactly the same magnitude in the series' volatility according to ARCH/GARCH models. Positive and negative news can have different effects on markets or financial assets, though.

Using the Threshold GARCH (T-GARCH) model developed by Zakoian in 1990 and Glosten, Jagannathan, and Runkle in 1993, econometricians have developed methods to capture the impact of the instability on financial assets as the financial market has grown more fragile. This model's primary objective is to identify imbalances in terms of negative/positive shocks. To test whether there is a statistically significant difference between positive and negative shocks, a multiplicative dummy variable must be added to the variance equation when using the T-GARCH model.

The TGARCH model was developed to identify the effects of leverage on financial markets. It also takes into account the possibility that unexpected information shocks could affect stock return volatility. (Mahajan & Thakan, 2022). The following is the conditional variance for the TGARCH model. (Francq & Zakoian, 2019)

## 3. Results

**Figure number (2): Returns volatility plots**




**Source:** Author.

Returns are the most recommended metric for determining price volatility. The figure 02 represents the returns of six energy commodities. For all the variables except

UK natural gas, it is clear to see that there is a sizable cluster of returns in the first semester of 2020, and during the years 2020 and 2021, there is a cluster of lower returns. It is also evident that the previously mentioned crisis periods cause a rise in conditional volatility, whilst the generally normal periods cause a fall in conditional volatility.

**Table number (3): Descriptive statistics**

| | RCO | RHO | RNG | Gasoline | RUKNG | RWTI |
|---|---|---|---|---|---|---|
| Mean | **-0.000655** | **-0.001381** | **-0.001610** | **-0.001157** | **0.000119** | **-0.001463** |
| Median | -0.003903 | -0.003408 | -0.002182 | -0.004325 | 0.002053 | -0.002997 |
| Std. Dev. | **0.053845** | **0.031362** | **0.046442** | **0.038235** | **0.101879** | **0.061522** |
| Skewness | 1.571351 | 1.003447 | -0.336747 | 2.006597 | -0.318077 | -0.012818 |
| Kurtosis | 18.93707 | 11.80793 | 12.73367 | 26.88613 | 6.786391 | 20.89597 |
| | | | | | | |
| Jarque-Bera | 7641.142 | 2363.211 | 2756.772 | 16988.49 | 426.8878 | 9274.378 |
| Probability | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |

**Source:** Author.

Having a fundamental grasp of the data series is a must before processing the data (Descriptive characteristics). Table 01 shows an overview of descriptive information for the six returns series. The mean, Standard deviation as well as Jarque-Bera; skewness and Kurtosis are included. With the exception of UK natural gas, all the examined variables' means are negative, which is consistent with the market for energy commodities. This finding explains why the variables performed poorly, in other word the declining value throughout the chosen time period was indicated by the negative mean of returns. Additionally, the standard deviation, which was distributed between 10.18%and 3.13% percent, indicated greater volatility across the entire period. Moreover, the skewness indicates that the returns series are positively/negatively skewed, which means that the data has a tail on both the right and left sides. As a result, the data have a prominent peak since the value of Kurtosis is greater than the value of the standard distribution (3). The alternative hypothesis is accepted since the last characteristic Jarque-Bera value is higher than the average distribution value (5.88). Hence, the Returns series appeared to follow a skewed distribution with positive/negative skewness rather than the normal distribution.

- **Data Stationarity**

**:(03( Table numberUnit root test results table (ADF)**

| At Level | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variables** | | **RCO** | **RHO** | **RNG** | **GASL** | **RUKNG** | **RWTI** |
| With Constant | t-Statistic | -24.1741 | -11.2059 | -12.4481 | -5.1865 | -20.099 | -25.7277 |
| | Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | | *** | *** | *** | *** | *** | *** |
| With Constant & Trend | t-Statistic | -24.1684 | -11.2972 | -12.4464 | -5.1869 | -20.091 | -25.7073 |
| | Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0000 |
| | | *** | *** | *** | *** | *** | *** |
| Without Constant & Trend | t-Statistic | -24.1806 | -11.1786 | -12.3827 | -5.1696 | -20.113 | -25.7364 |
| | Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | | *** | *** | *** | *** | *** | *** |

**Source:** Authors.

Given that the GARCH model assumes that the data will be stationary; testing stationary is an important component of modelling. According to P-value in Table 02, which is less than 5% under the ADF test and Akaike information criteria (AIC), the returns series is stationary. We evaluated the stationary at the first difference to make sure that there is no white noise present in the data series before fitting our data to the GARCH model.

**Table 03. Data stationary at the first order (ADF)**

| At First Difference | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | d(RCR) | d(RHO) | d(RNG) | d(GASL) | d(RUKNG) | d(RWTI) |
| With Constant | t-Statistic | -10.4473 | -11.3965 | -12.6501 | -10.7536 | -10.6214 | -8.9203 |
| | **Prob.** | **0.0000** | **0.0000** | **0.0000** | **0.0000** | **0.0000** | **0.0000** |
| | | *** | *** | *** | *** | *** | *** |
| With Constant & Trend | t-Statistic | -10.4394 | -11.3864 | -12.6450 | -10.7450 | -10.6132 | -8.9773 |
| | **Prob.** | **0.0000** | **0.0000** | **0.0000** | **0.0000** | **0.0000** | **0.0000** |
| | | *** | *** | *** | *** | *** | *** |
| Without Constant & Trend | t-Statistic | -10.4553 | -11.4009 | -12.6597 | -10.7607 | -10.6282 | -8.9084 |
| | **Prob.** | **0.0000** | **0.0000** | **0.0000** | **0.0000** | **0.0000** | **0.0000** |
| | | *** | *** | *** | *** | *** | *** |

**Source:** Author

According to the P-value equal zero, or less than 1% of significance, the table 03 shows that the returns series can be regarded as stationary and free of white noise at the initial difference, which suggests to accept the alternative hypothesis.

**Table 04. Heteroscedasticity Test**

| ARCH TEST | C-oil | H. OIL | N. Gas | Gasoline | UKNG | LSWCR |
|---|---|---|---|---|---|---|
| Obs*R-squared | 37.70 | 26.20 | 0.21 | 55.86 | 18.80 | 16.25 |
| Prob. Chi-Square(1) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Source:** Author**.**

GARCH models are designed to capture the oscillations of heteroscedastic data, means it is essential to validate the data's heteroscedasticity before using it for modelling, which is possible using the ARCH effects test because ARCH effects only appear in heteroscedastic data.

The ARCH effect's pattern involves an initial large fluctuation followed by a second large fluctuation; Another pattern that the ARCH effect follows is one in which a very slight variation is typically followed by another very slight fluctuation. The ARCH-LM test is used in this study to examine the ARCH effects in the return's series. The ARCH-LM test's null hypothesis states that there are no ARCH effects in the data series, hence the null hypothesis should be disregarded if the P-value is less than 5% of significance. The Prob-Chi Square is significant in Table 04, which indicates the outcome of the ARCH-LM test return series. This signifies that the null hypothesis should be rejected at a significance level of 1%, indicating that the data series has an ARCH effect and that GARCH models can be used.

**Table number (5): Threshold GARCH model Crude oil, Heating-oil and Natural Gas**

| **TGARCH** | | **Crude oil** | | **Heating Oil** | | **Natural Gas** | |
|---|---|---|---|---|---|---|---|
| C (Omega) | | 2.32E-05 | | 04.10E-05 | | 1.91E-05 | |
| RESID(-1)^2 (Alpha) | | 0.219324 | | 0.312963 | | 0.122646 | |
| RESID(-1)^2*(RESID(-1)<0) (Gamma) | Prob | -0.1034 | 0.000 | -0.0879 | 0.000 | -0.0533 | 0.000 |
| GARCH (Beta) | Prob | 0.8230 | 0.000 | 0.7141 | 0.000 | 0.9062 | 0.000 |

**Source:** Author**.**

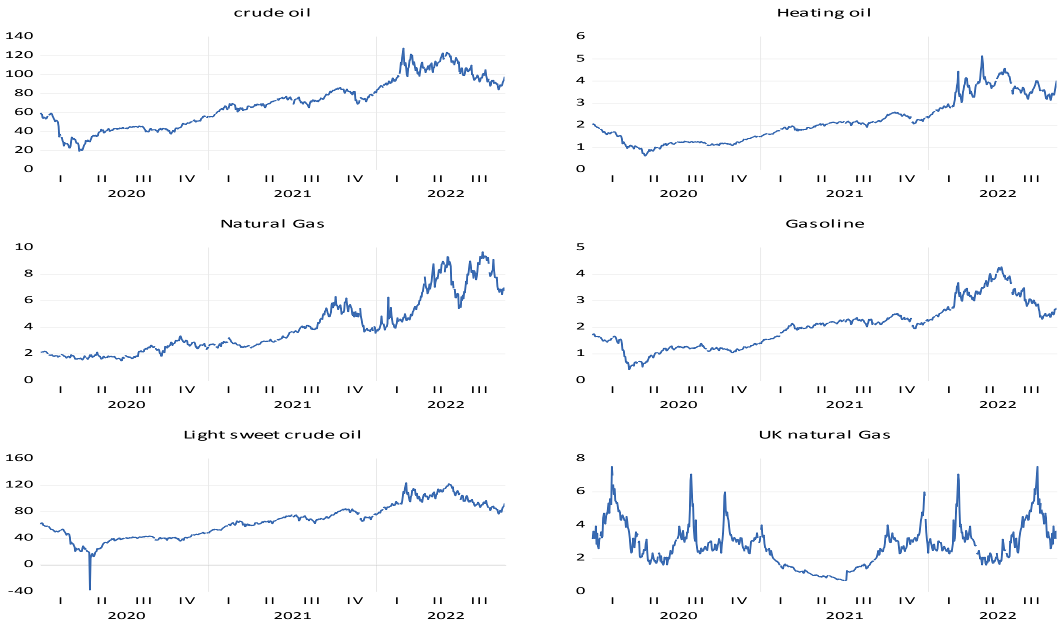
**Table number (6): Threshold GARCH model Gasoline, UK Natural gas and Light sweet crude**

| TGARCH | | RBOB Gasoline | | UK N.Gas | | Light Sweet.C | |
|---|---|---|---|---|---|---|---|
| C (Omega) | | 2.62E-05 | | 0.001729 | | 3.13E-05 | |
| RESID(-1)^2 (Alpha) | | 0.1736 | | 0.131887 | | 0.303233 | |
| RESID(-1)^2*(RESID(-1)<0)(Gamma) | Prob | -0.0775 | 0.000 | 0.1682 | 0.000 | -0.2057 | 0.000 |
| GARCH(-1) (Beta) | Prob | 0.8510 | 0.000 | 0.6360 | 0.000 | 0.7909 | 0.000 |

**Source:** Author.

At a 1% level of significance, the variance equation's coefficients are all statistically significant. The negative gamma coefficient indicates that the model's results cannot be used to infer anything about the leverage effect. In other words, the volatility of the pricing of energy commodities is less affected by negative news than by good news. The price behaviour throughout the chosen period serves as evidence for this result.

**Figure number (3): The Prices behaviour**




**Source:** Author.

It is evident that the prices of energy commodities have increased overall, with the exception of the first quarter of 2020, when they declined due to difficulties from the Covid-19 pandemic. Overall, we can conclude that the price series saw more positive shocks than negative ones, in the case of the oil-exporting countries.

**Table number (7). Forecasting Volatility using GARCH (1.1) crude oil, Heating oil and Naturak gas**

| Performance on MAE | | | | | | |
|---|---|---|---|---|---|---|
| **GARCH (1.1)** | Crude Oil | | Heating Oil | | Natural Gas | |
| | 9M | 2Years | 9M | 2Years | 9M | 2Years |
| | 0.024 | 0.020 | 0.029 | 0.018 | 0.036 | 0.045 |
| Performance on RMSE | | | | | | |
| | 0.033 | 0.034 | 0.041 | 0.028 | 0.049 | 0.030 |

**Source:** Author**.**

**Table number (8): Forecasting Volatility using GARCH (1.1) Gasoline, UK natural gas and Light sweet crude oil**

| Performance on MAE | | | | | | |
|---|---|---|---|---|---|---|
| **GARCH (1.1)** | Gasoline | | UK N.GAS | | WTI C.O | |
| | 9M | 2Years | 9M | 2Years | 9M | 2Years |
| | 0.024 | 0.022 | 0.091 | 0.064 | 0.026 | 0.023 |
| Performance on RMSE | | | | | | |
| | 0.035 | 0.041 | 0.122 | 0.094 | 0.033 | 0.043 |

**Source:** Author**.**

- **Performance comparison under MAE and RMSE**

The mean absolute error gauges how accurately a forecasting technique makes predictions, the MEP equation given by:

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{A_k - F_k}{A_k}\right|$$

A quadratic scoring mechanism known as the RMSE determines the average error's magnitude.. The equation of the RMSE is as bellow:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \overline{x_i})^2}{N}}$$

The variation in mistakes in a group of forecasting methods can be diagnosed by combining the RSME and the MAE.
The outcome demonstrates a slight variance between MAE and RMSE, which translates to a slight fluctuation from the real values between the returns.

## 4. Discussion

The primary aims of the current study were multiple. The initial task was examining the impact of the successive shocks caused by Covid-19 and Ukraine war complications on energy commodities prices; Crude oil, Natural Gas, UK Natural Gas, Gasoline, Heating oil and WTI light sweet crude oil. The second task is comparing the volatility forecasting using Mean absolute error (MAE) and Root mean square error under GARCH (1.1) model. The study covered the period of 03rd January 2020 to 07th October 2022, the time period is split into two major time periods; the first one covers the Covid-19 pandemic from 03rd January 2020 to 31st December 2021, the second covers 9 months from 2022 which includes the Ukraine war crisis. Due to the presence of ARCH effects, the study concluded that the returns series' volatility is interestingly heteroscedastic. The T-GARCH model was used to examine the impact of leverage on the return series. One can observe that the majority of the model parameters are positive Omega and Alpha , which is required to obtain a positive conditional volatility. The negative correlation between the shocks to the return and subsequent shocks to volatility is explained by the leverage effect shown on Gamma, which was negative. In other words, the negative leverage effect brought on by the fact that future volatility is far more influenced by negative than positive returns. The results of utilizing GARCH (1.1) to forecast volatility revealed a negligible difference between the MAE and RMSE for the chosen periods. These results account for the little variation in returns over a period of 2 years and 9 months.

## Conclusion

In the midst of growing difficulties like high inflation rates, tightening monetary policies by prominent central banks, rising interest rates, and persistent supply chain problems, global economic growth has entered a phase of severe uncertainty and deteriorating macroeconomic conditions. Furthermore, there is still uncertainty regarding geopolitical threats, COVID-19-related lockdown extensions, and pandemic flare-ups in the Northern Hemisphere throughout the winter. Countries around the world are experiencing a dual shock from energy prices: first, the collapse of oil prices during the Covid-19 epidemic era, followed by a rapid increase in prices due to issues from the Ukraine war. The main objective of the research was testing the reaction of the energy returns against the dual shocks in the last two years using T-GARCH model and forecasting volatility modelling. The primary findings of the empirical study indicated a negative correlation between the return’s shocks and subsequent shocks to volatility. We can explain these results firstly, by the consequences of Covid-19 pandemic when the oil prices fallen down dramatically; the primary causes of this collapse are the adverse supply shock caused by a direct reduction in labour as a result of virus infection among the workers, and indirectly as a result of travel restrictions, quarantine, as well as supply being impacted by lower levels of resources, capital, and intermediate inputs owing to interruptions in global trade and business in all countries. On the other hand, the global economic downturn and the disruption of global value chains have resulted in a decrease in demand for energy products, particularly for gasoline, natural gas, and the most commonly utilized energy commodities, which include oil. The recovery in energy prices following the Covid-19 Pandemic was the subject of the second part of this study. Commodity prices increased during the first quarter of 2022 due to the impact of the Ukraine conflict, ongoing demand growth, and a variety of supply-side constraints. Since the beginning of the year, energy costs have risen significantly across the board. Some commodities, including coal, natural gas, gasoline, and crude oil, reached record highs in March 2022. Sanctions against the import of Russian energy were issued by a number of nations, including Canada, the United States, and the United Kingdom. Some energy-producing firms also indicated that they would stop doing business in Russia.; and due to the challenges in getting insurance on shipments or conducting transactions, several dealers decided to stop trading in Russia oil. To sum up, we can say that due to Russia's position as a major exporter of gas and oil, energy prices have experienced particularly considerable increases. The price of Brent crude oil is now anticipated to average $100 per barrel in 2022, a year-over-year increase of 42%; however, the price of European natural gas is projected to double, leaving it ten times higher than it was in 2020; prices are therefore anticipated to remain 31% above pre-war forecasts.

- **Research limitation**

The content of this study has to be seen in light of some limitations such as the collection of the data that includes only the energy commodities that are highly vulnerable to the global instability in financial market, since the econometric models we used (GARCH &T-GARCH) are suitable only for the high volatility time series.

- **Future research**

After a thorough analysis of data, the following recommendations are hereby made:

- ✓ The relationship between the energy security and food security;
- ✓ The transition to the renewable energies for oil-importing countries;
- ✓ The impact of energy security on increasing poverty in the world**.**

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