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Forecasting stock market volatility using GARCH models: A comparative study of the U.S. and Saudi markets

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ABSTRACT

The paper analyzes the volatility trends of the Saudi Arabian Tadawul All Share Index (TASI) and the S&P 500 index, focusing on the COVID-19 pandemic as a key market shock. The analysis incorporates daily stock return data covering the period from January 2015 to May 2025. The volatility of emerging and developed markets is examined through EGARCH and GARCH approaches to study characteristics such as volatility clustering and asymmetry. The effect of the pandemic is directly embedded by introducing COVID-19 dummy variables into the models. Empirical findings suggest that both indices are characterized by volatility clustering, and the EGARCH model is more appropriate than the GARCH model for estimating asymmetric volatility, particularly during crisis periods. Additionally, the COVID-19 dummy variable is statistically significant in the EGARCH model, as opposed to the GARCH model. The results support the leverage effect, indicating that negative shocks have a more significant impact on market volatility than positive ones. The S&P 500 showed a faster recovery after the COVID-19 crisis, whereas TASI was slower in mean reversion, indicating structural and behavioral divergence between the markets. This comparative study contributes to the literature by providing a clear picture of volatility dynamics in diverse financial contexts and highlighting the superiority of EGARCH models during crisis periods. The findings offer guidance to policymakers aiming to improve market stability and to investors seeking diversification into both developing and mature markets.

Contribution/Originality: This study contributes to the literature by utilizing sophisticated models such as GARCH and EGARCH to analyze the volatility environments of the Saudi stock market following COVID-19. It extends previous research by capturing the pandemic's long-term, asymmetric effects and provides a comparative analysis with the relatively understudied developed market, the S&P 500.

1. INTRODUCTION

The performance of the financial markets has a substantial impact on the health of a national economy. These markets include a wide range of institutions that promote the trading of financial assets across different sectors such as equity, derivatives, bonds, and money markets. The stock market primarily plays a role in boosting economic growth, especially when used as a pivot of exchange in the sharing of shares among participants. Financial markets also increase liquidity as they allow assets to be converted easily to address imbalances, and they promote the accumulation of capital to finance ventures that foster entrepreneurship and innovation.

An unbalanced short-term relationship between risk and reward is the major cause of asset price fluctuations in the financial markets. This volatility depends on many factors, which include changes in macroeconomic conditions, changes in investors' confidence, changes in policies, and geopolitical events. As a result, the forecasting of volatility is critical in various other financial applications, such as "Value-at-Risk (VaR)" estimation, pricing options, and managing portfolios (Gabriel, 2012). Governments and investors also need to track financial market volatility, particularly during crises or pandemics, like COVID-19. Price volatility is compounded during a bearish market, caused by asymmetric reactions to bad news, which diminishes the efficacy of diversification (Amonlirdviman & Carvalho, 2010). The aftermath of the COVID-19 pandemic is extensively discussed in recent studies, specifically regarding volatility patterns in stock markets. Results also validate the substantial impact the pandemic had on disrupting financial markets, causing above-average volatility levels (Khan, Kayani, Khan, Mughal, & Haseeb, 2023; Pavlyshenko, 2020).

In the modern world of high geopolitical tension, with heightened market uncertainty and global interconnectedness, forecasting the stock markets' volatilities has received considerable attention over the past few years. In developed stock markets, with the U.S. "S&P 500" index being a model, stock indices tend to exhibit higher liquidity and are characterized by regulatory stability. An increased participation by institutional investors, highly complex financial products, and aggressive trading regions contribute to more predictable and consistent volatility patterns. In contrast, emergent markets are marked by a lack of liquidity, excessive volatility, and a high level of structural changes (Raza et al., 2025). Many studies, including Chowdhury, Dhar, and Stasi (2022); Srinivasan (2011); Awartani and Corradi (2005) and Chen (1997) have explored the volatility in the U.S. stock market. There is extensive literature covering this topic. However, the literature related to the dynamics of the Saudi Arabian stock market is comparatively limited.

The study conducts a comparative analysis of volatility between two primary markets: the emerging Market of "TASI" and the developed Market of the "S&P 500" index. It is an empirical investigation examining the time-series characteristics of both markets from January 2015 to May 2025. This period enables the analysis of market behavior during times of turbulence as well as stability. The primary objective is to analyze crisis-driven volatility in an emerging market, which is less extensively researched, in comparison to a developed market, to observe how volatility differs between the two and identify the key distinctions.

To accomplish this, the analysis will use both the "EGARCH" and "GARCH" models to examine volatility in the two markets and determine how volatility in the past will affect future volatility in the markets. "GARCH" models are thought to be more adequate at forecasting and modeling volatility in the stock market than traditional methods, which do not allow for actual variations in the market because they assume a constant variance. "GARCH" models are, therefore, effective in dealing with volatility shifts, clustering, and persistence (Raza et al., 2025).

Moreover, the study aims to determine the best forecasting scheme that can be used to forecast activity in "TASI" and the "S&P 500". It aims to cover the gap regarding the comparative volatility analysis by algebraically furnishing empirical data on the relative volatility of "TASI" versus the "S&P 500", focusing on the impact on the volatility dynamics of both markets impacted by "COVID-19". The following questions are addressed by this study:

1. "To what extent does stock return volatility differ between the emerging Saudi Tadawul All Share Index (TASI) and the developed U.S. S&P 500 index?"
2. "To what extent can the EGARCH and GARCH models effectively capture the volatility dynamics in both markets?"
3. "To what extent did the COVID-19 pandemic influence the volatility dynamics of the TASI and S&P 500 markets?"

The research contributes to understanding volatility behavior by employing "GARCH" and "EGARCH" models to analyze the U.S. "S&P 500" and the emerging "TASI" during the pandemic. The impact of the pandemic is directly incorporated through the introduction of "COVID-19" dummy variables into the models. Additionally, the analysis offers valuable insights into how markets with different structures respond to shocks, providing a comparative view of the developed "S&P 500" and the emerging "TASI". The findings assist investors in anticipating and analyzing the Saudi stock market, thereby enhancing portfolio management, risk mitigation techniques, and educating investors interested in diversifying their portfolios between emerging and developed markets. Furthermore, the results support policymakers in formulating regulatory strategies to maintain market stability and resilience, attracting both domestic and foreign investments.

The research paper is structured into sections, including a review of the literature, a description of the dataset, and the methodological approach used. It is followed by the presentation of empirical findings and the conclusion of the work.

2. LITERATURE REVIEW

It is crucial to be familiar with the theoretical background of volatility modeling and forecasting, as well as the empirical background. The positions of Fama (1995) considered that the efficient market hypothesis (EMH) has a significant effect on how people perceive financial markets. According to the theory proposed by Fama, share prices fully reflect all available information; there is simply no consistent way to achieve an abnormally high rate of return, nor a positive alpha. The Efficient Market Hypothesis indicates that the stock market is rational and that prices reflect all relevant information. This suggests that the market prices of securities are constantly converging towards their intrinsic value. To achieve an excess rate of return, Fama (1970) categorized market efficiency into weak, semi-strong, and strong forms: (1) the weak form, where only historical information is considered because it has already been incorporated into current stock prices; (2) semi-strong form, where publicly available data is fully reflected in stock prices, making it impossible to predict the market to attain excess returns; and (3) strong form, where all available data, both public and private, are already factored into stock prices, thus preventing the use of any information to generate excess returns.

2.1. Persistent Asymmetric Volatility

Although Fama's efficient market hypothesis implies that predicting stock prices is not possible, further consistent financial market anomalies have been observed. For instance, Warren Buffett, Ben Graham, Peter Lynch, and others have consistently beaten the market over long periods (Hagstrom, 2013). However, the success of Buffett is linked to his unique ability to identify companies with strong fundamentals (Buffett & Clark, 2008). Stock prices are unpredictable, and researchers have investigated alternative approaches to forecast market behavior and understand market trends. Kumar and Thenmozhi (2014) note that two widely acknowledged approaches exist, one based on available information and the other based on past stock price performance. Fundamental analysis relies on economic, financial, and firm-specific factors to assess a stock's value.

Financial markets are inherently volatile and are influenced by various factors, including changing macroeconomic indicators, investor confidence, policy changes, and geopolitical events. A considerable body of research has examined the association between stock returns and volatility, finding that volatility consistently produces a negative alpha, a phenomenon commonly referred to as "asymmetric volatility " (see (Bekaert & Wu, 2000; Zakoian, 1994)).

Numerous origins of asymmetric volatility have been investigated in the literature. According to Black (1976) there is evidence to support the "Leverage Effect," which states that as stock prices decline, a company's debt-to-equity ratio (also known as its leverage ratio) rises, making it a riskier investment and increasing the volatility of stock returns. Daniel, Hirshleifer, and Subrahmanyam (1998) investigate "Investor Behavior" to find evidence that investors' reactions towards negative news are greater, which causes trading activity to increase and share prices to decline more sharply after bad news, resulting in increased volatility (Daniel et al., 1998). Thus, Bekaert and Wu (2000) and other scholars discovered that "Volatility Feedback," in which the expected rise in volatility in the future causes the required rate of return for holding a risky asset this period to rise, causes a fall in share price along with heightened volatility.

2.2. Modelling Choices

In numerous research publications, the "GARCH" models are now frequently used for modeling and forecasting stock market indices. Al Janabi, Hatemi-J, and Irandoust (2010) for instance, used the "GARCH-M model" to assess the volatility and stock market returns of nations in the MENA and GCC regions. In all of the countries considered, empirical results show that volatility is time-varying, or that the level of risk varies over time. Al Rahahleh and Kao (2018) used daily returns data from September 10, 2007, to February 26, 2015, to forecast the "TASI" and the "Tadawul Industrial Petrochemical Industries Share Index (TIPISI)" using an "Asymmetric Power ARCH model." According to the study's findings, the "Asymmetric Power ARCH model" can better describe and predict volatility for two stock indices. Al Rahahleh (2014) investigated forecasting volatility using multiple "GARCH-class models" and the history of the Qatar Stock Exchange (QSE) index. According to the findings, traders, politicians, and foreign investors with an interest in retaining risk in the petrochemical business may want to learn that advanced analysis tools are a resourceful resource.

2.3. Developed Vs Developing Financial Markets

To better understand the risk dynamics in relatively more developed American and European markets, Meher et al. (2024) examine and compare the volatility of three major stock market indices: the Dow Jones Industrial Average (DJIA), the S&P 500 (United States), and the ATX Index (Austria). They use threshold GARCH, exponential GARCH, and Power ARCH models in their analysis to confirm asymmetric volatility (the market exhibits greater response to negative information) and the existence of volatility clustering across all three indices. Moreover, the U.S. markets exhibited more patterns of persistent volatility. Their study highlights the increased accuracy and value of ARCH-based models as tools for forecasting.

Srinivasan (2011) employs two models, namely, Exponential GARCH (1, 1) and Threshold GARCH (1, 1), to build a forecast and simulate volatility of the U.S. stock market using the returns of the S&P 500 Index in 1996-2010. Their findings not only prove that there is an influence effect that suggests negative news causes greater fluctuations in stock values compared to positive news. Although the leverage effect exists, when the analysis is conducted, a symmetric GARCH model becomes more competent to forecast volatility in the S&P 500 returns compared to complex asymmetric models. This result is relevant to the study conducted by Gokcan (2000) who studied the returns daily at seven distinct stock markets in several nine-year periods (from 1988 to 1996). The study found that the symmetric version of the "GARCH model" performs better than the asymmetric version concerning the forecasting of the conditional variance and has also employed the linear form of the "GARCH(1,1)" and non-linear (EGARCH) forms of the "GARCH model". In the same light, Goudarzi and Ramanarayanan (2010) employed both the "ARCH and GARCH models" to study the daily closing prices of the Indian BSE 500 stock index between 2000 and 2009 to determine the volatility of the Indian stock market, and found that the "GARCH(1,1) model" provides the best model that explains the volatility of the BSE.

However, Gabriel (2012) assessed the volatility in the stock market of Romania. Specifically, the paper employed some "GARCH-type" specifications to estimate the daily returns of the Romania-based "Bucharest Exchange Trading Index (BET)" index from March 9, 2001, to February 29, 2012. Their results inferred that the "Threshold GARCH (TGARCH) model" is the best in predicting the BET index. Similarly, Tripathy and Garg (2013) have also estimated the volatility in six evolving economies of Asia and South America, specifically in China, Brazil, India, Russia, Mexico, and South Africa, between 1999 and 2010, leveraging the "ARCH, GARCH, GARCH-M, EGARCH, and TGARCH" models. To aid the leverage effect, the analysis has determined the asymmetry in the market returns in all the countries, which means that negative news events, or the so-called negative shocks, can make the stock prices move more significantly. Based on the study, investors should study the previous news when developing their portfolios in an attempt to determine future trends.

In the same manner, Kumar et al. (2023) chose May 1993 to March 2023, applied a series of "GARCH-related models," for instance, the following: "GARCH (1,1)," "GJR-GARCH," "EGARCH," "TGARCH," and "MGARCH." They find evidence that the leverage effect is present and that it can explain the volatility of the Brazilian stock markets, whose index is the IBOVESPA. Their study confirms the presence of a leverage effect, asymmetric volatility, and volatility clustering, the latter applied in the context that negative shocks could have a significant impact on stock prices. Most significantly, the findings point to an unequal response to information, indicating the extreme impact of news on volatility, supporting previous research that volatility responds asymmetrically to information shocks. In other words, for future volatility, good and bad news have different predictability (Engle & Ng, 1993).

In financial decision making, one of the most significant tasks is accurate prediction of volatility. Hybrid models, which integrate GARCH-type models and artificial neural networks, have shown outstanding performance gains. In this regard, Koo and Kim (2022) employed 16 financial indices and proposed a hybrid model (VU-GARCH-LSTM), mitigating concentration property of volatility, and transforming pointed and extremely left-biased volatility distribution to a volume-upped distribution shifted to the right. This hybrid model obtained 21.03% performance gain compared to existing hybrid models combining GARCH and LSTM. When GARCH and LSTM models are compared for forecasting volatility, previous research has shown that overall GARCH models had performed slightly better than LSTM models; however, in predicting the index volatility's direction, both models fared equally well. On the other hand, in predicting the value of volatility, GARCH models outperformed the LSTM model (Mahajan, Thakan, & Malik, 2022). Sharma (2016) evaluates the capability of several models to predict volatility. Unlike the classic "GARCH," which uses only daily returns, the paper considers "GARCH." This study examines the conditional variance of 16 worldwide stock indices over 14 years. According to the researchers, the performance in a forecasting comparison between the "GARCH" and "EGARCH" models is nearly dependent on the selection of the loss criterion.

Previous research, investigating the major global stock indexes (S&P 500, NIKKEI 225m Hang Seng Index, and FTSE 100) volatility dynamics have underscored the significance of using advanced GARCH models, such as TGARCH to predict volatility accurately in global financial markets, where TGARCH is found effective in addressing asymmetries (Marisetty, 2024). Generally, to capture volatility series, the ARMA-GARCH model is used, with Granger causality examining the causal directions. Lim, Goh, Sim, Mokhtar, and Thinagar (2023) in the context of FTSE, Stock Exchange of Thailand (SET), Indonesian LQ45, and Bursa Malaysia KLCI, found EGARCH model as the best-fitted in estimating volatility. The study also explained higher volatility during the period of financial crisis. It shows that forecasting stocks' volatility is crucial for investors since it enables them to quantify related trading risks. Research has also shown that the combination of ARIMA and GARCH models could result in improved prediction. For instance, Rubio, Palacio Pinedo, Mejía Castaño, and Ramos (2023) assessed that to address linear and non-linear patterns in volatility timeseries, hybrid models (wavelet ARIMA and GARCH) could be effective. These models can be optimized for executing fast predictions, detecting arbitrage and market opportunities and reducing risks.

Recent years have seen numerous studies devoted to the aftermath of the COVID-19 crisis, particularly on the volatility patterns (Khan et al., 2023; Khan & Khan, 2021; Ncube, Sibanda, & Matenda, 2024; Ouchen, 2023; Petkov, Shopova, Varbanov, Ovchinnikov, & Lalev, 2024; Zhang, Hu, & Ji, 2020). To illustrate, the paper by Khan et al. (2023) used the "GARCH (1, 1)", "GJR-GARCH (1, 1)", and "EGARCH (1, 1)" models in a study of daily returns between November 2018 and June 2021. They further used six financial resources: *"cryptocurrency, exchange rate, stock index, metal, oil, and agriculture."* It was revealed that in all the studied markets, volatility persistence was high during the COVID-19 epidemic. Ouchen (2023) oppositely, makes some predictions of daily returns of five of the major indexes and, of course, "S&P 500", "SSE", "FTSE 100", "CAC 40", "DAX", and "Nikkei 225" before and after COVID-19 using "GARCH" and "EGARCH models". The report indicates that all markets were characterized by market volatility in the wake of the COVID-19 pandemic. The report also reveals that among all the markets discussed, the Frankfurt stock market was the most resilient.

Zhang et al. (2020) investigated the connection between stock market volatility and returns in China and advanced countries around the world. It investigates how COVID-19 affects volatility patterns and explores the implications for China's stock market. The study employed the TGARCH model. The findings indicate significant volatility within each month of 2020. The study demonstrates fat-tailed return distributions by confirming the existence of a leverage effect, highly erratic intraday market movements. Similarly, Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020) show that COVID-19 had a detrimental impact on the Chinese stock market, pointing out that all businesses incurred losses during the epidemic.

Moreover, Alfaro, Chari, Greenland, and Schott (2020) stated that COVID-19 significantly impacted U.S. stock returns negatively. Similarly, Petkov et al. (2024) tried to document how COVID-19 affected the volatility pattern of the SOFIX index of Bulgarian stocks. The study also looked at the impact of the financial crisis of 2008. The empirical data captures the financial crisis and the COVID-19 epidemic and includes daily closing prices from 2000 to 2024. Utilizing "GARCH," "EGARCH," "IGARCH," "CGARCH," and the "GJR-GARCH," the study investigated share price trends.

Focusing on the context of Saudi Arabian financial markets, prior studies have primarily focused on stock price behavior in response to volatility in oil prices (Hammoudeh & Aleisa, 2004; Onour, 2007). Yet, little research has investigated the dynamics of volatility and return within the Saudi stock market. A few studies, such as Al Rahahleh (2014), have attempted to forecast the volatility of the Saudi stock market using an advanced model specification, such as GARCH models; however, the analysis was conducted before COVID-19 and does not capture crisis-induced volatility. While Wasiuzzaman (2022) attempted to investigate the impact of COVID-19, the study was limited to data from December 2019 to July 2020. It relied only on the "GARCH(1,1) model," which restricts its ability to fully capture the prolonged and asymmetric impact of the pandemic. Furthermore, comparative analysis on volatility between emerging markets such as Saudi Arabia and developed markets, such as the "S&P 500," remains scarce, and none appear to address the post-pandemic period using advanced models like "GARCH" and "EGARCH."

Recent studies have utilized AI tools to develop effective volatility prediction models. Chen and Hu (2022) is one of those studies which developed and compared stock index volatility prediction models based on AI's synergic use, such as long short-term (LSTM) network, artificial neural network (ANN) and auto-encoder (AE). It is argued that conventional models like GARCH and AR models rely critically on data quality. Thus, the study applied a variety of AI techniques on financial trading data of the US and China and compared models' performances in predicting stock volatilities and observed that all AI models outperformed EGARCH in predicting stock returns' volatility.

3. DATA AND RESEARCH METHODOLOGY

3.1. Sample Data

This empirical analysis leverages a large dataset of daily stock returns covering the period from January 2015 to May 2025. The study period was carefully chosen because it encompasses several significant global and regional events that had a substantial impact on financial markets. These include the oil price crash, the Brexit referendum, the China-U.S. trade tensions, and most importantly, the COVID-19 crisis. The pandemic is regarded as a turning point event during this period, with a profound impact on stock markets worldwide, including those in Saudi Arabia and the U.S. "TASI" declined into large losses at this time, mainly because of declining oil prices and the ambiguity regarding the economic implications of the pandemic. At the same time, the U.S. stock market experienced greater volatility as the "S&P 500" lost more than 34% of its value within three months of the pandemic, caused by significant selling activities as investors turned pessimistic following the pandemic (Statista Reports). Hence, this is an appropriate period to forecast stock market volatility. During this period, the study would be able to accommodate different market behaviors because it captures volatile and steady periods and provides insights into how different markets react to uncertainty, including emerging economies and developed economies.

In analyzing stock market volatility, it uses the daily log returns of two indices. The sample involves the use of time series data on the "TASI" of Saudi Arabia, as well as the "S&P 500" index of the U.S. stock market. Closing prices of the "TASI" have been obtained through the Tadawul site and the Ticker chart. Its closing prices on the U.S. "S&P 500" have been gathered daily from Investing.com. These two indices were chosen to reflect two considerably different kinds of markets, with "TASI" being an emerging market that has a significant connection to the oil industry, and "S&P 500" being a developed market that is more mature and advanced.

Table 1. Descriptive statistics.

LOG_RETURN	S&P 500	TASI
Mean	0.0004	0.0001
Median	0.0007	0.0006
Maximum	0.0909	0.0712
Minimum	-0.1277	-0.0868
Std. Dev.	0.0115	0.0105
Skewness	-0.6444	-1.0090
Kurtosis	18.5730	12.8180
Jarque-Bera	26595.1000	10837.5500
Observations	2614	2589

Table 1 shows the descriptive statistics of the day-to-day log returns of the "S&P 500" and the "TASI". The statistics help in the selection of the optimum models of volatility forecasting and offer a ground-level comprehension of the pattern of returns. Descriptive statistics of the "S&P 500" showed that the mean daily returns were higher (0.0004) than those of the "TASI" (0.0001), which indicated that the U.S. equities market has performed better between 2015 and 2025. The results of the U.S. index are more erratic and diverse, as shown by the higher standard deviation (0.0115) compared to the "TASI" (0.0105). The maximum and minimum values of the "S&P 500" are greater than the "TASI". This illustrates the "S&P 500"'s notable variability over the study period. The significantly lower skewness of the "S&P 500" (-0.6444) and "TASI" (-1.009) indicates that their returns are more extreme in the negative direction. However, the "TASI's" more prominent left skewness shows that the Saudi market is more likely to see downward price movements. The kurtosis for both indexes is much higher than the normal benchmark of 3, demonstrating that the "TASI" and "S&P 500" indexes are high-kurtosis series. The large kurtosis for both series indicates leptokurtosis by having thicker tails and sometimes higher peaks, suggesting a greater possibility of either very high or very low returns than usual. The larger kurtosis value of the "S&P 500" implies it is more likely to have extreme events than "TASI".

3.2. Model Specification

Volatility forecasting is the practice of predicting future price changes by analyzing the historical behavior of prices. In this study, the "TASI" and the "S&P 500" are both measured as the first difference of the natural logarithms of daily closing prices, capturing the daily return change in the index. Thus, the daily returns are calculated by Equation 1.

$$R_{m,t} = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

Where $R_{m,t}$ Denotes the daily return on index m (weighted indices for either "TASI" and "S&P 500" at time t. The variable ln (·) refers to the natural logarithm function, where P_t is the closing price on trading day t (the current trading day), and P_{t-1} Is the closing price on the previous trading day. Equation 1 offers several advantages. Log returns can be used to represent growth in scenarios involving many time frames because of their time additivity.

Further, when compared to simple returns, log returns are frequently more normally distributed, which aids statistical models intended for volatility predictions. Additionally, using log returns is simpler mathematically, especially when dealing with ongoing compounding and when employing models like ARCH, GARCH, EGARCH, and GJR-GARCH.

The following two charts illustrate the Historical Price Trend for the "S&P 500 and the TASI" indices. Figure 1 shows how the "S&P 500" index climbed steadily from 2015 until the start of the pandemic in late 2019. The pandemic initially produced a rapid 7.6% decline in the index, yet it fully recovered its value by the middle of 2020. This relatively quick recovery revealed the strength of the U.S. equities market to weather significant global economic shocks. This resilience was partly due to the actions taken by policymakers, who built up global public trust in the U.S. financial markets. The sudden index drop and its quick rebound illustrate how developed markets respond positively to monetary policy stimulus and fiscal policy support from the central government.

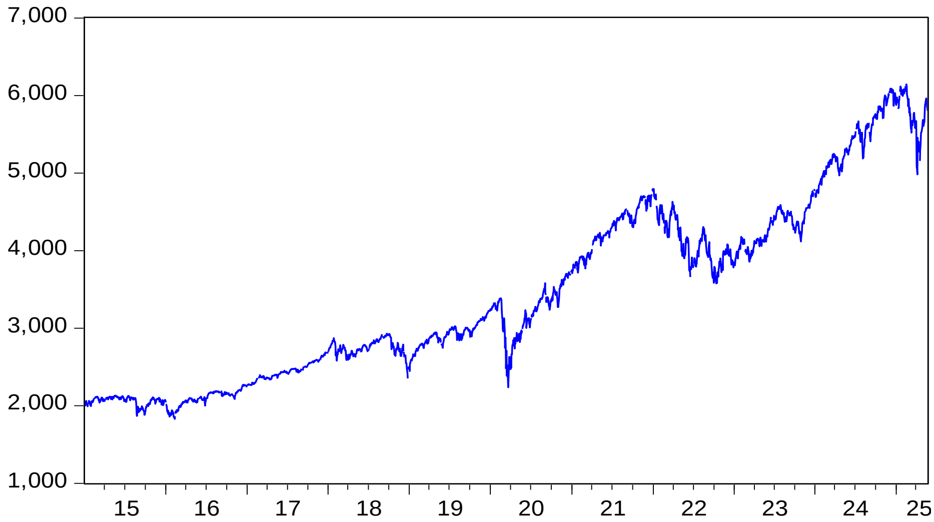

Figure 1. Historical price trend of S&P 500.

In contrast, Figure 2 shows that "TASI" has primarily exhibited modest rises and sporadic declines during this sample period. While the COVID-19 pandemic induced a much larger 31% decline in the "TASI" index value, it recovered the index value in a similar amount of time, taking only a quarter longer to regain its losses.

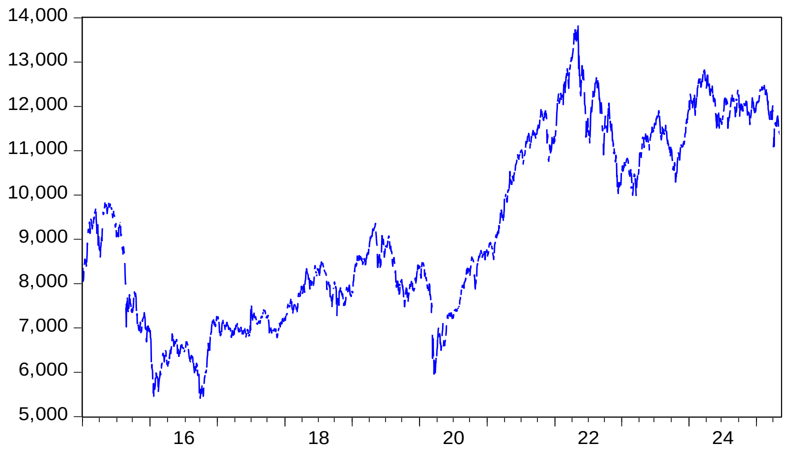

Figure 2. Historical price trend of TASI.

The next two charts illustrate the return fluctuations for the "S&P 500 and the TASI" indices. The plot in Figure 3 reveals how the "S&P 500" log returns exhibit greater volatility in clusters, especially during major economic difficulties such as COVID-19. Extreme volatility can be observed in the return series at times because the U.S. market is strongly affected by events happening across the globe. There is a clear increase in dispersion across stock indexes during the pandemic, mainly due to investor uncertainty and rapid market fluctuations. These observations highlight the importance of having robust volatility models in risk management.

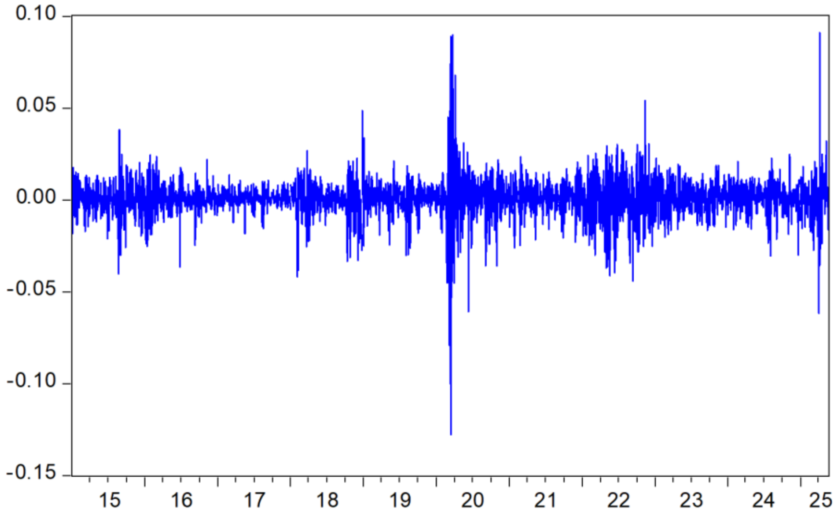

Figure 3. Daily log returns of S&P 500.

Figure 4 shows the daily log return of the "TASI". The frequent and sudden negative spikes in it prove that confidence in the Saudi finance market dropped quickly during stressful moments. Volatility in returns increased markedly during the COVID-19 era. The "TASI" exhibited more negative skews than the "S&P 500", which suggests it has a higher chance of sharp declines when the market is turbulent.

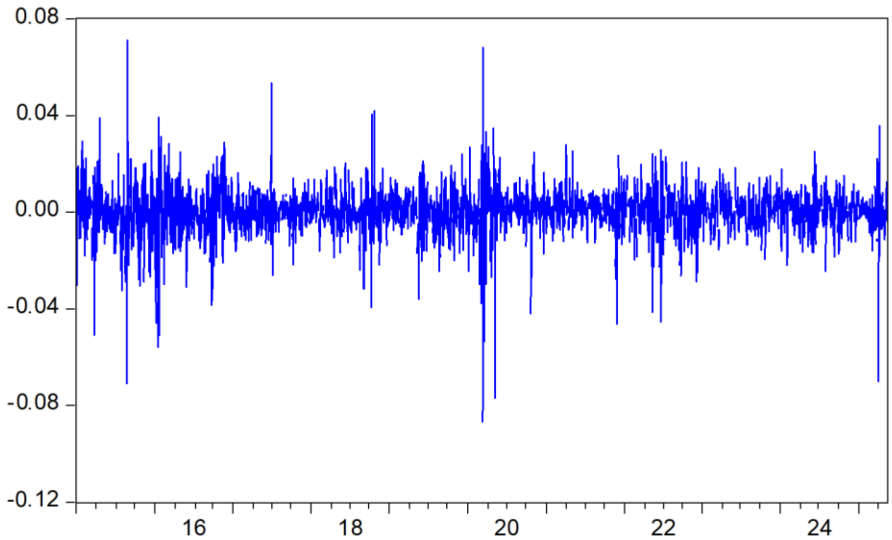

Figure 4. Daily log returns of TASI.

3.3. Data Suitability Testing

The following Table 2 tabulates the "Augmented Dickey-Fuller (ADF)" test results for the data sample. The ADF test is employed to examine the stationary nature of the log returns for the "S&P 500" and the "TASI". A time series must be stationary before it can be used to construct accurate models and forecast volatility (Brooks, 2014; Engle, 1982; Nelson, 1991).

The test statistic for both the "S&P 500" data and the "TASI" data is less than the critical values at the *"1%, 5%, and 10% significance levels"*. Since the null hypothesis is rejected, the log returns for both indices remain stationary at all reasonable significance levels.

Table 2. Stationarity (ADF) test results.

Log_Return	Test specification	ADF statistic	1% CI	5% CI	10% CI	p-value	Stationary	Integrated order
S&P 500	Level	-58.339	-3.433	-2.862	-2.567	0.000***	Yes	I(0)
	Trend	-58.331	-3.962	-3.412	-3.128	0.000***	Yes	I(0)
TASI	Level	-45.431	-3.433	-2.862	-2.567	0.000***	Yes	I(0)
	Trend	-45.427	-3.962	-3.412	-3.128	0.000***	Yes	I(0)

Note: *** indicates the significance level at a 1% confidence interval.

3.4. Rationale for Methodology

The paper examines a series of log returns of the "TASI" and "S&P 500" indices within a time frame that encompasses the COVID-19 outbreak. The research aims to demonstrate the ability of "EGARCH" and "GARCH" models to elucidate market stock volatility.

These two models have been evaluated to determine which one has greater effectiveness in addressing the volatility caused by the COVID-19 pandemic. Therefore, the study employs two models from the "GARCH" family to explore variations in volatility over time in both markets.

The popularity of these models is explained by their capacity to reflect market conditions, such as periods of normal functioning that precede high volatility. Additionally, a COVID-19 dummy variable was used as a metric to examine the pandemic's effects on market volatility. The application of both models will help determine which produces more effective results and provide deeper insights into how financial markets react to stressful situations.

3.5. GARCH Model Specification

Bollerslev created the "Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model" in 1986, leveraged for risk modeling and financial forecasting. The "GARCH model" is a useful model for forecasting stock market volatility since it is a time series model that can account for volatility clustering and responds symmetrically to shocks.

This model is a generalization of the "ARCH model" in that the conditional variance can be conditioned on previous variances and squared shocks. Endri, Aipama, Razak, Sari, and Septiano (2021) applied the "GARCH model" to assess the Indonesian stock market. The equation below represents the GARCH model regression:

Mean Equation:

$$r_t = \mu + \epsilon_t \quad (2)$$

Where:

- μ = Constant Term.
- ϵ_t = Error term at time t.

Variance Equation

$$(h_t) = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \delta COVID_t \quad (3)$$

Where:

- ω: Constant term.
- α: ARCH term (Effect of recent shocks).
- β: GARCH term (Effect of past variance).
- δ: Coefficient on the COVID-19 dummy variable.

3.6. EGARCH Model Specification

To improve upon the "GARCH model", Nelson (1991) came up with the "Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model" that rectifies some of the shortcomings of the former. The "EGARCH model" provides improved estimates of impact when the sample includes high-volatility time periods since this model offers better capture of the irregular impact of market shocks.

Further, in the estimation of conditional variances, the "EGARCH model" has provisions for the introduction of new lags. The "EGARCH model" is a practical tool that may be utilized in an analysis of financial time series because it allows the finding of volatility clustering and distinct reactions to market news, both favorable and unfavorable. Brooks (2014) asserted that the "EGARCH model" indicates that adverse information increases volatility in the market when compared to positive information.

It is, therefore, useful in planning, as well as understanding the trends more insightfully. The "EGARCH model" has the regression formula as shown below:

Mean Equation:

$$r_t = \mu + \epsilon_t \qquad (4)$$

Where:

- μ = Constant Term.
- ϵ_t = Error term at time t.

Variance Equation:

$$\ln(h_t) = \omega + \alpha \left|\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma\left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta \ln(h_{t-1}) + \delta COVID_t \qquad (5)$$

Where:

- h_t = Conditional variance at time t.
- ω = Constant term.
- α = Coefficient of magnitude effect.
- γ = Leverage effect.
- β = Persistence parameter.
- $COVID_t$ = Dummy 1 for the COVID-19 time period otherwise 0.

δ: Coefficient on the COVID-19 dummy variable.

4. EMPIRICAL RESULTS AND MODEL COMPARISON

Table 3 displays the outcomes of the "GARCH model" for the "TASI". These findings show that the "constant term (C)" in the mean equation is statistically insignificant. The findings in the variance equation indicate that the "GARCH" term GARCH(-1) and the ARCH term RESID(-1)^2 are both statistically significant at the 1% level. Short-term volatility clustering is evident from the value of the ARCH coefficient estimate (0.150), which shows that past squared residuals significantly impact current volatility.

The persistence in volatility is captured by the "GARCH" coefficient estimate of 0.600. This implies that, although not as slowly as in models with very high persistence (e.g., values above 0.9), volatility shocks do diminish over time. A stable variance process and the suggestion that volatility does not last forever are indicated by the "ARCH" and "GARCH" coefficients (0.75) added together being less than 1.

It is interesting to note that the DUMMY_COVID variable, which was designed to measure how the COVID-19 period affected volatility, is utterly irrelevant. This suggests that the model finds no discernible volatility impact attributed to COVID-19 after adjusting for the "ARCH" and "GARCH" effects.

Table 3. TASI GARCH model results.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
μ	0.000	0.001	0.188	0.851
	Variance equation			
ω	0.000	0.000	3.125	0.002***
RESID(-1)^2	0.150	0.052	2.877	0.004***
GARCH(-1)	0.600	0.121	4.971	0.000***
DUMMY_COVID	0.000	0.000	0.000	1.000
Log likelihood	7687.914			
Durbin-Watson statistic	1.775			
Akaike Information Criterion	-5.935			
Schwarz criterion	-5.924			
Hannan-Quinn criterion.	-5.931			

Note: *** indicates the significance level at a 1% confidence interval.

The "EGARCH model" findings for the "TASI" are shown in Table 4, and they show that the "constant term (C)" in the variance equation (ω = -0.667) is substantial and negative. The magnitude effect (α = 0.268) is statistically significant and positive, suggesting that shock size, independent of direction, significantly affects volatility. There is asymmetry in the volatility process, as evidenced by the statistically significant and negative leverage effect (γ = -0.119). In particular, negative shocks heightened volatility more than good news, which is in line with both empirical expectations and financial theory.

Table 4. TASI EGARCH model results.

Variable	Coefficient	Std. error	z-statistic	Prob.
μ	0.000	0.000	1.613	0.107
Variance equation				
ω	-0.667	0.058	-11.535	0.000***
α	0.268	0.016	16.534	0.000***
γ	-0.119	0.009	-13.078	0.000***
β	0.951	0.005	180.878	0.000***
δ	0.025	0.006	4.126	0.000***
Log likelihood	8571.990			
Durbin-Watson statistic	1.775			
Akaike Information Criterion	-6.617			
Schwarz criterion	-6.604			
Hannan-Quinn criterion.	-6.612			

Note: *** indicates the significance level at a 1% confidence interval.

A high degree of volatility persistence is indicated by the persistence parameter (β = 0.951), which is close to one. It reflects that volatility shocks have a lasting impact. Notably, the COVID-19 dummy variable (δ = 0.025) is positive and statistically significant, demonstrating that the market was more volatile during the COVID-19 period. The empirical results thus confirm the presence of both asymmetric volatility and volatility clustering in the TASI index value. These findings are consistent with those of Kumar et al. (2023), which demonstrate that emerging markets often exhibit volatility clustering.

Table 5 displays the "S&P 500" index's "GARCH model" findings. According to these results, the mean equation's "constant term (C)" is not statistically significant. The model captures certain important volatility aspects within the variance equation. Both the "GARCH" term GARCH(-1) = 0.600 (p = 0.000) and the "ARCH" term RESID(-1)^2 = 0.150 (p = 0.004) are statistically significant, as is the constant in the variance equation. These numbers suggest that current volatility is significantly influenced by both historical volatility and past squared shocks. Given that the "ARCH" and "GARCH" terms add up to 0.75, which is less than 1, it may be concluded that the variance process is stationary and that volatility shocks diminish over time as opposed to continuing forever.

This model suggests that COVID-19 had no discernible effect on market volatility. This is wildly unrealistic and demonstrates a structural flaw in the typical "GARCH" model: it assumes symmetric effects, which means it ignores the reality that markets more frequently respond to adverse information (Pandemics, crashes, etc.). Consequently, it is unable to identify the impact of asymmetric or exceptional events on volatility.

Table 5. S&P 500 GARCH model results.

Variable	Coefficient	Std. Error	z-statistic	Prob.
μ	0.000	0.001	0.531	0.595
	Variance equation			
ω	0.000	0.000	3.639	0.000***
RESID(-1)^2	0.150	0.052	2.899	0.004***
GARCH(-1)	0.600	0.108	5.581	0.000***
DUMMY_COVID	0.000	0.000	0.000	1.000
Log likelihood	7560.310			
Durbin-Watson statistic	2.263			
Akaike Information Criterion	-5.781			
Schwarz criterion	-5.769			
Hannan-Quinn criterion.	-5.777			

Note: *** indicates the significance level at a 1% confidence interval.

Table 6 displays the "S&P 500" index's "EGARCH model" findings. These results show that the mean equation's "constant term (C)" is statistically significant at the 5% level. Every important element in the variance equation is highly significant at the 1% level, suggesting a robust and well-defined volatility model. Since variance in "EGARCH models" is described in logarithmic form, this flexibility is common, and the constant term ($\omega = -0.646$) is negative and statistically significant. The magnitude impact ($\alpha = 0.215$) is positive and substantial, indicating that the magnitude of previous shocks, irrespective of their direction, significantly influences the volatility that exists today. The presence of asymmetry in the volatility process, where negative shocks (adverse news) have a greater impact on volatility when compared with positive ones, is confirmed by the statistically significant and negative leverage effect ($\gamma = -0.170$). This is consistent with the idea of financial market behavior, particularly in times of crisis or uncertainty.

A high degree of volatility persistence is indicated by the persistence parameter ($\beta = 0.950$), which is very close to one. This suggests that volatility shocks are long-lasting and diminish gradually over time. Importantly, the COVID-19 dummy variable ($\delta = 0.037$) is positive and statistically significant ($p < 0.01$), indicating a substantial increase in market volatility during the COVID-19 period. The results align with the existing literature (Meher et al., 2024; Srinivasan, 2011). The findings highlight the importance of using the "EGARCH model", especially during periods of market stress.

Table 6. S&P 500 EGARCH model results.

Variable	Coefficient	Std. error	z-statistic	Prob.
μ	0.000	0.000	2.265	0.024**
	Variance equation			
ω	-0.646	0.047	-13.817	0.000***
α	0.215	0.016	13.439	0.000***
γ	-0.170	0.010	-16.803	0.000***
β	0.950	0.004	226.002	0.000***
δ	0.037	0.006	6.048	0.000***
Log likelihood	8683.859			
Durbin-Watson statistic	2.263			
Akaike Information Criterion	-6.640			
Schwarz criterion	-6.626			
Hannan-Quinn criterion.	-6.635			

Note: ***, ** indicates the significance level at a 1% and 5% confidence interval, respectively.

Since the EGARCH model has lower (AIC, BIC) and greater log-likelihood values, it is generally more effective at modeling and forecasting the values of the TASI index as well as the S&P 500. For both the TASI and the S&P 500 indices, the empirical results from the EGARCH model show compelling evidence of asymmetric volatility and volatility clustering. Additionally, the EGARCH model can identify structural disruptions that the GARCH model was unable to identify, such as the COVID pandemic. Therefore, before acting in the future, investors and policymakers should evaluate how wars, crises, pandemics, or price collapses have affected previous financial market performance using the EGARCH model.

Ultimately, the "EGARCH" results for the "TASI" and "S&P 500" return series provide substantial evidence of the leverage effect and volatility clustering. Both indices show negative and significant leverage (γ), implying that the effect of adverse news outweighs the positive news of a similar qualitative nature. This demonstrates that investors react more strongly to any negative news in the market. The persistence parameter (β) in both models is strong and substantial, indicating volatility clustering, where periods of high and low volatilities are followed by similar periods, respectively, meaning that volatility is not constant and tends to cluster over time.

However, while considering volatility modeling, it is crucial to confirm that the model has sufficiently taken into account all sources of conditional heteroskedasticity in the return series. This is true even after estimating an "EGARCH model," which is especially built to capture time-varying and asymmetric volatility. The residuals of the fitted "EGARCH model" are subjected to the "ARCH-LM" test to confirm this. Using the "ARCH-LM" test helps verify whether any residual "ARCH" effects are present, even though "EGARCH models" are sophisticated and adaptable. The model has effectively represented the volatility structure if the test reveals no discernible "ARCH" effects, meaning that no additional "ARCH-type" modeling is necessary. This phase acts as a diagnostic check to ensure that the given variance equation is adequate and accurate.

Table 7 shows the results of the "ARCH-LM" test on the residuals of the "TASI" and "S&P 500" return series. Since both indices' p-values exceed the selected significance level, this indicates that there are no signs of conditional heteroskedasticity in the residuals. It reveals that the volatility dynamics of both return series have been adequately captured by the "EGARCH models". This confirms that the models are properly specified and that the variance equations used are appropriate (Bollerslev, 1986; Enders, 2015; Engle, 1982).

Table 7. ARCH-LM test results.

Statistic	TASI	S&P 500
F-statistic	0.045	0.903
P-value	0.832	0.342

Figures 5 and 6 present the forecasted variance graph. The "EGARCH" forecast plots of "TASI" and "S&P 500" both provide useful information about return behavior and volatility dynamics. In both indices, the top graph demonstrates that the log returns fluctuate around zero with narrow confidence intervals in normal periods, reflecting relative market stability. Nonetheless, both indices experienced a sharp increase in early 2019 and 2020, coinciding with the COVID-19 shock, with wider error bands and increased uncertainty.

The lower panel plots of the forecasted variance indicate that there was a sharp spike in volatility in 2020 in both markets, but with the "S&P 500" recording a more pronounced and sudden volatility spike relative to "TASI". The findings imply that the "S&P 500" had recorded greater sensitivity and volatility in response to the pandemic because of its larger international investor base as well as its stronger link with the global economy. In contrast, "TASI" exhibited relatively less peak volatility, suggesting a more contained market response to the crisis. Furthermore, "TASI" volatility decreased more consistently after the shock, showing stronger mean-reverting tendencies.

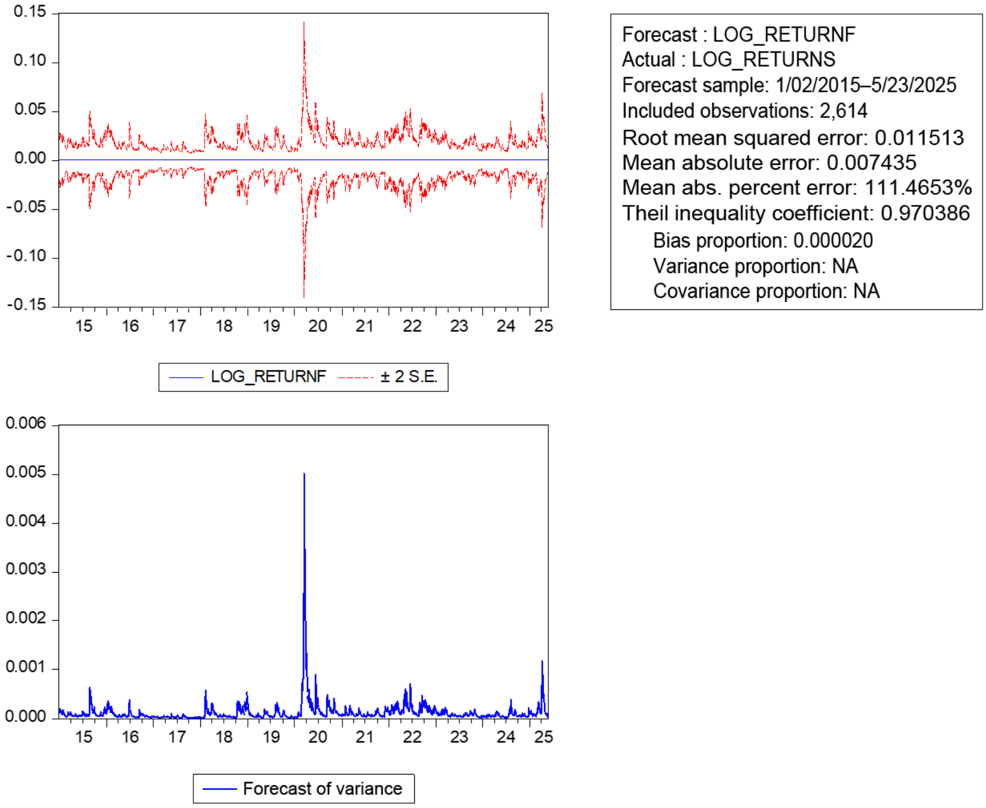

Figure 5. Forecasted Variance of S&P 500.

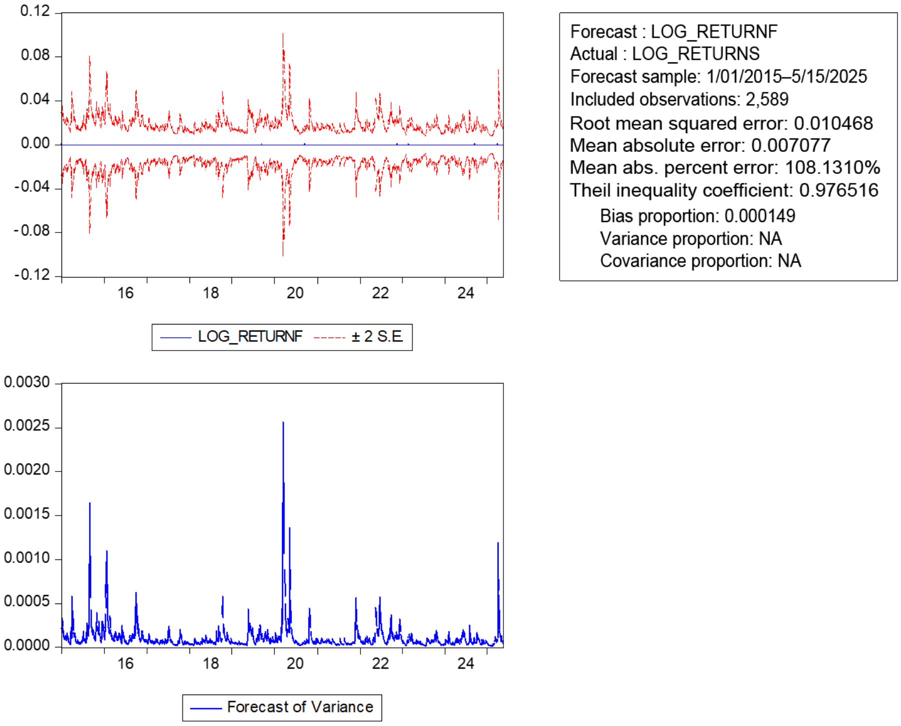

Figure 6. Forecasted variance of TASI.

5. CONCLUSION

The study evaluates the time-series behavior of stock returns on the "TASI" and the "S&P 500" stock market indices. The dataset of daily stock returns spans from January 2015 to May 2025, covering a period that includes major market disruptions such as the "COVID-19 pandemic." Based on preliminary tests between the two indices, it appears that the "S&P 500" recovered more quickly following the crisis; this may be attributed to its diverse composition and the adequacy of institutional responses. Conversely, the "TASI" experienced a slower recovery, possibly due to its strong dependence on the oil market and regional limitations. Additionally, forecasted variance graphs highlighted a wave of increased volatility in the "S&P 500," which was more severe compared to that in the "TASI," where results remained stable in other zones. This research aims to reveal the variation in volatility in returns between a developing market and a developed market. The analysis is based on two models: the "EGARCH model" and the "GARCH model," to assess the depth and duration of financial market volatility and to support the leverage effect on market volatility.

The "EGARCH model" performed better in capturing the distinct impact of "COVID-19" on the volatility observed in the market. These empirical findings were obtained based on the log returns of the "TASI" and "S&P" financial markets. The findings provided substantial evidence of the leverage effect and volatility clustering across the pandemic event. Specifically, both stock indices show statistically significant evidence of negative and significant leverage (γ), implying that the impact of unfavorable news on the markets outweighs the impact of good news. This suggests that investors in both developed economies and emerging economies tend to respond more sharply to negative market news. Furthermore, the persistence parameter (β) in both models is statistically strong and quantitatively substantial. This indicates the existence of volatility clustering in the returns for both developed and emerging financial markets. This phenomenon proposes that volatility is not random and tends to cluster over time.

This paper contributes to the current body of literature by offering insights into the volatility patterns of an emerging stock market, as represented by the "TASI" stock index, and comparing it to the "S&P 500" stock index. The "EGARCH model" confirmed significant leverage effects for the "TASI" market index, demonstrating that unfavorable news amplified volatility more than favorable news, a pattern that the symmetric "GARCH model" failed to capture.

These findings emphasize the need for tailored volatility models in developed "S&P 500" and emerging "TASI" markets, with event-driven dummies (e.g., COVID-19). Policymakers and investors should prioritize asymmetric risk modeling, diversification, and crisis-responsive strategies to mitigate systemic shocks. Future research could explore sector-specific volatility within these indices or extend the analysis to other black-swan events.

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