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Modeling Volatility Spillovers across emerging and developed stock markets using GARCH models: An empirical case study on the USA and Romania

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Abstract:
The main aim of this research paper is to investigate volatility spillovers across emerging and developed stock markets using GARCH models based on an empirical case study on the USA and Romania. The financial econometric approach is based on a relevant sample data that covers the time period from February 2019 to January 2025 which includes the impact of recent extreme events such as the COVID-19 pandemic or the war between Russia and Ukraine. This research study contributes to the expansion of the literature by obtaining relevant empirical results regarding the behavior of emerging and developed stock markets.

Keywords: *GARCH models, heteroscedasticity, emerging stock market, developed stock market, volatility*

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Modeling Volatility Spillovers across emerging and developed stock markets using GARCH models: An empirical case study on the USA and Romania

Introduction

Financial markets are inherently volatile, influenced by macroeconomic conditions, investor sentiment, and geopolitical events. Understanding and quantifying volatility is crucial for investors, policymakers, and financial analysts, as it provides insights into risk levels and potential investment opportunities. While developed markets, such as the United States' S&P 500 stock market index, are characterized by high liquidity and regulatory stability, emerging markets, like Romania's Bucharest Stock Exchange (BSE), often exhibit higher volatility due to economic fluctuations, lower trading volumes, and evolving market structures. This study aims to provide a comparative volatility analysis between these two distinct financial environments using modern Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models.

The S&P 500 index, a benchmark for the U.S. stock market, represents a mature and diversified financial landscape with a vast array of institutional investors, high-frequency trading, and advanced financial instruments that contribute to relatively predictable volatility patterns. In contrast, the Bucharest Stock Exchange, as an emerging market, is subject to different risk factors, including political instability, currency fluctuations, and lower market capitalization, making its volatility behavior unique. Given these disparities, this study seeks to determine how the volatility dynamics of an emerging market compare to a well-established global benchmark.

GARCH models have become a widely accepted tool for modeling and forecasting financial volatility, offering a robust framework to capture time-varying volatility clustering and persistence. Traditional financial models often assume constant variance, which does not accurately reflect real-world market conditions where volatility tends to exhibit long memory and reacts asymmetrically to market shocks. By employing variations of GARCH models, such as GARCH(1,1), EGARCH, and GJR-GARCH models, this study will analyze volatility patterns in both markets and assess the extent to which past volatility influences future fluctuations.

This research contributes to the existing literature by providing empirical evidence on the volatility characteristics of a developing financial market compared to a leading global index. The findings will offer valuable insights for investors seeking to diversify their portfolios across developed and emerging markets, as well as for policymakers aiming to enhance market stability. By leveraging advanced econometric techniques, this study aims to bridge the knowledge gap in comparative market volatility and provide a data-driven foundation for future risk management strategies.

Literature review

The specialized literature includes a wide variety of empirical studies on the behavior of emerging and developed stock markets, such as: Trivedi and Birau (2013), Kumar et al. (2023), Hawaldar et al. (2020), Trivedi et al. (2022). Kumar et al. (2023) investigated the complex behavior of the emerging stock market from Brazil based on GARCH models for the very long time sample period from May 1993 until March 2023, considering IBOVESPA stock index. Meher et al. (2024a) have conducted a comparative research study between the stock markets from USA and Austria based on GARCH type models for the long time sampled horizon from January, 2000 until September, 2023. Moreover, Meher et al. (2024b) have managed to highlight a comparative analysis on the behavior of the stock markets in USA and China for the sample period from January 2000 to March 2023.

Thorbecke (2023) investigated the stock market volatility in U.S. considering the effects of monetary policy and the turbulence generated by the negative impact of COVID-19 pandemic. Han and Xu (2025) also investigated the complex behavior of the developed stock market from U.S.A. Setiawan et al. (2021) have conducted a research study on both developing and developed stock markets behavior in the context of extreme events such as COVID-19 pandemic.

Petkov et al. (2024) managed to provide a case study based on financial econometrics using ARMA and GARCH models applied on Bulgarian emerging stock market for a very long time period from 2000 to 2024 which covers several extreme events, including global financial crisis of 2007-2008 but also COVID-19 pandemic. Mamilla et al. (2023) have also conducted an empirical study on the emerging stock market in India, such as National Stock Exchange (NSE) during COVID-19 pandemic using GARCH family models.

On the other hand, Machmuddah et al. (2020) examined the impact of COVID-19 pandemic and non - economic factors on stock market behavior. Moreover, Spulbar et al. (2022) have conducted a literature survey on certain key certain key aspects of modern financial theory such as Efficient Market Hypothesis, Fractal Markets Hypothesis, but also Adaptive Market Hypothesis. In this sense it was analyzed in a comparative manner the impact of this essential paradigms such as EMH, AMH and FMH.

Research Methodology

The study uses secondary data, and the nature of the data is quantitative. This research explores methods for quantifying the impact of the BET (Bucharest Exchange Trading) index and S&P 500 index volatility analysis for 1445 daily observations from 15/02/2019 to 30/01/2025. To make data stationary, the Log return has been calculated. Volatility clustering was observed in the data, leading to applying the ARCH LM test to assess for heteroscedasticity in the return series residuals. The study probes volatility using the different GARCH models with various distributions, including the Normal (Gaussian), Student's t, and Generalized Error (GED) distributions, both with and without specified parameters. Based on the values of AIC, SC, and Log Likelihood, the appropriate GARCH model is used for analysis. The software package used for analysis is EViews10.

Significance of the study

This research offers valuable benefits to society by providing a deeper understanding of how financial markets operate. Advanced GARCH models are used to observe the volatility of the BET index and S&P 500 index. A deep understanding of market volatility is vital for investors, Financial Institutions, and the government as it allows them to reduce the risks and helps to make strategies more efficient and effective. The existing literature on this subject is scarce, and no research has yet explored individual analysis of BET and the S&P 500 index. The study's findings can be used to create more accurate models, leading to better market regulations. This study provides valuable insights for promoting financial resilience in Romania and the United States.

Limitations of the study

Although the study uses daily price data to provide a detailed volatility analysis, however, its reliance on statistical methods, exclusion of real-world complexities, and focus on conditional return variance create a generalized framework. This approach may not fully address all the relevant questions; interpreting focuses on theoretically more than practical.

- Limited availability of data: Data was sourced from BET (Bucharest Exchange Trading) index and S&P 500 index database, which is freely available. However, due to a lack of financial support, this study takes a broad approach, foregoing a detailed analysis of specific micro-level variations.
- Generalization of result: While the APARCH model is versatile, capturing leverage and volatility decay and even containing several GARCH models, it can't fully account for subjective, real-world complexities.
- Model Interpretability: PARCH model excels at modeling volatility dynamics, but its complexity makes it less suitable for identifying the specific, underlying causes of that volatility in a given scenario.
- Market dynamics and external variables: Because every market situation is different, even the sophisticated APARCH model can't ideally account for all the specific, complex, and interacting factors.

Considering the specific strengths and weaknesses of the APARCH and GARCH models, we will proceed with this research's analysis and estimation phase.

Empirical analysis, Estimation, and Results

This part has been bifurcated into two sections to understand both indices better. The first section deals with the Bucharest Exchange Trading (BET) index, and the other deals with the S&P 500 index.

Bucharest Exchange Trading (BET) index

To thoroughly understand price movements, a visual representation is essential. The graph below illustrates the actual price fluctuations.

The below graph represents the BET price index for almost 5 years. From the graph, it is visible that nearly in 2020, there was a dip, which may be because of some systematic and non-systematic reasons, and COVID-19 pandemic may be a reason for it. However, after 2021, there is a spike in the graph, and again, there is a dip between 2021 and 2022 due to some economic crisis. But after the middle of 2022, there is always an increase in the price. However, there was a high volatility rate during the entire duration.

Figure 1. Daily Closing Price of Index

Source: author's Computation using EViews 10

To make returns stationary, Log return has been calculated. The below graphical representations are of Log returns. As previously discussed, there is a spike in nearly 2020 and the middle of 2021 and 2022 for various reasons.

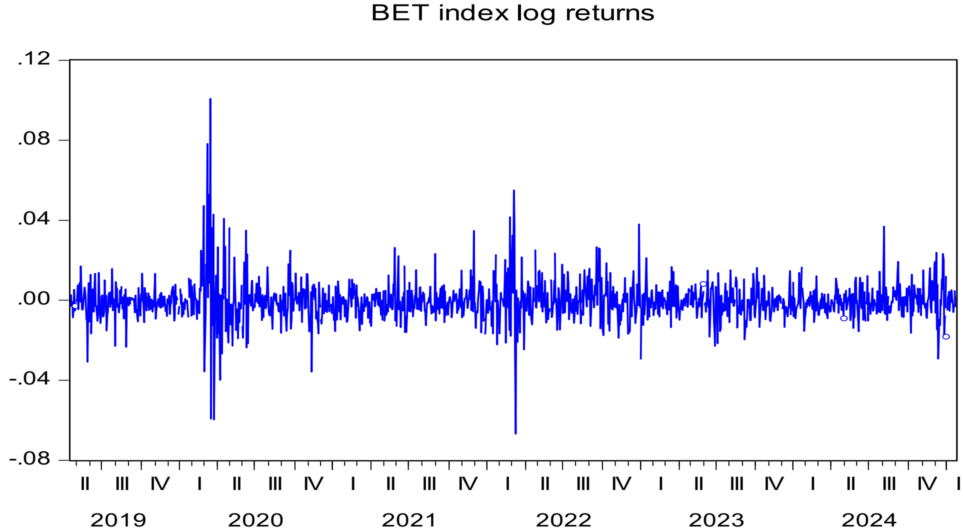


Figure 2 Log Returns Graph

Source: author's Computation using EViews 10

While a visual assessment indicates possible heteroscedasticity, it is imperative first to conduct a test for stationarity.

Test of stationarity

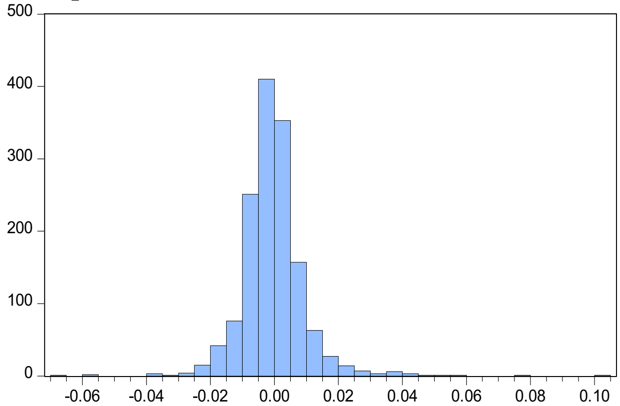
Table 1: Heteroscedasticity Test

Null Hypothesis: BET_INDEX_LOG_RETURNS has a unit root			
Exogenous: Constant			
Lag Length: 1 (Automatic - based on SIC, maxlag=23)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.77573	0.0000
Test critical values:	1% level	-3.434680	
	5% level	-2.863339	
	10% level	-2.567777	
*MacKinnon (1996) one-sided p-values.			

Source: Author's Computation using EViews 10

The above test is the Augmented Dickey-fuller (ADF) test. It can be observed that the probability value is less than 0.05,and test statistics are lower in value than the critical value at 5% interval; thus, we can say that data is a unit root and is stationary.

Descriptive Statistics



Series: BET_INDEX_LOG_RETURNS
Sample 4/15/2019 1/30/2025
Observations 1443

Mean	-0.000500
Median	-0.001001
Maximum	0.100753
Minimum	-0.066789
Std. Dev.	0.010118
Skewness	1.221821
Kurtosis	17.66368
Jarque-Bera	13287.32
Probability	0.000000

Figure 3 Test Distribution Analysis
Source: Author's computation using EViews 10

The above test statistics show that the average log return is slightly negative, indicating a slight downward trend. The central value is close to zero, suggesting a nearly symmetric distribution. The positive skewness indicates a distribution with a longer right tail, meaning occasional significant positive returns. A high kurtosis value signifies a leptokurtic distribution, indicating frequent extreme values compared to a normal distribution. Distributions are not expected due to high kurtosis and positive skewness.

Heteroscedasticity Test

Table 2: ARCH effect test

Heteroskedasticity Test: ARCH			
F-statistic	99.31456	Prob. F(1,1440)	0.0000
Obs*R-squared	93.03595	Prob. Chi-Square(1)	0.0000

Source: Author's computation using EViews 10

The low probability value validates the presence of heteroscedasticity. The null hypothesis is rejected, affirming that the volatility depends on past residuals.

GARCH family models are chosen over ARCH due to the limitations in considering weights, and many studies suggest that GARCH is appropriate for estimating the conditional variance of parsimonious models. For the appropriate GARCH model, GARCH, IGARCH, TARCH, EGARCH, PARCH, and APARCH were estimated across the five distributions.

After executing GARCH family models across Gaussian Normal Distribution, Student's t distribution, Generalized Error Distribution (GED), t distribution with fixed parameter, and GED with fixed parameter, it can be concluded from the below table that APARCH Student's t distribution is the appropriate model for having the lowest Akaike info criterion (-6.841217), lowest Schwarz criterion (-6.811959), and highest log likelihood (4940.518).

Table 3. Decision Table

		GARCH	IGARCH	TARCH	EGARCH	PARCH	APARCH
Normal Distribution	*Akaike info criterion*	-6.753	-6.689123	-6.766181	-6.763894	-6.752953	-6.769872
	Schwarz criterion	-6.734714	-6.678151	-6.744237	-6.74195	-6.731009	-6.744272
	Log Likelihood	4873.913	4825.858	4884.416	4882.767	4874.879	4888.078
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
Student's T	*Akaike info criterion*	-6.837877	-6.798128	-6.841858	-6.835358	-6.83649	-6.841217
	Schwarz criterion	-6.815933	-6.783499	-6.816257	-6.809757	-6.810889	-6.811959
	Log Likelihood	4936.109	4905.45	4939.979	4935.293	4936.109	4940.518
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
Generalized Error	*Akaike info criterion*	-6.830299	-6.792333	-6.83535	-6.830953	-6.829036	-6.835513
	Schwarz criterion	-6.808355	-6.777704	-6.809749	-6.805352	-6.803435	-6.806255
	Log Likelihood	4930.645	4901.272	4935.287	4932.117	4930.735	4936.405
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
T distribution (Parameter)	*Akaike info criterion*	-6.822788	-6.784195	-6.82925	-6.816092	-6.821459	-6.8294
	Schwarz criterion	-6.804501	-6.773223	-6.807306	-6.797805	-6.799516	-6.803799
	Log likelihood	4924.23	4894.404	4929.889	4919.402	4924.272	4930.998
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
Generalised Error (Parameter)	*Akaike info criterion*	-6.818672	-6.776025	-6.826056	-6.821848	-6.817632	-6.827042
	Schwarz criterion	-6.800386	-6.765053	-6.804112	-6.799904	-6.795688	-6.801441
	Log Likelihood	4921.262	4888.514	4927.586	4924.552	4921.513	4929.297
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. APARCH (1,1) models, Student's t-distribution

Dependent Variable: BET_INDEX_LOG_RETURNS Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps) Date: 02/08/25 Time: 01:02 Sample (adjusted): 4/17/2019 1/30/2025 Included observations: 1442 after adjustments Convergence achieved after 41 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) @SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000797	0.000183	-4.350860	0.0000
BET_INDEX_LOG_RETURNS(-1)	0.076512	0.026895	2.844874	0.0044
	Variance Equation			
C(3)	3.99E-05	7.66E-05	0.521605	0.6019
C(4)	0.163536	0.035661	4.585837	0.0000
C(5)	-0.257256	0.113378	-2.269019	0.0233
C(6)	0.779451	0.039415	19.77533	0.0000
C(7)	1.602745	0.410115	3.908040	0.0001
T-DIST. DOF	4.899650	0.702168	6.977889	0.0000
R-squared	-0.001729	Mean dependent var		-0.000502
Adjusted R-squared	-0.002425	S.D. dependent var		0.010121
S.E. of regression	0.010133	Akaike info criterion		-6.841217
Sum squared resid	0.147859	Schwarz criterion		-6.811959
Log likelihood	4940.518	Hannan-Quinn criter.		-6.830296
Durbin-Watson stat	2.097910			

Source: Author's computation using EViews 10

From the above APARCH(1,1) models analysis, it can be concluded that variance equations show volatility clustering asymmetric leverage effect, a high tenacity of volatility propound, and that market turbulence tends to last over time. The student's t-distribution indicates heavy tails, which means extreme returns. Model diagnostics, including a log-likelihood (4940.518) and AIC (-6.8412), suggest a well-fitting model. The result also emphasizes market risks, which is critical for investors and risk managers. The model is as follows:

$$y_t = x_t \xi + \varepsilon_t$$
$$t = 1,2 \dots T$$
$$\sigma_t^\delta = \omega + \sum_{j=1}^{q} \alpha_j \left(|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j} \right)^\delta + \sum_{i=1}^{p} \beta_i (\sigma_{t-i})^\delta$$
$$\varepsilon_t = \sigma_t z_t \text{ , } z_t \sim N(0, 1)$$

$k(\varepsilon_{t-j}) = |\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j}$

The APARCH equation has to satisfy the following conditions:

1. $\omega > 0$, $\alpha_j \geq 0$, $j = 1,2,\ldots q$, $\beta_i \geq 0$, $i = 1,2,\ldots p$ when $\alpha_j = 0$, $j = 1,2,\ldots q$, $\beta_i = 0$, I $=1,2,\ldots p$, then $\sigma_t^2 = \omega$. Due to this, the variance is positive, so $\omega > 0$.
2. $0 \leq \Sigma^q_{i=1} \beta_i \leq 1$

Table 1. APARCH Coefficients and their meanings

Notation	**Meaning**
ω C (3)	A constant term representing the baseline of volatility
α C (4)	Persistence of Volatility/Positive Shock
γ C (5)	Leverage Effect
β C (6)	Persistence of Volatility/Negative Shock
δ C (7)	Decay Rate/Power Term

Source: Author's computation

From the above APARCH model analysis, it can be estimated that ω is not statistically significant. Stock returns are driven by company-specific factors like shocks, leverage, asymmetry, and volatility, not market trends. α represents the persistence of shocks at0.163536, which states the presence of positive shocks but not at a significant level. β represents the persistence of negative shocks and the effect of volatility at0.779451, which states that negative shocks' strong influence on volatility may be because of COVID-19 pandemic and other economic problems. δ represents the decay rate/power term at 1.602745,which means that there is a high decay rate and the effects of decay are long-lasting. γ values are -0.257256, which indicates asymmetric results and volatility clustering, resulting in long-term volatility.

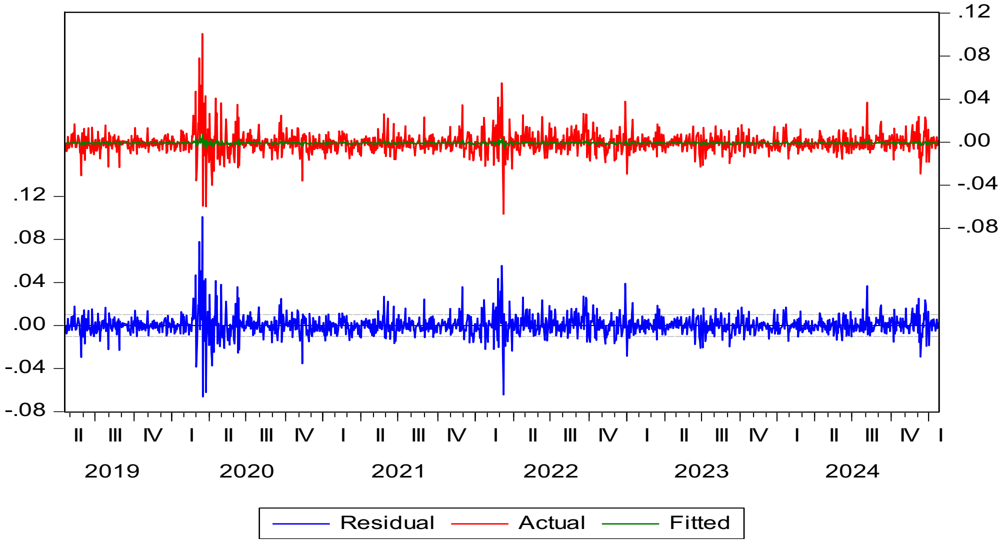
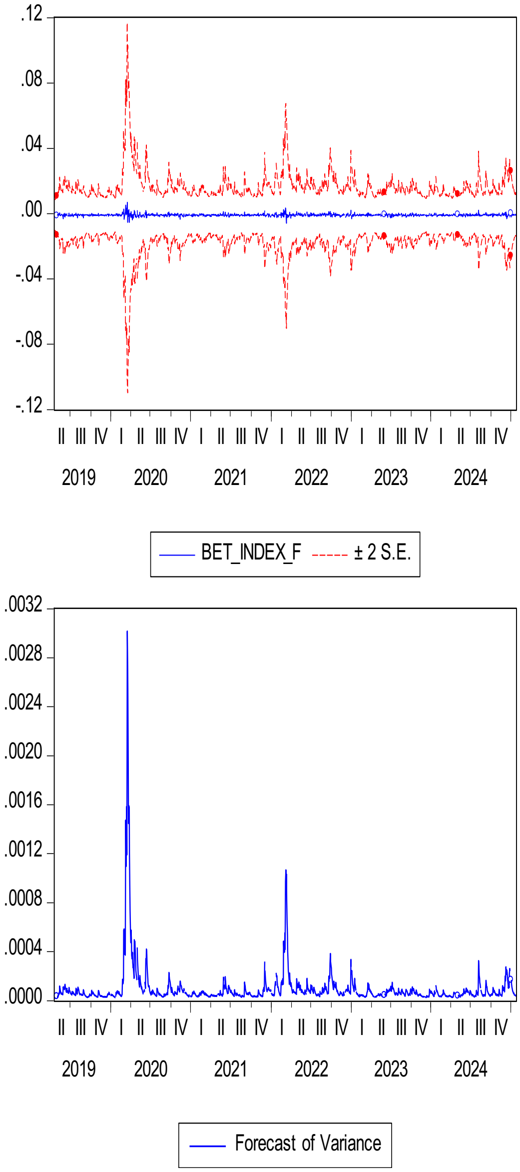


Figure 4. Graphical representation of estimated volatility
Source: author's Computation using EViews 10



Forecast: BET_INDEX_F	
Actual: BET_INDEX_LOG_RETURNS	
Forecast sample: 4/15/2019 1/30/2025	
Adjusted sample: 4/17/2019 1/30/2025	
Included observations: 1442	
Root Mean Squared Error	0.010126
Mean Absolute Error	0.006546
Mean Abs. Percent Error	143.1198
Theil Inequality Coefficient	0.898619
Bias Proportion	0.001081
Variance Proportion	0.851352
Covariance Proportion	0.147567
Theil U2 Coefficient	0.929768
Symmetric MAPE	159.0766

Figure 5 Graphical representation of Forecast of Prices Returns and Volatility
Source: author's Computation using EViews 10

From the above graphical representations, we can easily conclude that there was volatility around 2020 due to COVID-19 pandemic. Graphs explain the nature of volatility, and residual graphs correspond to the actual volatility.

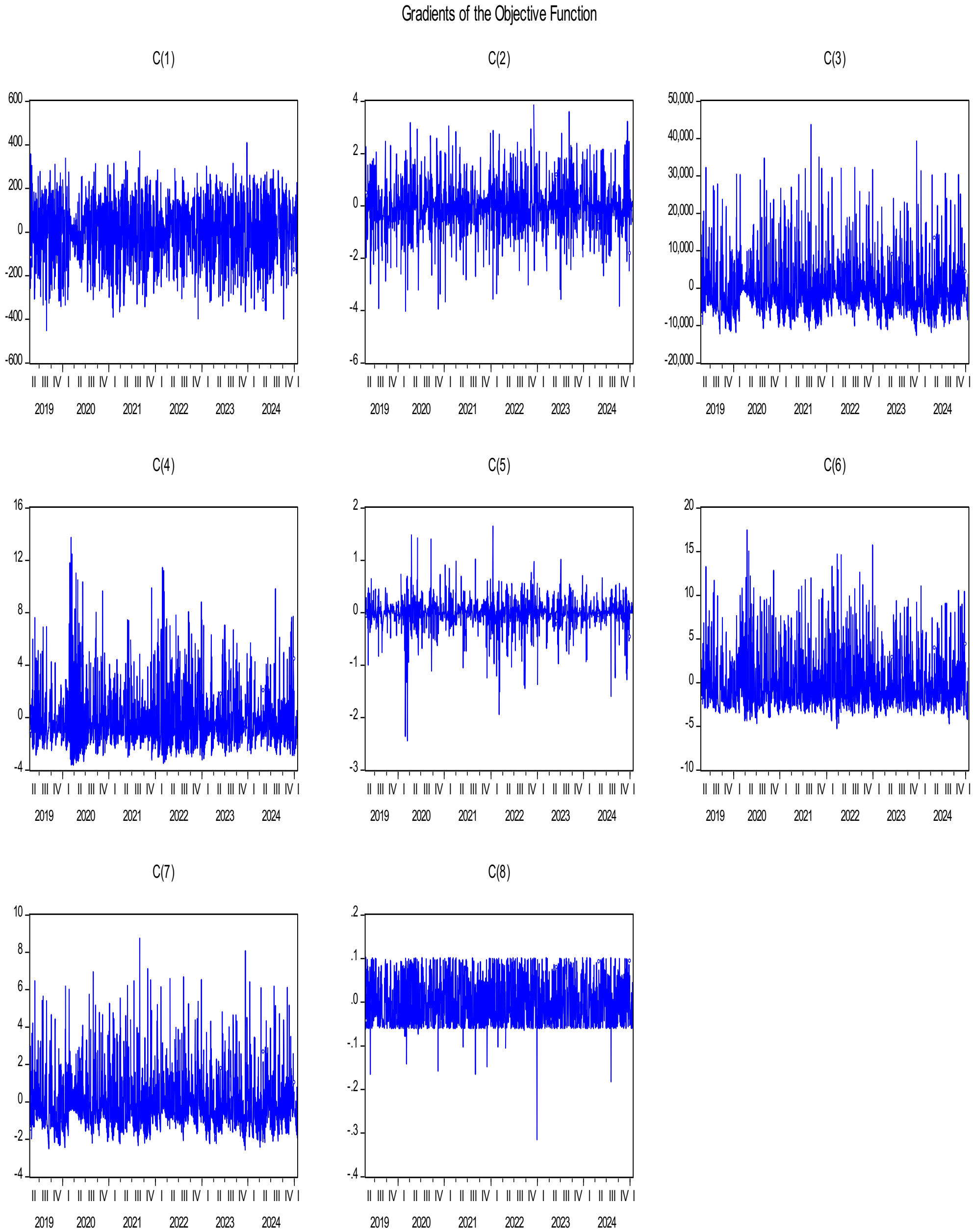


Figure 6 Gradients of the objective function

Source: author's Computation using EViews 10

The above graphs are the gradients of the objective functions from the parameters C1 to C8, which contribute a crucial role in the optimization process. From the graphs, we can see that gradients indicate high fluctuations initially. Still, after some time, most of the gradients stabilize to nearly zero, which means that the model is appropriately linked up and estimates have reached the optimum value.

Coefficients C3, C6, and C7 show huge variances in gradients, which means that the parameters might be sensitive to the market. Spikes in gradients suggest high market uncertainty.

Now, we are moving forward with the analysis for the rest part of the paper.

S&P 500 INDEX

Below is the graphical representation of the S&P 500 index price over five years, and from the graph, it is clearly visible that there is a sharp dip in nearly 2020; this may be because of some financial problems and the COVID-19 pandemic. After 2020, the economic situation has changed as the graph shifts upward. During the entire framework, there is high volatility.

Figure 7. Daily Closing Price of S&P 500 index

Source: author's Computation using EViews 10

To make returns stationary, Log return has been calculated. The below graphical representations are of Log returns. As discussed earlier, there is a spike in nearly 2020, and during the entire period, there is high volatility.

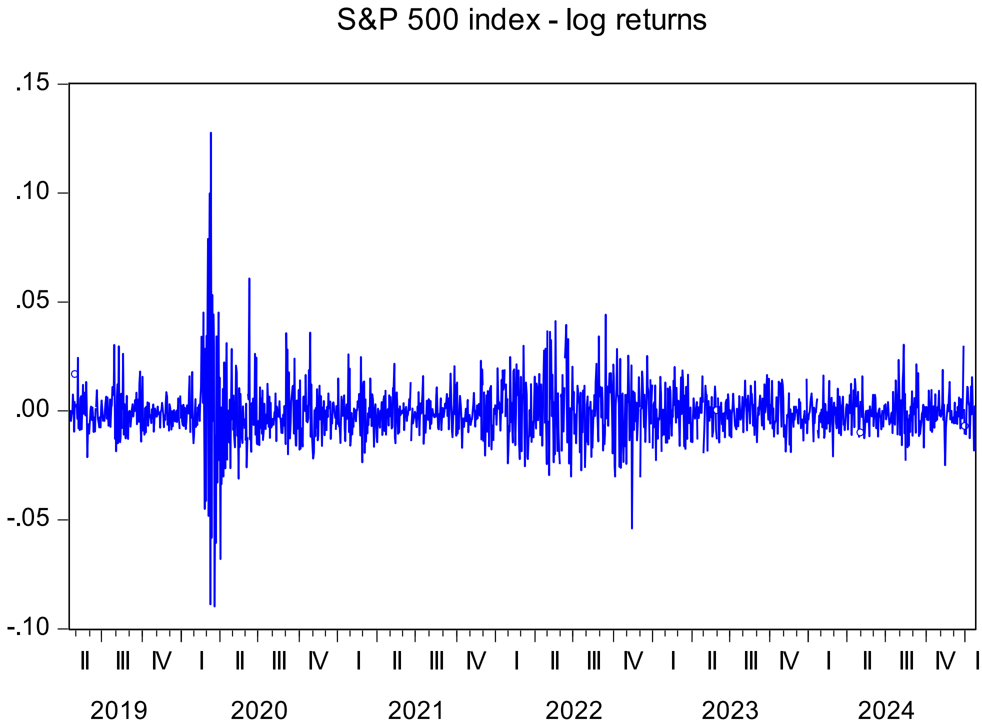


Figure 8. Log Returns Graph
Source: author's Computation using EViews 10

While a visual assessment indicates possible heteroscedasticity, it is imperative first to conduct a test for stationarity.

Test of stationarity

Null Hypothesis: S_P_500_INDEX___LOG_RETURNS has a unit root			
Exogenous: Constant			
Lag Length: 9 (Automatic - based on AIC, maxlag=23)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.36657	0.0000
Test critical values:	1% level	-3.434705	
	5% level	-2.863351	
	10% level	-2.567783	
*MacKinnon (1996) one-sided p-values.			

Table 6: Heteroscedasticity Test
Source: Author's Computation using Eviews 10

The above test is the Augmented Dickey-fuller (ADF) test. It can be observed that the probability value is less than 0.05, and test statistics are lower in value than the critical value at 5% interval; thus, we can say that data is a unit root and is stationary.

Descriptive Statistics

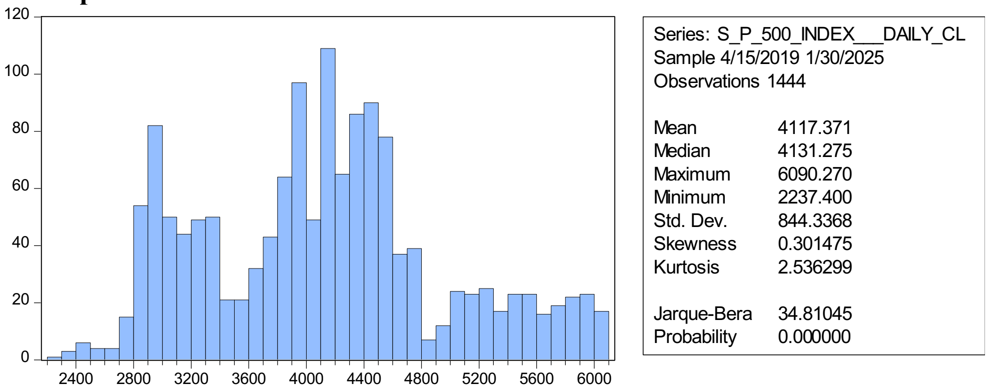


Figure 9 Test Distribution Analysis
Source: Author's computation using EViews 10

The above histogram and statistical summary show significant growth, ranging from 2,237.40 to 6,090.27,with a median of 4131.275, which shows a balanced distribution. Standard deviation shows high ups and downs in the market. Positive skewness (0.301475) shows a higher index value. Kurtosis suggests that data has peaked slightly more than usual.

Heteroscedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	453.2161	Prob. F(1,1440)	0.0000
Obs*R-squared	345.1997	Prob. Chi-Square(1)	0.0000

Table 7: ARCH effect test
Source: Author's computation using EViews 10

The ARCH heteroskedasticity test results indicate a variance of errors in time series that is constant or slightly changing over aperiod of time. From the above data, the null hypothesis is rejected, confirming heteroskedasticity's presence and affirming that the volatility depends on past residuals.

GARCH family models are chosen over ARCH due to the limitations in considering weights, and many studies suggest that GARCH is appropriate for estimating the conditional variance of parsimonious models. For the appropriate GARCH model, GARCH, IGARCH, TARCH, EGARCH, PARCH, and APARCH were estimated across the five distributions.

After executing GARCH family models across Gaussian Normal Distribution, Student's t distribution, Generalized Error Distribution (GED), t distribution with fixed parameter, and GED with fixed parameter, it can be concluded from the below table that APARCH Student's t distribution is the appropriate model for having the lowest Akaike info criterion (-6.457557), lowest Schwarz criterion (-6.428299), and highest log likelihood (4663.898).

Table 8. Decision Table

		GARCH	IGARCH	TARCH	EGARCH	PARCH	APARCH
	Akaike info criterion	-6.368797	-6.327358	-6.392204	-6.397646	-6.374493	-6.409433
	Schwarz criterion	-6.357825	-6.316386	-6.37026	-6.375702	-6.352549	-6.383832
	Log Likelihood	4594.903	4565.025	4614.779	4618.703	4602.01	4628.201
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
Normal Distribution	*significant coefficient*	Yes	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	-6.417951	-6.394172	-6.444504	-6.449703	-6.396354	-6.457557
	Schwarz criterion	-6.396007	-6.379543	-6.418903	-6.424102	-6.374411	-6.428299
	Log Likelihood	4633.343	4614.198	4653.487	4657.236	4617.771	4663.898
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
Student's T	*significant coefficient*	Yes	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	-6.411993	-6.384431	-6.430444	-6.433808	-6.410606	-6.441572
	Schwarz criterion	-6.390049	-6.369802	-6.404843	-6.408207	-6.385005	-6.412314
	Log Likelihood	4629.047	4607.175	4643.35	4645.775	4629.047	4652.374
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
Generalized Error	*significant coefficient*	Yes	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	-6.416382	-6.392051	-6.442412	-6.447657	-6.414995	-6.456366
	Schwarz criterion	-6.398095	-6.381079	-6.420468	-6.425713	-6.393051	-6.430766
	Log likelihood	4631.211	4611.669	4650.979	4654.76	4631.211	4662.04
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
T distribution (Parameter)	*ARCH LM-Test*	No	No	No	No	No	No

	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	-6.411835	-6.381729	-6.430182	-6.43385	-6.410453	-6.442165
	Schwarz criterion	-6.393549	-6.370757	-6.408238	-6.411907	-6.38851	-6.416564
	Log Likelihood	4627.933	4604.227	4642.161	4644.806	4627.937	4651.801
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
Generalised Error (Parameter)	*significant coefficient*	Yes	Yes	Yes	Yes	Yes	Yes

Source: author's tabulation using MS Office

Table 9. APARCH (1,1) Student's t-distribution

Dependent Variable: S_P_500_INDEX___LOG_RETURNS
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 02/11/25 Time: 00:18
Sample (adjusted): 4/17/2019 1/30/2025
Included observations: 1442 after adjustments
Failure to improve likelihood (non-zero gradients) after 87 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000698	0.000217	-3.216976	0.0013
S_P_500_INDEX___LOG_RETURNS(-1)	-0.013445	0.026652	-0.504458	0.6139
	Variance Equation			
C(3)	0.000734	0.000648	1.131951	0.2577
C(4)	0.117672	0.019040	6.180191	0.0000
C(5)	-0.982022	0.142006	-6.915357	0.0000
C(6)	0.873757	0.019680	44.39819	0.0000
C(7)	0.888089	0.173228	5.126697	0.0000
T-DIST. DOF	7.085502	1.144930	6.188589	0.0000

R-squared	0.004258	Mean dependent var	-0.000498
Adjusted R-squared	0.003566	S.D. dependent var	0.012924
S.E. of regression	0.012901	Akaike info criterion	-6.457557
Sum squared resid	0.239671	Schwarz criterion	-6.428299
Log likelihood	4663.898	Hannan-Quinn criter.	-6.446635
Durbin-Watson stat	2.317234		

Source: Author's computation using EViews 10

The above APARCH(1,1) analysis reveals significant insights into market volatility. The mean equation shows a small negative average return, which indicates that past returns do not strongly influence future returns. The model effectively captures the persistence and asymmetry of volatility in the S&P 500, highlighting that market fluctuations are influenced more by negative shocks and tend to remain high once they increase.

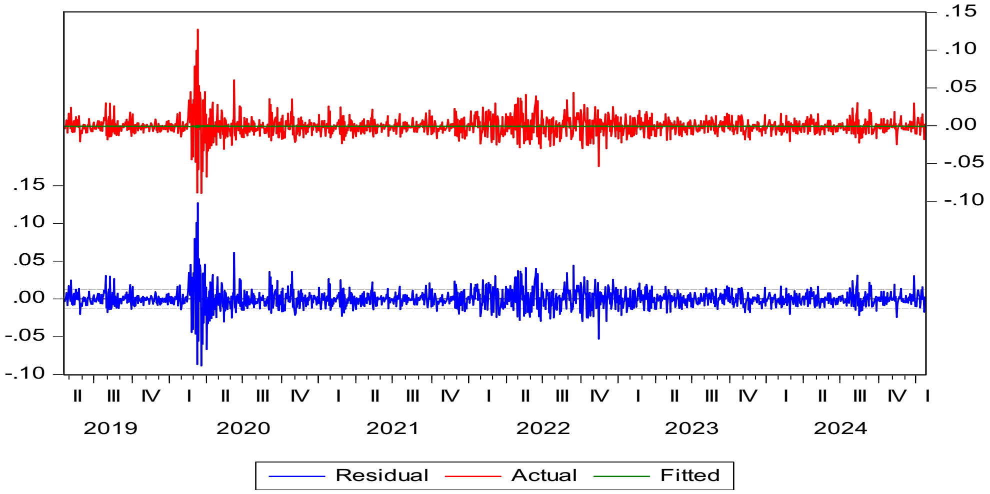
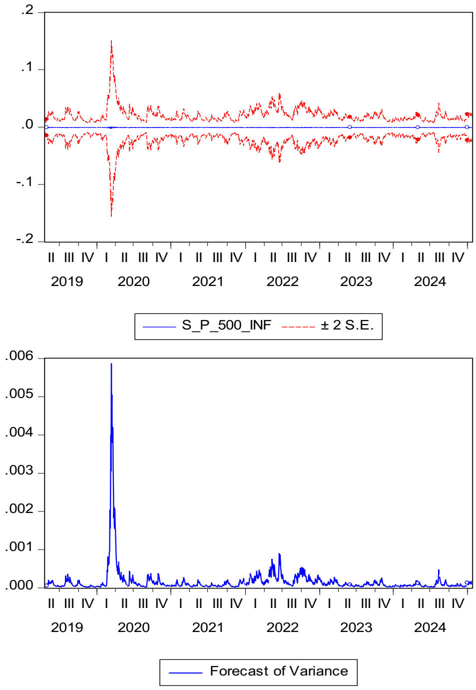


Figure 10. Graphical representation of estimated volatility
Source: author's Computation using EViews 10



Forecast: S_P_500_INF	
Actual: S_P_500_INDEX___LOG_RETURNS	
Forecast sample: 4/15/2019 1/30/2025	
Adjusted sample: 4/17/2019 1/30/2025	
Included observations: 1442	
Root Mean Squared Error	0.012892
Mean Absolute Error	0.008422
Mean Abs. Percent Error	132.0330
Theil Inequality Coefficient	0.945016
Bias Proportion	0.000226
Variance Proportion	0.977458
Covariance Proportion	0.022315
Theil U2 Coefficient	0.930855
Symmetric MAPE	169.0323

Figure 11. Graphical representation of Forecast of Prices Returns and Volatility
Source: author's Computation using EViews 10

The above forecast analysis for S&P 500 log returns provides insights into model accuracy and volatility behavior. Root Mean Squared Error (0.012892) and Mean Absolute Error (0.008422) indicate a moderate level of forecasting accuracy, and Mean Absolute Percentage Error (132.03%) suggests large percentage deviations in some of the cases. The forecast variance shows that market volatility spiked significantly around 2020, likely due to external shocks such as the COVID-19 pandemic and other economic problems, but stabilized after some time, though with some occasional fluctuations.

The model captures volatility clustering, but its predictive accuracy remains limited due to high variance and unexpected market shocks. Future improvements could involve refining the model with longer lags, exogenous variables, or alternative GARCH specifications to capture sudden market shifts better.

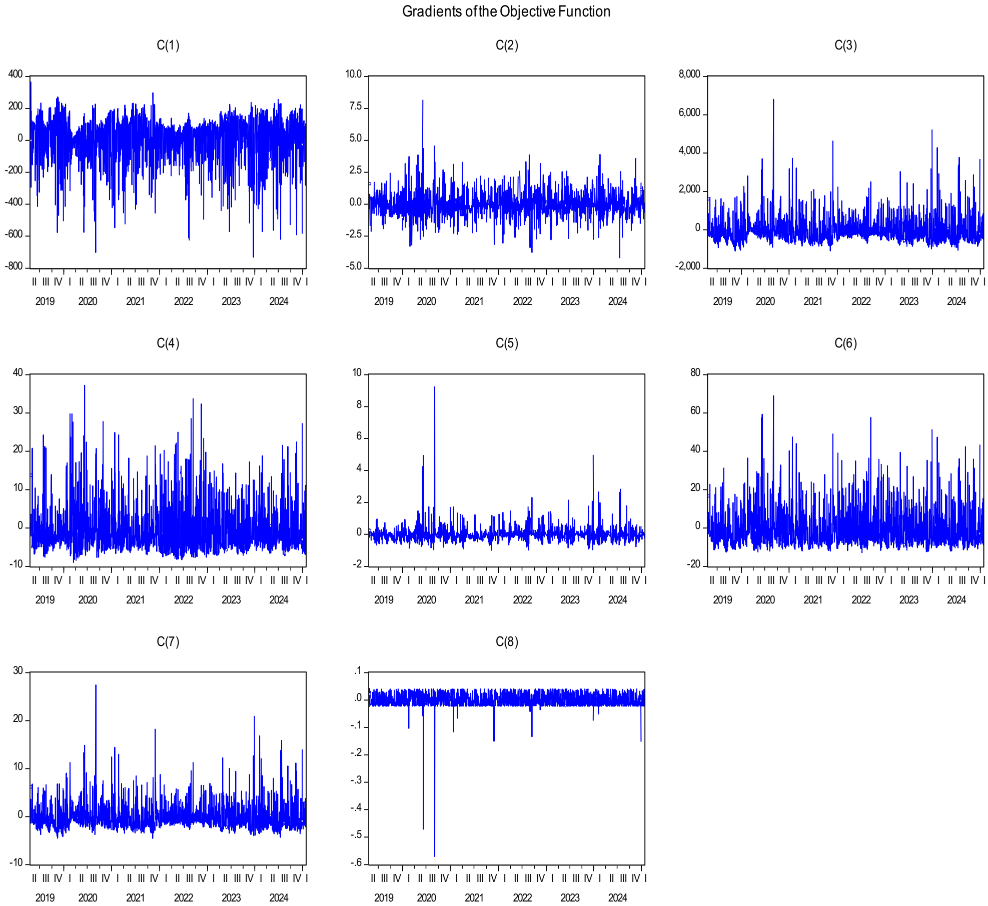


Figure 12 Gradients of the objective function

Source: author's Computation using EViews 10

The above graphs are the gradients of the objective functions from the parameters C1 to C8, which contribute a crucial role in the optimization process. The charts show that gradients indicate that coefficients exhibit high variability, indicating that the model adjusts to changing market conditions. Parameters such as C2, C5 and C7 show spikes likely because of extreme market events or financial crises, reflecting the presence of volatility clustering. C8 remains the same, suggesting it is less sensitive to market fluctuations.

The coefficient changes show that the model adjusts well to market ups and downs. However, more analysis is needed to check if the parameters remain stable over time and improve predictions' accuracy.

Conclusions

APARCH (1,1) is the fittest model for studying the volatility of BET and S&P 500 stock market indices. We observed asymmetry, volatile clustering, leverage effect, and volatility in both indexes. It may be because of the COVID-19 pandemic and other associated variables such as inflation, demand-supply asymmetric, and microeconomic factors.

A study comparing GARCH, TGARCH, IGARCH, EGARCH, PARCH, and APARCH models across six different distributions found that the APARCH model with a Student's t-distribution provided the best fit for the data. This conclusion was based on the lowest Akaike Information Criterion (AIC), lowest Schwarz Criterion (SC), and highest Log Likelihood measures.

Even though APARCH model is a good model, it is imperfect because it can't measure what might influence things. Sometimes, it portrays them less accurately. For the academic community, it is essential to do an in-depth analysis for the finest details to avoid generalization. For this, various models, such as Machine Learning, COPULA, AI, and VaR, can show the larger picture and assess more information that benefits society, investors, and policymakers.

Authors' Contributions:
The authors contributed equally to this work.

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