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Forecasting Volatility Spillovers Using Advanced GARCH Models: Empirical Evidence for Developed Stock Markets from Austria and USA

Bharat Kumar Meher[*], Puja Kumari[**], Ramona Birau[***], Cristi Spulbar[****], Abhishek Anand[*****], Ion Florescu[******]

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ABSTRACT

The research study voyage commences with the foundational objective of fitting a suitable Generalized Autoregressive Conditional Heteroscedastic (GARCH) model to assess market volatility, a fundamental pillar of financial analysis. This research embarks on an ambitious quest to predict and understand stock market volatility within the realms of the DJIA and S&P 500 of USA and ATX index of Austria using different sophisticated GARCH models. The dataset used in this study comprises daily stock market data for two key indices: the S&P 500 Index, representing the USA stock market, and the ATX Index, representing the Austria stock market. Additionally, the DJIA Index, another representative of the USA stock market, was included. The dataset consists of 5967 daily observations over the specified time period from January 3, 2000, to September 21, 2023. The observation of results, analysis and discussion depicts that PARCH model shows most promising results and found suitable to model the volatility patterns of the selected indices. The findings and methodologies presented in this paper can be seen as a solid foundation upon which to build future investigations, refining our ability to anticipate market movements and make informed decisions in an uncertain financial landscape. In closing, this research not only contributes to the body of knowledge in financial econometrics but also underscores the importance of modeling long-term stock market behavior with precision and diligence.

1. Introduction

The global financial landscape is a multifaceted and dynamic realm, where fortunes are made and lost in the blink of an eye. At the heart of this intricate ecosystem lie the stock markets, which serve as barometers of economic health, vehicles for wealth creation, and arenas of relentless speculation(Davis, 2009)(Lawrence & Buller, 2022). Within this volatile arena, the concept of stock market volatility stands as a paramount determinant of investment decisions, risk management strategies, and the broader economic outlook (Knight, 1998)(Langley, 2008)(Chava & Purnanandam, 2010)(Habib et al., 2018)(Kakran et al., 2023). In this research paper, we embark on a profound journey into the world of financial markets, with a particular focus on three influential indexes: the Dow Jones Industrial Average (DJIA) and the S&P 500 Index, representing the United States, and the ATX Index, reflecting the Austrian economy. Our overarching objective is to dissect and predict stock market volatility with precision and depth, employing advanced models including Threshold GARCH, Exponential GARCH (EGARCH), and Power ARCH (PARCH) models(Engle, 2002). Our pursuit is driven by a fundamental desire to address key questions and unlock insights that can shape the decisions of investors, analysts, and policymakers (Liu et al., 2021).

The research study voyage commences with the foundational objective of fitting a suitable Generalized Autoregressive Conditional Heteroscedastic (GARCH) model to assess market volatility, a fundamental pillar of financial analysis. The DJIA and S&P 500 are not just icons of the American financial landscape but also global benchmarks (Lim et al., 2013)(Chen et al., 2016)(Novotný & Jaklová, 2021). The ATX Index, representing Austria's economic endeavors (Samitas et al., 2022), adds a unique dimension to our analysis. By utilizing GARCH models, we aim to distill the intricate essence of these indexes' volatility patterns, providing stakeholders with a profound understanding of the risks and opportunities that shape market dynamics (Mun, 2010). Our pursuit of this objective is rooted in the recognition that stock market volatility is not an ephemeral

[*]PG Department of Commerce, Purnea University, Purnia, Bihar, India, [**]Department of Commerce and Business Management, Ranchi University, Ranchi, India, [***] Faculty of Economic Science, University Constantin Brancusi of Tg-Jiu, Romania, [****]University of Craiova, Faculty of Economics and Business Administration, Craiova, Romania, [*****]PG Department of Economics, Purnea University, Purnia, Bihar, India, [******]University of Craiova, "Eugeniu Carada" Doctoral School of Economic Sciences, Craiova, Romania. E-mail addresses: bharatraja008@gmail.com, (B. K. Meher), pujakumari254678@gmail.com (P. Kumari), ramona.f.birau@gmail.com (Corresponding author – R. Birau), cristi_spulbar@yahoo.com (C. Spulbar), abhi2eco@gmail.com (A. Anand), ionut.florescu2021@yahoo.com (I. Florescu).

notion but a dynamic, quantifiable phenomenon that plays a pivotal role in shaping investor sentiment and market behavior (Fabozzi et al., 2006).

Beyond the rudimentary assessment of volatility, our research extends its reach to unravel the tapestries of volatility patterns that cloak these financial markets. We acknowledge that volatility is not a uniform entity; it unfolds in complex, asymmetric ways, responding differently to positive and negative shocks(Vogl, 2022). This recognition prompts us to employ both symmetric and asymmetric models, such as EGARCH and PARCH, to delve into the intricate volatility patterns within the USA and Austria stock markets. Through this multifaceted approach, we aspire to unearth the latent dynamics that underlie market turbulence. Our intent is clear: to equip investors and analysts with a more nuanced view of volatility that transcends simplistic metrics and provides actionable insights into market behavior (Seetharam, 2022).

The study also sets sail on a quest to explore the impact of leverage within the daily return series of these stock markets. Leveraging is a phenomenon where volatility exhibits a disproportionate response to negative shocks compared to positive ones (Fornari & Mele, 1997)(Aymanns & Farmer, 2015)(Bollerslev et al., 2020). It is a phenomenon that can magnify risks and create opportunities(Burg et al., 2022). By utilizing asymmetric models that excel at capturing leverage effects, we aim to discern their presence and magnitude(Singh & Singh, 2017)(Hope & Wang, 2018)(Chalissery et al., 2022)(P. Kumar et al., 2022). This exploration is pivotal in enhancing our understanding of the risk profiles associated with the DJIA, S&P 500, and ATX indexes, enabling more informed risk management strategies and investment decisions.

The final destination within this research endeavor is the evaluation of the GARCH family models' suitability for capturing essential details regarding index returns and fits. The GARCH family comprises a spectrum of models, each with its own unique characteristics and assumptions(Bauwens et al., 2006)(Francq & Zakoian, 2019). By meticulously comparing these models and their performance within the context of our chosen indexes, we endeavor to identify which model, or combination thereof, best aligns with the intricacies of each index's return data(Weber & Zhang, 2012). This evaluation serves as a critical compass for ensuring that our modeling approach accurately captures volatility, offering insights that are both robust and actionable(Kwok, 2021).

This research also embarks on an ambitious quest to predict and understand stock market volatility within the realms of the DJIA, S&P 500, and ATX indexes. Our findings, driven by a multifaceted approach and advanced modeling techniques, seek to illuminate the path ahead for investors, analysts, and policymakers. By addressing fundamental questions and unlocking insights, we contribute to the body of knowledge that underpins financial decision-making in an ever-evolving global economy. Our journey into the intricate world of stock market volatility promises to enrich our comprehension and empower those who navigate the unpredictable seas of financial markets.

2. Review of literature

The GARCH family model has been used in numerous studies all over the world to investigate stock market behavior and volatility trends. Such as GJR-GARCH, EGARCH, M GARCH, GARCH (1,1), TGARCH and PGARCH. These studies also concluded that which GARCH family model is most perfect GARCH model. (S. Kumar, Meher, Birau, Simion, Anand, et al., 2023)EGARCH, TGARCH, MGARCH and PGARCH models used in this study to test the volatility of S& P / Toronto index. This paper concluded that the GARCH-GJR is more appropriate model. (S. Kumar, Meher, Birau, Simion, Ion, et al., 2023)GARCH (1,1), GJR-GARCH,EGARCH, M GARCH, and TGARCH models are used in this study to measures the volatility IBOVESPA index.Apart from that this study evaluated the accuracy of volatility forecasts using both univariate and multivariate models.(Maqsood et al., 2017)GARCH-M (1,1), EGARCH (1,1), TGRACH (1,1), and PGARCH (1,1) used in this study to measures the volatility of Nairobi securities exchange. They came to the conclusion that TGARCH (1,1) model is better suitable in terms of capturing the volatility clustering and leverage impact of the NSE stock market out of various symmetric and asymmetric type heteroscedastic processes.(S. Kumar, Anand, et al., 2023)This work analyses conditional variance objectively or empirically estimates the price volatility spillover transmission in the daily returns of IPC Mexico index from Mexico stock market using the GJR- GARCH model.(Leite & Lima, 2023)revealed the extreme volatility of the spot price in Brazil. Institutional issues and the rising proportion of renewable energy in the electrical mix are linked to this high volatility.(Birau et al., 2023)It was found that the GARCH (1, 1) model's perfect fit, which takes into account the impacts of GARCH and ARCH, shows that the volatility in the Sweden market has persisted throughout time. (Bonga, 2019)The volatility of the Zimbabwean stock market is modeled using GARCH family. It was found that the EGARCH(1,1) is the best model.(Cristi et al., 2022)Observed volatility during the COVID-19 pandemic has been demonstrated to form a "V" shape pattern where an unpredictable, sharp negative slope is generated. This was entirely different from the pattern created during the global financial crisis.(Bonga, 2019)concluded that both positive and negative shocks affect stock market returns differently. Both positive and negative news will boost the volatility of stock market returns, but to varying degrees.(Sokpo et al., 2017)The study also discovered that the model series had high persistence, meaning that a positive or negative shock to the stock market return series caused by either good news or bad news will have a long-lasting impact on the market.(Cristi et al., 2023)The negative effects of the global financial crisis have made it clear that the Poland stock market did not provide investors any worthwhile profits. Furthermore, adverse shocks occur more frequently than favorable ones.(Bonga, 2019)Concluded that there is positive relationship exists between Volatility & risks and returns. The financial market becomes increasingly unstable as market volatility increases. (Meher et al., 2020)Investigated the market volatility during the COVID-19 pandemic. The adverse information, however, has far stronger ramifications.

3. Research Gap

The study addresses a critical research gap in the field of financial econometrics. While extensive research has been conducted on stock market volatility prediction, limited attention has been given to comparative analysis and modeling of volatility in the USA and Austria. Moreover, the utilization of advanced GARCH models, such as TGARCH, EGARCH, and PARCH, in this context remains relatively unexplored. By bridging this gap, our research contributes to a deeper understanding of the unique dynamics and asymmetric volatility patterns within these two distinct markets, offering valuable insights for investors, policymakers, and financial analysts.

4. Objectives of the Study

- To fit a suitable GARCH model to assess market volatility based on the DJIA index and S&P 500 Index of USA and ATX Index of Austria.
- To investigate the volatility pattern of indices of USA and Austriastock market using symmetric and asymmetric models.
- To assess the presence of leverage effect in stock market volatility and modelling with asymmetric GARCH model that could depict such effect.
- To assess the suitability of Generalized Autoregressive Conditional Heteroscedastic (GARCH) family models, which better capture key details regarding index returns and fits.

5. Research Methodology

The research methodology employed in this empirical study is outlined in this section. The primary objective of this research is to model the behavior of stock markets in the USA and Austria while focusing on capturing changes, volatility clusters, assessing the fitness of econometric models, and identifying volatility patterns. To achieve this, we utilized data spanning from January 3, 2000, to September 21, 2023.

Data Collection:

The dataset used in this study comprises daily stock market data for two key indices: the S&P 500 Index, representing the USA stock market, and the ATX Index, representing the Austria stock market. Additionally, the DJIA Index, another representative of the USA stock market, was included. The dataset consists of 5967 daily observations over the specified time period, and it is essential to note that the volatility assessment was performed on the basis of daily returns. The daily returns were calculated using the log of the first difference of the daily closing prices.

Model Selection:

To model the volatility of these stock market indices, we employed GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models as introduced by Bollerslev in 1986. Specifically, we employed three well-known asymmetric volatility models: TGARCH (Threshold GARCH), EGARCH (Exponential GARCH), and PARCH (Power ARCH). These models were selected due to their ability to capture asymmetry in volatility, which is often observed in financial time series data.

Stationarity Testing:

Before applying the GARCH models, it is crucial to ensure that the data is stationary. To assess stationarity, we employed several statistical tests. The Autocorrelation Function Plot was used to visualize the autocorrelation in the data, while the Augmented Dickey Fuller test and Phillips-Perron test were conducted to formally assess stationarity. These tests are essential to ensure that the time series data meet the necessary assumptions for GARCH modeling.

Model Estimation:

To estimate the GARCH models (TGARCH, EGARCH, and PARCH), we utilized the E-Views 12 Econometrics package. This software package provides robust tools for econometric modeling and time series analysis. The ARCH Lagrange Multiplier (LM) test was employed to investigate the presence of heteroscedasticity in the residual series of the return data. Identifying heteroscedasticity is crucial in choosing the appropriate GARCH model.

Model Evaluation:

The selection of the most suitable GARCH model was based on the evaluation of three GARCH family models: GARCH/TARCH, EGARCH, and PGARCH, all using the Student t's Distribution. The choice of the best model was made considering the model's goodness-of-fit, diagnostic tests, and the ability to capture the specific characteristics of the volatility in the stock market data.

This research methodology involved the collection of daily stock market data for the USA and Austria, the application of GARCH models, rigorous stationarity testing, and careful model selection and evaluation.

These steps were essential to accurately capture and model the volatility patterns and changes in the selected stock market indices, providing valuable insights into their behavior over the study period.

6. Empirical Results and Discussion

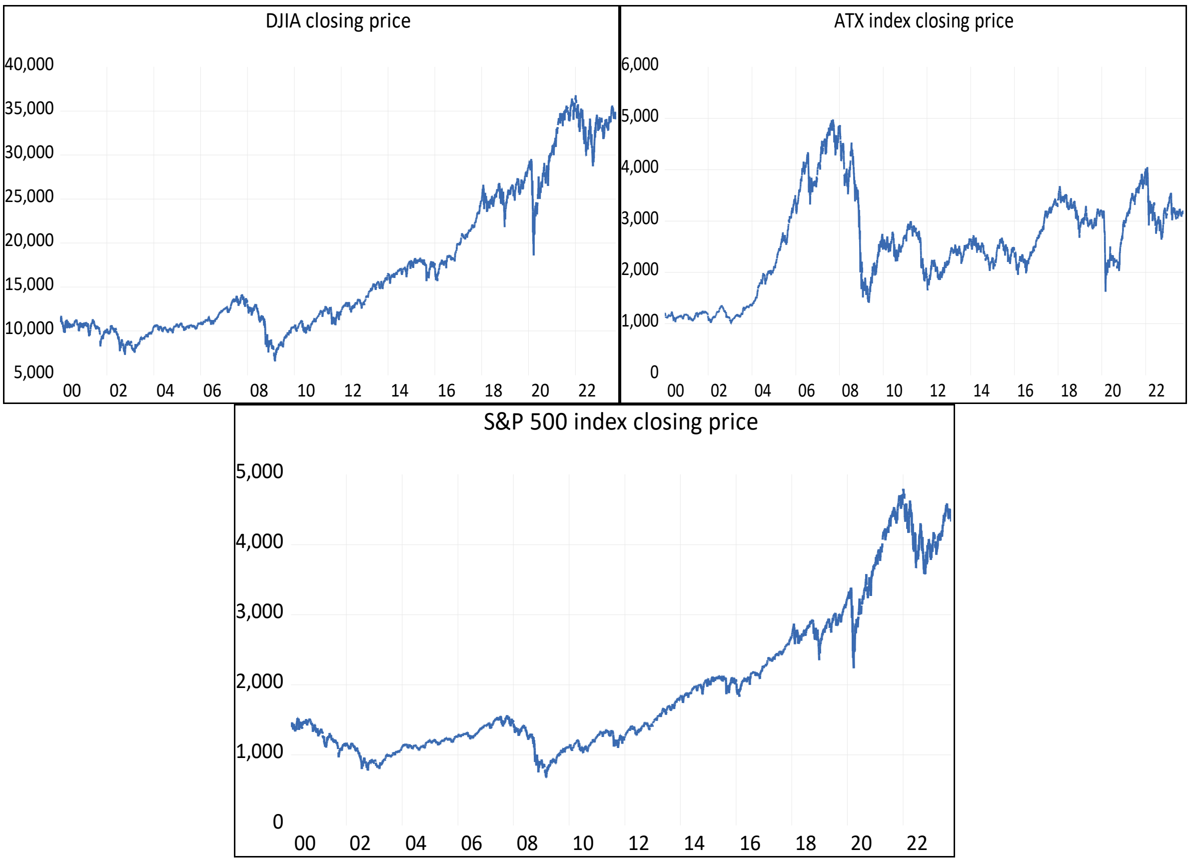
In this paper, the daily closing prices of the S&P 500 index, DJIA indexand ATX index over the period from 03 January 2000 to 21 September 2023 resulted in total observations of 5967 excluding public holidays. Various descriptive statistics are calculated and exhibited in Table 1.1 providing 0.000164, 0.000184, and 0.000183mean with 0.014301, 0.011830 and 0.012424 degree of Standard Deviation. A high value of kurtosis 12.25556, 15.63380 and 13.23124 which is greater than 3 indicates a leptokurtic distribution that is an apparent departure from normality while the skewness represents negative value it indicating data has long left skewed distribution.

The Jarque-Bera statistic is a crucial normality test, the p-value of JarqueBera is less than its critical value of 5% signifying the data is non-normal.

Table No. 1.1 - Descriptive Statistics of GARCH model

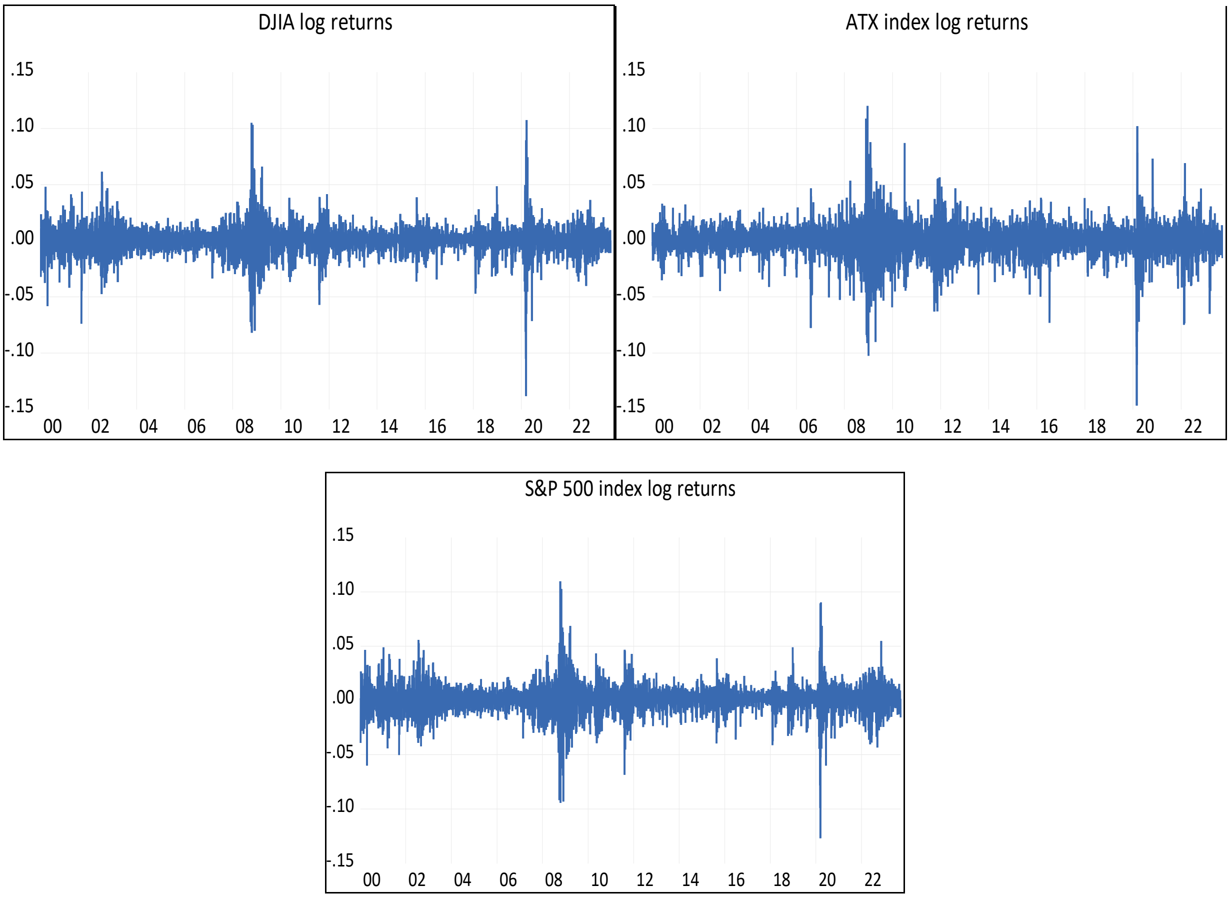
	DJIA_LOG_RETURNS	ATX_INDEX_LOG_RETURNS	S_P_500_INDEX_LOG_RETURNS
Mean	0.000184	0.000164	0.000183
Median	0.000485	0.000698	0.000566
Maximum	0.107643	0.120210	0.109572
Minimum	-0.138418	-0.146745	-0.127652
Std. Dev.	0.011830	0.014301	0.012424
Skewness	-0.368236	-0.569262	-0.375929
Kurtosis	15.63380	12.25556	13.23124
Jarque-Bera	39818.59	21620.84	26166.18
Probability	0.000000	0.000000	0.000000
Sum	1.098550	0.979570	1.090410
Sum Sq. Dev.	0.834987	1.220213	0.920843
Observations	5967	5967	5967

Source: Authors' Calculation using Eviews12



Graph 1.1: Movement Pattern of DJIA Index, ATX Index and S&P 500 Index

Source: Authors' Calculation using Eviews12



Graph 1.2: log returns of DJIA Index, ATX Index and S&P 500 Index

Source: Authors' Calculation using Eviews12

Graph 1.1 shows the movement patterns of the DJIA, ATX and S&P 500 Indexes' Stationary Series during the hypothetical period from 03 January 2000 to 21 September 2023. Graph 1.2 shows the graphical presentation of the log returns of the presence of volatility clustering using the DJIA Index, ATX Index and S&P 500 Index. In order to estimate the volatility of USA and Austria stock market, checking the stationary is the first step in the analysis of the return series(Maqsood et al., 2017). For this purpose, Autocorrelation Function Plot (ACF Plot), Augmented Dickey-Fuller (ADF)(Dickey & Fuller, 1979)test and Phillips Perron (PP) test(Phillips & Perron, 1988) are usedto establish the stationarity of the DJIA, ATX and S&P 500 index sample data series. The test results are presented with the help of following tables:

Table: 1.2 Autocorrelation FunctionPlotof djia Index

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.104	-0.104	64.025	**0.000**
| |	| |	2	0.009	-0.002	64.527	**0.000**
| |	| |	3	0.019	0.020	66.782	**0.000**
| |	| |	4	-0.022	-0.018	69.644	**0.000**
| |	| |	5	-0.011	-0.016	70.394	**0.000**
| |	| |	6	-0.046	-0.049	82.856	**0.000**
| |	| |	7	0.044	0.035	94.235	**0.000**
| |	| |	8	-0.031	-0.023	100.16	**0.000**
| |	| |	9	0.042	0.038	110.82	**0.000**
| |	| |	10	-0.009	-0.004	111.26	**0.000**
| |	| |	11	-0.014	-0.015	112.43	**0.000**
| |	| |	12	0.037	0.032	120.82	**0.000**
| |	| |	13	-0.020	-0.008	123.17	**0.000**
| |	| |	14	0.004	-0.001	123.28	**0.000**
| |	| |	15	-0.062	-0.059	146.24	**0.000**
| |	| |	16	0.068	0.055	174.20	**0.000**
| |	| |	17	-0.014	-0.000	175.43	**0.000**
| |	| |	18	-0.037	-0.036	183.79	**0.000**
| |	| |	19	-0.004	-0.020	183.87	**0.000**
| |	| |	20	-0.001	0.001	183.88	**0.000**

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	21	-0.015	-0.020	185.20	**0.000**
| |	| |	22	-0.013	-0.007	186.19	**0.000**
| |	| |	23	0.011	0.000	186.90	**0.000**
| |	| |	24	-0.010	-0.005	187.45	**0.000**
| |	| |	25	-0.012	-0.017	188.34	**0.000**
| |	| |	26	-0.013	-0.019	189.36	**0.000**
| |	| |	27	0.029	0.033	194.28	**0.000**
| |	| |	28	-0.010	-0.009	194.87	**0.000**
| |	| |	29	0.011	0.010	195.61	**0.000**
| |	| |	30	-0.001	-0.003	195.62	**0.000**
| |	| |	31	-0.021	-0.014	198.33	**0.000**
| |	| |	32	0.002	-0.009	198.35	**0.000**
| |	| |	33	-0.014	-0.014	199.58	**0.000**
| |	| |	34	-0.044	-0.046	211.27	**0.000**
| |	| |	35	0.009	0.003	211.74	**0.000**
| |	| |	36	0.027	0.022	216.19	**0.000**

Source: Authors' Calculation using Eviews12

Table: 1.3 Autocorrelation Function of ATX Index

Included observations: 5967 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.065	0.065	24.969	**0.000**
| |	| |	2	0.009	0.005	25.503	**0.000**
| |	| |	3	-0.003	-0.004	25.565	**0.000**
| |	| |	4	-0.014	-0.014	26.716	**0.000**
| |	| |	5	0.005	0.007	26.873	**0.000**
| |	| |	6	-0.020	-0.020	29.156	**0.000**
| |	| |	7	0.035	0.037	36.316	**0.000**
| |	| |	8	-0.004	-0.009	36.420	**0.000**
| |	| |	9	-0.008	-0.008	36.815	**0.000**
| |	| |	10	0.005	0.005	36.948	**0.000**
| |	| |	11	-0.009	-0.009	37.452	**0.000**
| |	| |	12	0.007	0.007	37.736	**0.000**
| |	| |	13	0.015	0.016	39.066	**0.000**
| |	| |	14	0.007	0.003	39.333	**0.000**
| |	| |	15	0.018	0.017	41.211	**0.000**
| |	| |	16	0.005	0.004	41.360	**0.000**
| |	| |	17	0.006	0.005	41.566	**0.001**
| |	| |	18	-0.029	-0.028	46.432	**0.000**
| |	| |	19	0.024	0.029	49.954	**0.000**
| |	| |	20	0.020	0.016	52.257	**0.000**
| |	| |	21	0.014	0.013	53.509	**0.000**
| |	| |	22	0.018	0.015	55.550	**0.000**
| |	| |	23	-0.043	-0.044	66.593	**0.000**
| |	| |	24	-0.009	-0.005	67.118	**0.000**
| |	| |	25	0.059	0.065	88.102	**0.000**
| |	| |	26	0.020	0.010	90.413	**0.000**
| |	| |	27	-0.023	-0.029	93.548	**0.000**
| |	| |	28	-0.035	-0.032	100.90	**0.000**
| |	| |	29	0.016	0.019	102.43	**0.000**
| |	| |	30	0.016	0.017	103.90	**0.000**
| |	| |	31	0.001	0.001	103.91	**0.000**
| |	| |	32	0.000	-0.007	103.91	**0.000**
| |	| |	33	0.000	0.000	103.91	**0.000**
| |	| |	34	-0.029	-0.029	108.89	**0.000**
| |	| |	35	-0.025	-0.020	112.65	**0.000**
| |	| |	36	0.029	0.032	117.82	**0.000**

Source: Authors' Calculation using Eviews12

Table: 1.4 Autocorrelation Function of S&P 500 Index

Included observations: 5967 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.103	-0.103	63.447	**0.000**
| |	| |	2	-0.008	-0.019	63.848	**0.000**
| |	| |	3	0.010	0.007	64.471	**0.000**
| |	| |	4	-0.024	-0.023	68.012	**0.000**
| |	| |	5	-0.012	-0.017	68.895	**0.000**
| |	| |	6	-0.036	-0.040	76.589	**0.000**
| |	| |	7	0.031	0.023	82.367	**0.000**
| |	| |	8	-0.030	-0.026	87.622	**0.000**
| |	| |	9	0.042	0.037	98.034	**0.000**
| |	| |	10	-0.003	0.002	98.089	**0.000**
| |	| |	11	-0.010	-0.008	98.663	**0.000**
| |	| |	12	0.039	0.036	107.90	**0.000**
| |	| |	13	-0.011	-0.001	108.67	**0.000**
| |	| |	14	-0.002	-0.004	108.71	**0.000**
| |	| |	15	-0.060	-0.059	130.54	**0.000**
| |	| |	16	0.068	0.056	158.40	**0.000**
| |	| |	17	-0.007	0.007	158.67	**0.000**
| |	| |	18	-0.032	-0.029	164.94	**0.000**
| |	| |	19	-0.002	-0.016	164.97	**0.000**
| |	| |	20	0.006	0.007	165.17	**0.000**
| |	| |	21	-0.015	-0.019	166.53	**0.000**
| |	| |	22	-0.010	-0.008	167.12	**0.000**
| |	| |	23	0.004	-0.005	167.20	**0.000**
| |	| |	24	-0.009	-0.006	167.69	**0.000**
| |	| |	25	-0.006	-0.012	167.91	**0.000**
| |	| |	26	-0.013	-0.018	168.97	**0.000**
| |	| |	27	0.030	0.033	174.42	**0.000**
| |	| |	28	-0.006	-0.004	174.61	**0.000**
| |	| |	29	0.011	0.009	175.30	**0.000**
| |	| |	30	0.006	0.007	175.51	**0.000**
| |	| |	31	-0.014	-0.004	176.69	**0.000**
| |	| |	32	0.004	-0.003	176.79	**0.000**
| |	| |	33	-0.013	-0.013	177.81	**0.000**
| |	| |	34	-0.047	-0.049	191.25	**0.000**
| |	| |	35	0.015	0.010	192.66	**0.000**
| |	| |	36	0.029	0.025	197.69	**0.000**

Source: Authors' Calculation using Eviews12

Table: 1.5: Unit root Test (Augmented Dickey-Fuller test) and Phillips-Perron test of DJIA index

Null Hypothesis: DJIA_LOG_RETURNS has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-85.74128	**0.0001***
Test critical values:	1% level	-3.959575	
	5% level	-3.410557	
	10% level	-3.127051	

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-85.69481	**0.0001***
Test critical values:	1% level	-3.959575	
	5% level	-3.410557	
	10% level	-3.127051	

Source: Authors' Calculation using Eviews12

Table: 1.6: Unit root Test (Augmented Dickey-Fuller test) and Phillips-Perron test of ATX index
Null Hypothesis: ATX_INDEX_LOG_RETURNS has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-72.38189	**0.0000***
Test critical values:	1% level	-3.959575	
	5% level	-3.410557	
	10% level	-3.127051	

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-72.38968	**0.0000***
Test critical values:	1% level	-3.959575	
	5% level	-3.410557	
	10% level	-3.127051	

Source: Authors' Calculation using Eviews12

Table: 1.7: Unit root Test (Augmented Dickey-Fuller test) and Phillips-Perron test of S&P 500 index
Null Hypothesis: S_P_500_INDEX_LOG_RETURNS has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-85.72656	**0.0001***
Test critical values:	1% level	-3.959575	
	5% level	-3.410557	
	10% level	-3.127051	

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-86.06795	**0.0001***
Test critical values:	1% level	-3.959575	
	5% level	-3.410557	
	10% level	-3.127051	

Source: Authors' Calculation using Eviews12

Table 1.2 shows the Autocorrelation Function Plot of djia Index, Table 1.3 shows the Autocorrelation Function Plot of ATX Index andTable 1.4 shows the Autocorrelation Function Plotof S&P 500 Index. Autocorrelation Function Plot is a visual representation of ACF and PACF of a time series. Here statistical properties changes over time, it indicating that there is no trend hence the data isstationary. Table 1.5shows the Unit root Test (Augmented Dickey-Fuller test) and Phillips-Perron test of DJIA index, Table 1.6 shows the Unit root Test (Augmented Dickey-Fuller test) and Phillips-Perron test of ATX index and Table 1.7 shows the Unit root Test (Augmented Dickey-Fuller test) and Phillips-Perron test of S&P 500 index. The p values of Augmented Dickey-Fuller test and Phillips-Perron test are less than 0.05which leads to reject the null hypothesis hence, the sample data were found to be stationary since the probability values are significant at 10%, 5%, and 1% levels.

Testing for ARCH Effect:

It is crucial to look at the residuals for signs of heteroscedasticity. If conditional heteroskedasticity is present, the results might be deceiving if it is not taken into consideration. (SOKPO, IOREMBER, & USAR, Inflation and Stock Market Returns Volatility: Evidence from the Nigerian Stock Exchange 1995Q1-2016Q4: An E-GARCH Approach, 2018). The ARCH Lagrange Multiplier (LM) test is employed to determine whether heteroscedasticity exists in the return series' residual. Testing for conditional heteroskedasticity is crucial since if it's omitted adopting GARCH-type models would be improper.

Table 1.8: Heteroskedasticity Test: ARCH

DJIA index			
Heteroskedasticity Test: ARCH			
F-statistic	495.1899	Prob. F(1,5963)	**0.0000**
Obs*R-squared	457.3739	Prob. Chi-Square(1)	0.0000

ATX index			
Heteroskedasticity Test: ARCH			
F-statistic	303.9614	Prob. F(1,5963)	**0.0000**
Obs*R-squared	289.3156	Prob. Chi-Square(1)	0.0000

S&P 500 index			
Heteroskedasticity Test: ARCH			
F-statistic	473.2127	Prob. F(1,5963)	**0.0000**
Obs*R-squared	438.5675	Prob. Chi-Square(1)	0.0000

Source: Authors' Calculation using Eviews12

Table 1.8 shows the result of the ARCH-LM test for DJIA Index, ATX Index and S&P 500 Index.It inferred that data is highly significant. Theprobability of F-statistic (0.0000) shows that p value is less than0.05; the null hypothesis (i.e., no ARCH effect) is rejected at 1% level.The results support to estimate GARCH family models since, indicating the existence of ARCH effects in the residuals of time series models.This indicates the series under consideration is variable, requiring volatility modeling to account for volatility in the model.

Table 1.9: Selecting an appropriate model

DJIA Index			
Estimated model	**Akaike info criterion**	**Schwartz criterion**	**Log Likelihood**
GARCH/TARCH	-6.576149	-6.569417	19622.65
EGARCH	-6.610309	-6.602455	19725.55
PARCH	**-6.614454**	**-6.605478**	**19738.92**
ATX Index			
Estimated model	**Akaike info criterion**	**Schwartz criterion**	**Log Likelihood**
GARCH/TARCH	-6.103017	-6.096285	18211.3
EGARCH	-6.1193	-6.111446	18260.87
PARCH	**-6.122116**	**-6.11314**	**18270.27**
S&P 500 Index			
Estimated model	**Akaike info criterion**	**Schwartz criterion**	**Log Likelihood**
GARCH/TARCH	-6.480437	-6.473705	19337.14
EGARCH	-6.519938	-6.512084	19455.97
PARCH	**-6.523629**	**-6.514653**	**19467.98**

Source: Authors' Calculation using Eviews12

Table 1.9 Depicts three models of GARCH family. PGARCH with Student t's Distribution has the lowest Akaike info criterion and Schwartz criterion apart from that maximum Log Likelihood when compared to the other two. As a result, this model is thought to be the best one. The results of the selected PARCH Model for the DJIA index, ATX index, and S&P 500 Index are shown in the table below.

Table 1.10: PGARCH with Student's t distribution Error Construct of DJIA index

Dependent Variable: DJIA_LOG_RETURNS
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 10/05/23 Time: 18:06
Sample (adjusted): 1/05/2000 9/21/2023
Included observations: 5966 after adjustments
Convergence not achieved after 500 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	0.000410	9.48E-05	4.327361	**0.0000**
DJIA_LOG_RETURNS(-1)	-0.039604	0.013264	-2.985820	0.0028
		Variance Equation		
C(3)	0.000134	5.99E-05	2.243925	0.0248
C(4)	0.081998	0.005208	15.74337	0.0000
C(5)	0.999956	8.11E-07	1233030.	0.0000
C(6)	0.910789	0.005138	177.2819	0.0000
C(7)	1.090693	0.085345	12.77980	0.0000
T-DIST. DOF	7.339247	0.651054	11.27287	0.0000

R-squared	0.006317	Mean dependent var	0.000190
Adjusted R-squared	0.006150	S.D. dependent var	0.011824
S.E. of regression	0.011788	Akaike info criterion	**-6.614454**
Sum squared resid	0.828672	Schwarz criterion	**-6.605478**
Log likelihood	**19738.92**	Hannan-Quinn criter.	-6.611336
Durbin-Watson stat	2.126805		

Source: Authors' Calculation using Eviews12

Table 1.11: PGARCH with Student's t distribution Error Construct of ATX index

Dependent Variable: ATX_INDEX_LOG_RETURNS
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 10/05/23 Time: 18:03
Sample (adjusted): 1/05/2000 9/21/2023
Included observations: 5966 after adjustments
Convergence achieved after 56 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	0.000470	0.000129	3.655692	**0.0003**
ATX_INDEX_LOG_RETURNS(-1)	0.046941	0.013285	3.533262	0.0004
		Variance Equation		
C(3)	0.000108	7.16E-05	1.511677	0.1306
C(4)	0.087093	0.009205	9.461983	0.0000
C(5)	0.565449	0.080414	7.031717	0.0000
C(6)	0.899673	0.008305	108.3341	0.0000
C(7)	1.244175	0.145618	8.544087	0.0000
T-DIST. DOF	9.134306	0.979259	9.327775	0.0000

R-squared	0.003380	Mean dependent var	0.000162
Adjusted R-squared	0.003213	S.D. dependent var	0.014301
S.E. of regression	0.014278	Akaike info criterion	**-6.122116**
Sum squared resid	1.215837	Schwarz criterion	**-6.113140**
Log likelihood	**18270.27**	Hannan-Quinn criter.	-6.118998
Durbin-Watson stat	1.963762		

Source: Authors' Calculation using Eviews12

Table 1.12: PARCH with Student's t distribution Error Construct of S&P 500 index

Dependent Variable: S_P_500_INDEX_LOG_RETURNS
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 10/05/23 Time: 17:58
Sample (adjusted): 1/05/2000 9/21/2023
Included observations: 5966 after adjustments
Convergence achieved after 106 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)

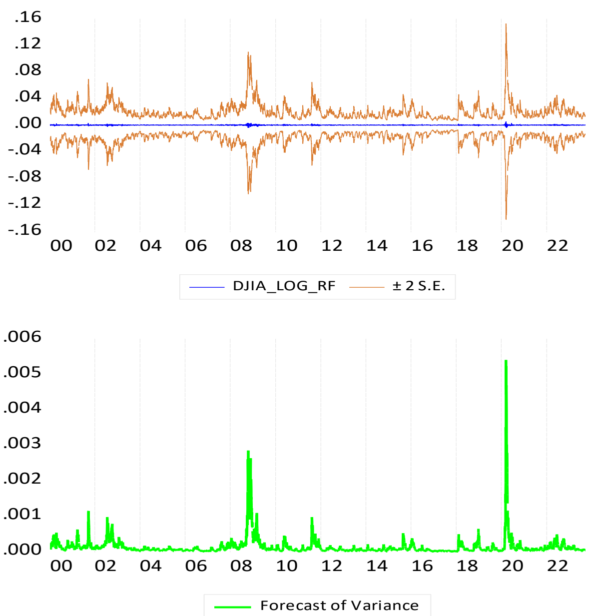
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000446	9.76E-05	4.571438	**0.0000**
S_P_500_INDEX_LOG_RETURNS(-1)	-0.048456	0.013447	-3.603385	0.0003
		Variance Equation		
C(3)	0.000245	9.73E-05	2.516566	0.0119
C(4)	0.090935	0.005119	17.76382	0.0000
C(5)	0.999863	5.75E-06	173928.5	0.0000
C(6)	0.909093	0.005284	172.0343	0.0000
C(7)	0.978762	0.077314	12.65962	0.0000
T-DIST. DOF	7.277275	0.591526	12.30255	0.0000

R-squared	0.007257	Mean dependent var	0.000189
Adjusted R-squared	0.007091	S.D. dependent var	0.012414
S.E. of regression	0.012370	Akaike info criterion	**-6.523629**
Sum squared resid	0.912628	Schwarz criterion	**-6.514653**
Log likelihood	**19467.98**	Hannan-Quinn criter.	-6.520511
Durbin-Watson stat	2.110460		

Source: Authors' Calculation using Eviews12

Above table are representing the PARCH model with Student's t distribution error construct of DJIA Index, ATX Index and S&P 500Index.Since Probabilities are lower than 0.05, the constant (C) isconsidered significant.

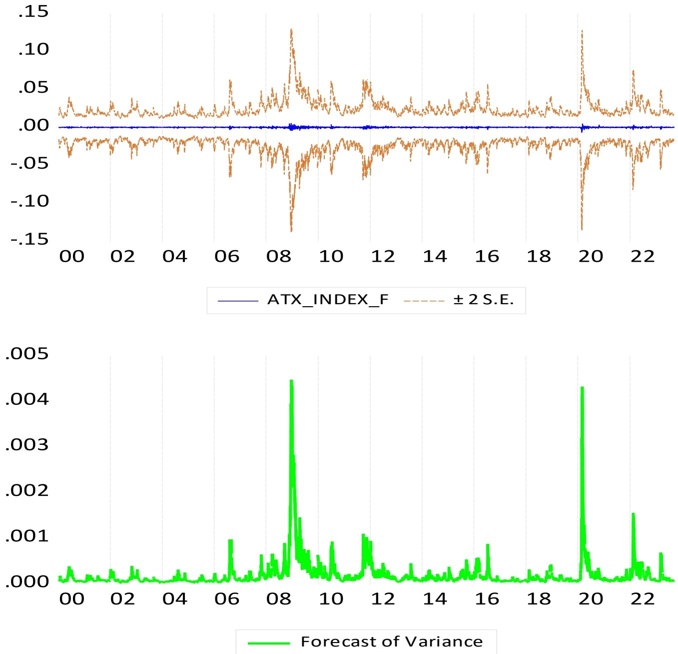
We can forecast the volatility of the USA Stock Exchange and Austria Composite indices using the aforementioned methodology using a data set of 5966 days. The charts below are intended to demonstrate the anticipated uneven price changes of the USA and Austria Stock Exchange Composite index throughout the corresponding time periods:



Forecast: DJIA_LOG_RF	
Actual: DJIA_LOG_RETURNS	
Forecast sample: 1/03/2000 9/21/2023	
Adjusted sample: 1/05/2000 9/21/2023	
Included observations: 5966	
Root Mean Squared Error	0.011786
Mean Absolute Error	0.007744
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.947208
Bias Proportion	0.000328
Variance Proportion	0.928182
Covariance Proportion	0.071490
Theil U2 Coefficient	NA
Symmetric MAPE	175.7005

Graph 1.3: Estimating volatility patterns using PARCH models ofDJIA Index
Source: Authors' Calculation using Eviews12

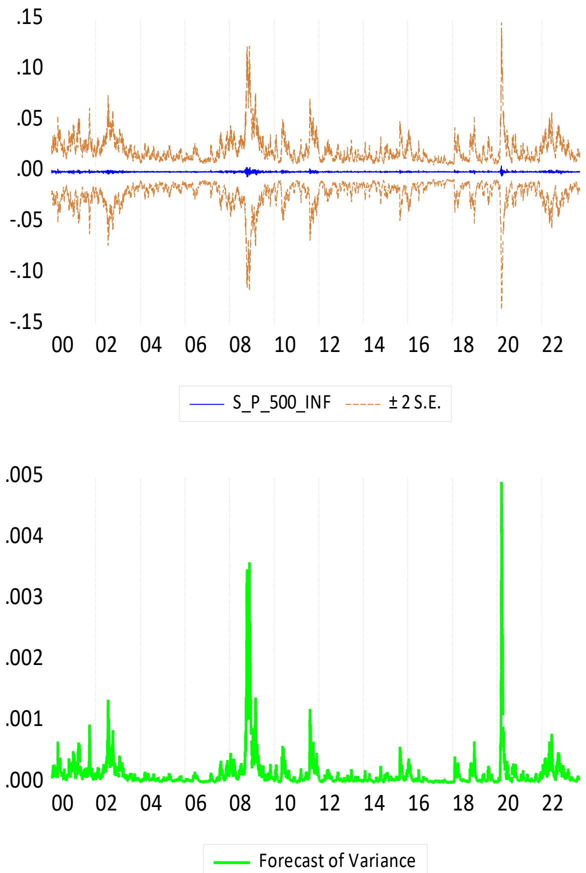
Forecasting volatility using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models is a common approach in financial econometrics. GARCH models help capture the time-varying nature of volatility in financial time series data. The need for the modeling and forecasting volatility is because investor are not interested in the average returns of a stock but also its risk. Market investors and speculators need information to analyze the gains or losses from the erratic behavior of the financial assets. Analysis volatility is helpful as it informs investor a measure of the risk involved in holding as assets.



Forecast: ATX_INDEX_F	
Actual: ATX_INDEX_LOG_RETURNS	
Forecast sample: 1/03/2000 9/21/2023	
Adjusted sample: 1/05/2000 9/21/2023	
Included observations: 5966	
Root Mean Squared Error	0.014276
Mean Absolute Error	0.009699
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.943868
Bias Proportion	0.000491
Variance Proportion	0.911402
Covariance Proportion	0.088107
Theil U2 Coefficient	NA
Symmetric MAPE	176.0410

Graph 1.4: Estimating volatility patterns using PARCH models of ATX Index

Source: Authors' Calculation using Eviews12



Forecast: S_P_500_INF	
Actual: S_P_500_INDEX_LOG_RETURNS	
Forecast sample: 1/03/2000 9/21/2023	
Adjusted sample: 1/05/2000 9/21/2023	
Included observations: 5966	
Root Mean Squared Error	0.012368
Mean Absolute Error	0.008169
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.939923
Bias Proportion	0.000402
Variance Proportion	0.911991
Covariance Proportion	0.087607
Theil U2 Coefficient	NA
Symmetric MAPE	174.3729

Graph 1.5: Estimating volatility patterns using PARCH models of S&P 500 Index

Source: Authors' Calculation using Eviews12

To forecast variance using financial time series data, we can use models like Generalized Autoregressive Conditional Heteroskedasticity (GARCH), which is specifically designed for volatility forecasting.Forecast variance, also known as forecast error or prediction error, is a measure of the difference between the predicted or forecasted values and the actual observed values in a forecasting model. It quantifies how well or poorly a forecasting model is performing by indicating the extent to which the predictions deviate from the actual outcomes. Forecast variance is a critical metric for assessing the accuracy and reliability of a forecasting model.Lower forecast variance, as indicated by lower values of RMSE, MAE, or percentage error, suggests that the forecasting model is more accurate. High forecast variance, on the other hand, indicates that the model's predictions deviate significantly from the actual outcomes, implying lower accuracy.The forecasting evaluation of the DJIA index from USA stock market, ATX index from Austria stock market and S&P 500 index from USA stock market series returns is highlighted in graph 1.3, 1.4 and 1.5 respectively for the sample period.In USA stock market both the index high volatility is visible in the graphical trend in 2008 due to global financial crisis. A high volatility can be seen at the year 2020. This time Pandemic Covid 19 erupted the US.On the other handATX index has also high volatility in 2008 and 2020 but the volatility at both the times was almost equal. Results reviled that the return on financial assets is stable but showsintense volatility in selected all financial sample data series.

7. Conclusions

The paper has been developed into the intricate world of stock market volatility prediction, focusing on the indices of two distinct but economically significant countries, the United States and Austria. Through the application of advanced GARCH models, including GARCH/TARCH, EGARCH, and PARCH, this research sought to illuminate the underlying patterns and behavior of these financial markets. The analysis centered on log returns derived from the DJIA index, ATX Index, and S&P 500 Index, spanning from January 3, 2000, to September 21, 2023. One crucial aspect of this investigation was the assessment of stationarity in the data series, as it forms the foundation upon which econometric models are built. The Autocorrelation Function Plot, Augmented Dickey Fuller test, and Phillips-Perron test all converged in their findings, indicating that the sample data were stationary. This essential confirmation allowed us to proceed with confidence in our modeling endeavors. Moreover, the identification of heteroscedasticity, a key element in understanding stock market volatility, was carried out using the ARCH Lagrange Multiplier (LM) test.

The compelling results of this test revealed the presence of ARCH effects in the residuals of our time series models. This discovery provided further support for the use of GARCH family models in our pursuit of accurate volatility forecasting. Among the three GARCH models considered, GARCH/TARCH, EGARCH, and PARCH, the selection of the most appropriate model hinged on several criteria, including the Akaike information criterion, Schwartz criterion, and maximum log likelihood. Remarkably, the PARCH model emerged as the favored choice, demonstrating its superiority in capturing the complexities of the data and offering a robust foundation for predicting stock market volatility. The results obtained through the application of the PARCH model, as showcased in Table 1.10 to 1.13, provide valuable insights into the dynamics of the DJIA Index, ATX Index, and S&P 500 Index. These findings unveil the intricate interplay of factors influencing stock market volatility, shedding light on the specific characteristics of each index and their responses to economic events, policy changes, and global influences.

In essence, this research represents a comprehensive endeavor to contribute to the understanding of stock market behavior in the USA and Austria. By harnessing advanced GARCH models and rigorous statistical analyses, we have advanced our comprehension of volatility patterns and their underlying drivers. These insights are not only valuable for investors and financial professionals but also for policymakers and analysts seeking to make informed decisions in the ever-evolving landscape of global financial markets. Furthermore, the methodology and techniques employed in this study can serve as a valuable reference for future research in the field of financial econometrics and volatility forecasting.

As the world of finance continues to evolve and grow increasingly complex, the need for accurate and robust models to predict stock market volatility becomes ever more pressing. The findings and methodologies presented in this paper can be seen as a solid foundation upon which to build future investigations, refining our ability to anticipate market movements and make informed decisions in an uncertain financial landscape. In closing, this research not only contributes to the body of knowledge in financial econometrics but also underscores the importance of modeling stock market behavior with precision and diligence. The utilization of advanced GARCH models and rigorous statistical tests has allowed us to unlock valuable insights into the dynamics of the US and Austrian stock markets, ultimately advancing our understanding of the intricate world of stock market volatility prediction.

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