
PREDICTIVE POWER OF ASYMMETRIC GARCH MODELS IN VOLATILITY ESTIMATION: A CASE STUDY FOR SWITZERLAND STOCK EXCHANGE

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Abstract:

IN THE STOCK MARKET, VOLATILITY IS A TERM USED TO DESCRIBE THE DEGREE TO WHICH THE PRICES OF ASSETS FLUCTUATE AND DETERMINES THE DEGREE OF RISK OR UNCERTAINTY. THE MAIN AIM OF THE PRESENT STUDY IS TO MODELING THE BEHAVIOR OF THE SWITZERLAND STOCK MARKET USING DATA FROM 4TH JANUARY, 2000 TO 9TH NOVEMBER, 2023. THROUGH THE APPLICATION OF GARCH FAMILY MODELS WHICH, INCLUDE GARCH/TARCH, EGARCH, COMPONENT ARCH (1,1), AND PARCH. THE STUDY USED A SAMPLE NUMBER OF 5994 DAILY OBSERVATIONS FOR SWISS STOCK INDEX REPRESENTING THE SWITZERLAND STOCK MARKET. WE USED SOME STATISTICAL TECHNIQUES SUCH AS PHILLIPS-PERRON AND AUGMENTED DICKEY FULLER TESTS STATISTIC. THE ARCH LAGRANGE MULTIPLIER (LM) TEST, PARCH MODEL. WE UTILIZED THE EViews 12 ECONOMETRICS PACKAGE. THIS STUDY HIGHLIGHTS THE SIGNIFICANCE OF ACCURATELY AND METICULOUSLY SIMULATING STOCK MARKET BEHAVIOR IN ADDITION



TO ADDING TO THE CORPUS OF KNOWLEDGE IN FINANCIAL ECONOMETRICS. THE CONCLUSIONS AND METHODS DISCUSSED IN THIS STUDY PROVIDE A STRONG BASIS FOR FURTHER RESEARCH, ENHANCING OUR CAPACITY TO PREDICT MARKET MOVEMENTS AND MAKE WISE CHOICES IN A VOLATILE FINANCIAL ENVIRONMENT.

Keywords: VOLATILITY CLUSTERS, SWITZERLAND STOCK MARKET, FORECASTING, GARCH FAMILY MODELS

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Introduction

In the stock market, volatility is a term used to describe the degree to which the prices of assets (which are seen as unpredictable) fluctuate and determines the degree of risk or uncertainty (Kim & Won, 2018). It swiftly causes prices to rise and fall (Badarla et al., 2021). A fortune may be made or lost in the blink of an eye in the complex and volatile world of global finance. In this erratic environment, the concept of stock market volatility is a critical factor in determining investment choices, risk and mitigation tactics. It is crucial to quantify and examine volatility in the financial markets in order to appropriately mitigate against instability. It's also beneficial to comprehend the level of risk associated with any specific market (Badarla et al., 2021). In the financial markets, volatility is important for hedging techniques, portfolio risk management, and derivative pricing.

As a result, accurate volatility prediction is paramount (Kim & Won, 2018). Since (Bollerslev, 1986) introduced model which is ARCH models, it is a statistical model used to analyze volatility in time series in order to forecast future volatility. Under the assumption that there is a probability density function of the returns series, the parameters of the ARCH class models are generally estimated using the parametric estimation method (Sun & Yu, 2019). Due to the capacity to capture volatility persistence or clustering, the ARCH class models are advantageous (Bollerslev, 1986; Vedat, 1989; Baillie, Bollerslev, & Mikkelsen, 1996). However, some existing studies have indicated that the ARCH class models must be transformed to provide good forecasting performance (Choudhry & Wu, 2008). In recent years, researchers have combined the GARCH model and computational intelligence-based techniques for financial time series forecasting. (Engle, 1982) suggested the GARCH model, it is a statistical model used in analyzing time-series data where the variance error is believed to be serially autocorrelated.

The Swiss Market Index (SMI) is Switzerland's blue-chip stock market index, which makes it the most followed in the country. It is made up of 20 of the largest and most liquid Swiss Performance Index (SPI) stocks. As a price index, the SMI is not adjusted for dividends. The present effort focuses on modeling the behavior of the Switzerland stock market using data from 4th January, 2000 to 9th November, 2023. Insightful details on historical trends and volatility are provided by the detail analysis



for a particular market, supporting any future decision-making. We propose generalized autoregressive conditional heteroscedasticity (GARCH) model to forecast stock price volatility in Switzerland stock market.

Review of literature

Numerous research projects have been conducted to modeling the volatility of stock markets with the help of various indexes. Birau et al. (2021) have studied the GARCH-based model behavior of the stock markets in Hong Kong and Spain. In addition, (Spulbar et al., 2020) examined the Hong Kong stock market's dynamics using short-term momentum effects. (Meher et al., 2020) investigated the fluctuations in the market during the COVID-19 outbreak. However, the adverse information has far stronger ramifications. Sokpo et al. (2017) conducted a study and found that the model series had strong persistence, indicating that the market will be affected for some time by a positive or negative shock to the stock market return series caused on by either good or bad news. (Spulbar et al., 2023) argued that it is evident from the detrimental impacts of the global financial crisis that investors were not able to make any significant profits from the Poland stock market. Furthermore, adverse shocks occur more frequently than favorable ones. Bonga (2019) concluded that there is a positive association between returns, risks, and volatility. As market volatility increases, the financial market becomes more volatile.

Several research conducted worldwide have examined the volatility patterns and behavior of the stock market using the GARCH family model such as Spulbar et al. (2022). Kumar et al. (2023b) conducted a research study where the S&P Toronto stock index's volatility was examined using the EGARCH, TGARCH, MGARCH, and PGARCH models. According to the paper's conclusion, the GARCH-GJR model is better suitable. Kumar et al. (2023c) elaborated an empirical study that used the GARCH (1,1), GJR-GARCH, EGARCH, M GARCH, and TGARCH models to assess the volatility of the IBOVESPA index from stock market in Brazil. Aside from that, this study used both univariate and multivariate models to assess the accuracy of volatility projections. Moreover, Maqsood et al. (2017) conducted a research study that employed GARCH-M (1,1), EGARCH (1,1), TGRACH (1,1), and PGARCH (1,1) models to measure the Nairobi Securities Exchange's volatility.

Out of different symmetric and asymmetric type heteroscedastic processes, they concluded that the TGARCH (1,1) model is more suited to capture the volatility clustering and leverage impact of the NSE stock market. Kumar et al. (2023a) have analyzed 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) 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) suggested that the volatility of the Zimbabwean stock market is modeled using GARCH family. It was found that the EGARCH (1,1) model is the best suitable model. Spulbar et al. (2022) have also 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.

Research Gap



A significant research gap in the field of financial econometrics is filled by this work. While an extensive amount of research has been done on forecasting stock market volatility, less focus has been placed on modeling and comparative analysis of volatility in Switzerland. Furthermore, there is still a dearth of research on the use of complicated GARCH models, including TGARCH, EGARCH, and PARCH models, in this particular setting. By bridging this gap, our study provides investors, policymakers, and financial analysts substantial understanding into the different dynamics and asymmetric volatility patterns within these two different markets.

Research Methodology

In order to capture changes, volatility clusters, the fitness of econometric models, and volatility patterns, the current work focuses on modeling the behavior of the Switzerland stock market using data from 4th January, 2000 to 9th November, 2023. We use GARCH models (Bollerslev, 1986). The study used a sample number of 5994 daily observations for Swiss Stock Index representing the Switzerland stock market. The time series data have been used for modeling volatility. The daily returns were calculated using the log of the first difference of the daily closing prices. Before doing any of these tests, the daily returns were compiled since volatility has been evaluated on return (r_t). The log of first difference of the daily closing price is used to compute the return series, which is as follows:

$$r_t = \log \frac{P_t}{P_{t-1}}$$

Where,

r_t = Logarithmic daily return for time t ,

P_t = Closing price at time t ,

P_{t-1} = Corresponding price in the period at time $t - 1$.

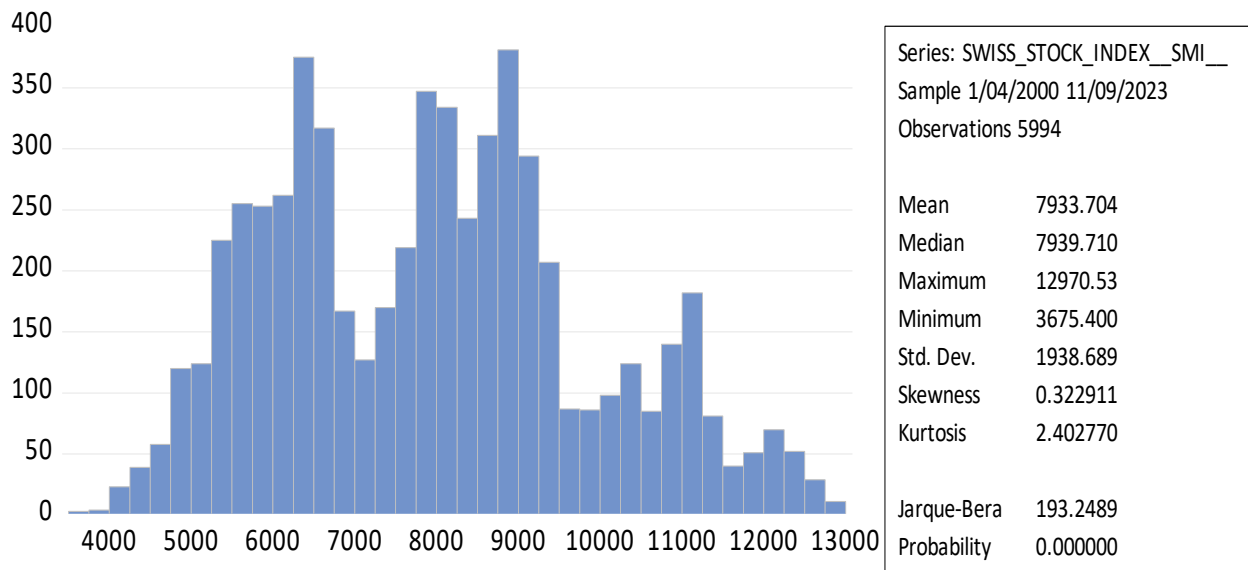
Before employing the GARCH models, we used some statistical techniques to evaluate stationarity. The data's stationarity was officially evaluated using the Phillips-Perron and Augmented Dickey Fuller tests statistic. The ARCH Lagrange Multiplier (LM) test was employed to investigate the presence of heteroscedasticity in the residual series of the return data. Identifying heteroscedasticity is crucial in choosing the appropriate GARCH model. To estimate the GARCH models (TGARCH, EGARCH, PARCH, and Component ARCH (1,1). we utilized the E-Views 12 Econometrics package. This software package provides robust tools for econometric modeling and time series analysis. The selection of the most suitable GARCH model was based on the evaluation of four GARCH family models: GARCH/TARCH, EGARCH, Component ARCH(1,1), and PARCH, all using the Student t 's Distribution.

Empirical Results and Discussion

In this paper, the daily closing prices of the Swiss stock index (SMI), over the period from 4th January, 2000 to 9th November, 2023 resulted in total observations of 5994 excluding public holidays. Various descriptive statistics are calculated and exhibited in Table 1.1 providing 7933.704 mean with 1938.689, degree of Standard Deviation. A high value of kurtosis 2.402770 which is less than 3 indicates a platykurtic distribution that is an apparent departure from normality while the skewness represents positive value it indicating data has long right skewed distribution.

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

Graph 1.1: Descriptive Statistics of the Swiss stock index



Source: Authors' Calculation using Eviews 12

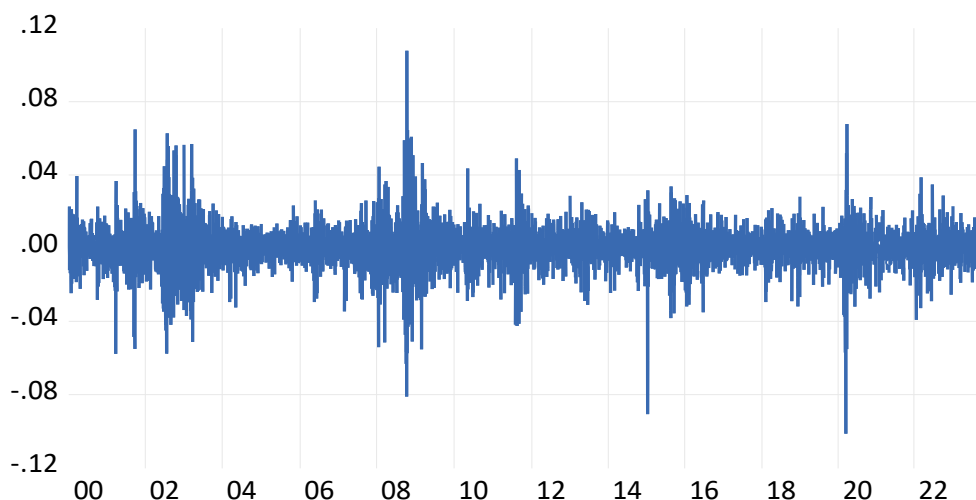
Graph 1.2: Movement Pattern of of the Swiss stock Index
Swiss stock index (SMI) closing price



Source: Authors' Calculation using Eviews12

Graph 1.3: log returns of the Swiss stock Index

Swiss stock index (SMI) log returns



Source: Authors' Calculation using Eviews 12

Graph 1.2 shows the movement patterns of the Swiss stockIndex's Stationary Series during the hypothetical period from 4th January, 2000 to 9th November, 2023. Graph 1.3 shows the graphical presentation of the log returns of the presence of volatility clustering using the Swiss stock Index. In order to estimate the volatility ofSwitzerlandstock market, checking the stationary is the first step in the analysis of the return series (Maqsood et al., 2017). For this purpose, Augmented Dickey-Fuller (Dickey & Fuller, 1979) test, Phillips Perron test (Phillips & Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin test are used to establish the stationarity of the Swiss stock index sample data series. The test results are presented with the help of following tables:

Table: 1.1: Unit root Test (Augmented Dickey-Fuller test, Phillips-Perron test and of Swiss stock index

Null Hypothesis: D(SWISS_STOCK_INDEX__SMI__CLOSING_PRICE) has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic - based on AIC, maxlag=33)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-33.92698	0.0000
Test critical values:		
1% level	-3.431263	
5% level	-2.861828	
10% level	-2.566966	

Null Hypothesis: D(SWISS_STOCK_INDEX__SMI__CLOSING_PRICE) has a unit root
Exogenous: Constant



Bandwidth: 17 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-76.14059	0.0001
Test critical values:		
1% level	-3.431262	
5% level	-2.861828	
10% level	-2.566965	

Source: Authors' Calculation using Eviews 12

Table 1.1 shows the Unit root Test (Augmented Dickey-Fuller test and Phillips-Perron test) of Swiss stock index. Table 1.2 shows the p values of Augmented Dickey-Fuller test and Phillips-Perron test statistic are less than 0.05 which 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 Lagrange Multiplier 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 et al., 2017). 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 1.3: Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH

F-statistic	0.327156	Prob. F(1,1662)	0.0000
Obs*R-squared	0.327247	Prob. Chi-Square(1)	0.0000

Source: Authors' Calculation using Eviews 12

Table 1.3 shows the result of the ARCH-LM test for Swiss stock index. It inferred that data is highly significant. The probability of F-statistic (0.0000) shows that p value is less than 0.05; 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 1.4: Selecting an appropriate model

Swiss stock Index			
Estimated model	Akaike info criterion	Schwartz criterion	Log Likelihood
GARCH/TARCH	-6.541506	-6.534799	19604.35
EGARCH	-6.584794	-6.576969	19735.04
PARCH	-6.588085	-6.579142	19745.90



Component ARCH (1,1)	-6.541095	-6.532152	19605.12
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Source: Authors' Calculation using Eviews 12

Table 1.4 Depicts four models of GARCH family. PGARCH with Student t's Distribution has the lowest Akaike info criterion with -6.588085 and Schwartz criterion with -6.579142 apart from that maximum Log Likelihood with 19745.90 when compared to the other three. As a result, this model is thought to be the best one. The results of the selected PARCH Model for the Swiss stock Index are shown in the table below.

Table 1.5: PARCH with Student's t distribution Error Construct of Swiss stock index

Dependent Variable: SWISS_STOCK_INDEX__SMI__LOG_RETURNS

Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)

Date: 11/23/23 Time: 21:19

Sample (adjusted): 1/06/2000 11/09/2023

Included observations: 5992 after adjustments

Convergence achieved after 174 iterations

Coefficient covariance computed using outer product of gradients

Presample variance: backcast (parameter = 0.7)

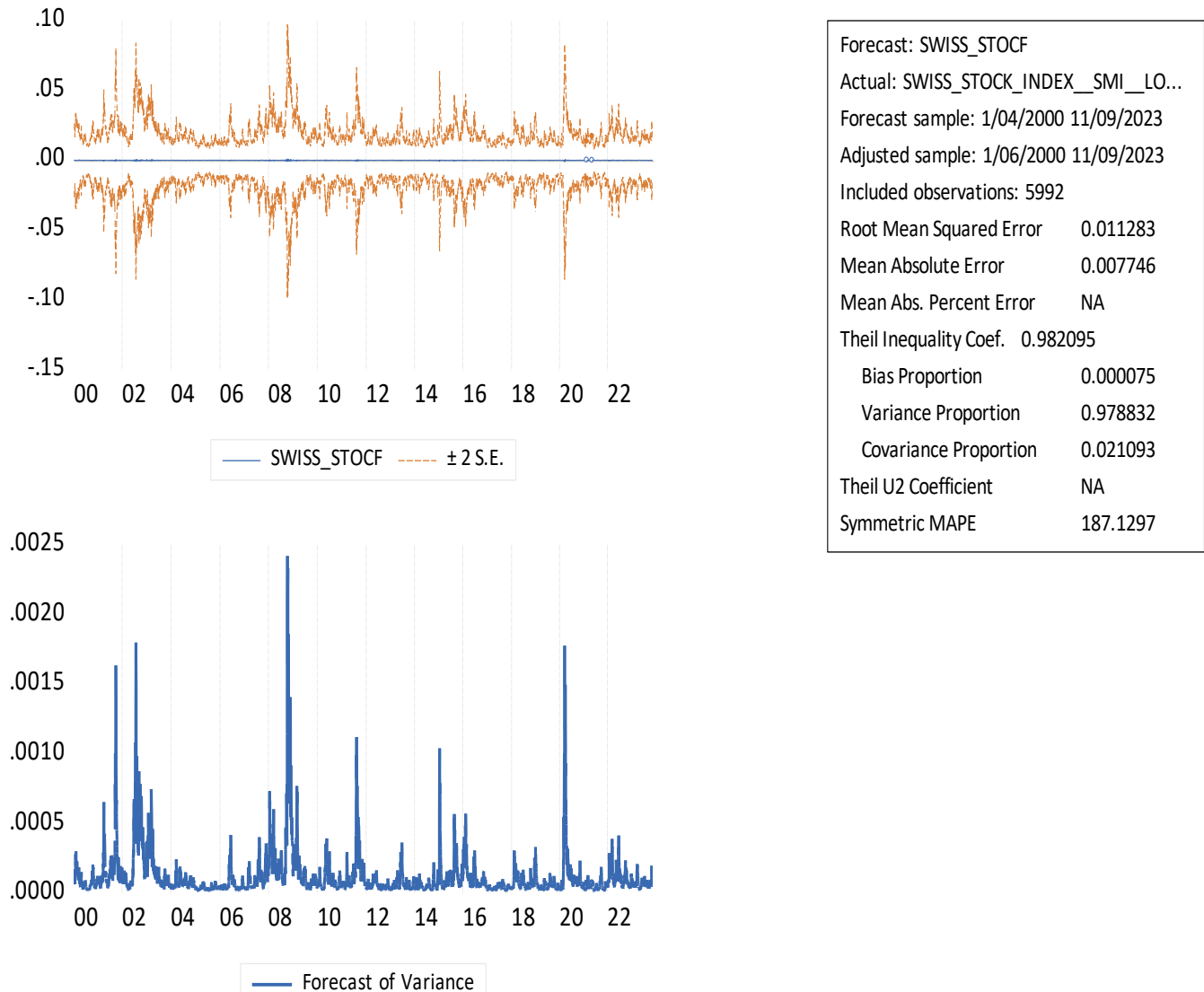
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000163	0.000101	1.613265	0.1067
SWISS_STOCK_INDEX__SMI__LOG_RETURNS(-1)	0.010790	0.013234	0.815317	0.4149
Variance Equation				
C(3)	0.000325	0.000132	2.463955	0.0137
C(4)	0.087259	0.005035	17.32881	0.0000
C(5)	0.999961	8.14E-07	1228087.	0.0000
C(6)	0.902459	0.006362	141.8461	0.0000
C(7)	0.977956	0.082126	11.90803	0.0000
T-DIST. DOF	9.795678	0.910934	10.75344	0.0000
R-squared	0.000304	Mean dependent var	6.57E-05	
Adjusted R-squared	0.000137	S.D. dependent var	0.011286	
S.E. of regression	0.011285	Akaike info criterion	-6.588085	
Sum squared resid	0.762885	Schwarz criterion	-6.579142	
Log likelihood	19745.90	Hannan-Quinn criter.	-6.584979	
Durbin-Watson stat	1.973995			

Source: Authors' Calculation using Eviews 12

Above table are representing the PARCH model with Student's t distribution error construct of Swissstock Index. Since Probabilities are lower than 0.05, the constant (C) is considered significant.

Graph 1.4: Estimating volatility patterns using PARCH models of Swiss Stock Index



Source: Authors' Calculation using Eviews 12

We can forecast the volatility of the Switzerland Stock Exchange composite indices using the aforementioned methodology using a data set of 5994 days. The Graph 1.4 demonstrates the anticipated uneven price changes of the Switzerland Stock Exchange.

Conclusions

To forecast variance using financial time series data, we used model i.e., Generalized Autoregressive Conditional Heteroskedasticity (GARCH), which is specifically designed for volatility forecasting. The main aim of the present study is to modeling the behavior of the Switzerland stock market using data from 4th January, 2000 to 9th November, 2023. Through the application of GARCH family models which, include GARCH/TARCH, EGARCH, Component ARCH (1,1), and PARCH. The analysis centered on log returns derived from the Swiss Stock Index. We used some statistical techniques to evaluate stationarity. The Augmented Dickey Fuller test, and Phillips-Perron test, and Kwiatkowski-



Phillips-Schmidt-Shin test statistic. Findings indicating that the sample data were stationary. The ARCH Lagrange Multiplier (LM) test was employed to investigate the presence of heteroscedasticity in the residual series of the return data.

The results of this test revealed the presence of ARCH effects in the residuals of our time series models. The selection of the most suitable GARCH model was based on the evaluation of four GARCH family models that is GARCH/TARCH, EGARCH, Component ARCH (1,1), and PGARCH using Student t's distribution. As a result, PARCH Model were selected with the help of the lowest Akaike info criterion, Schwartz criterion and maximum Log Likelihood.

The results obtained through the application of the PARCH model, as showcased in Table 1.5, provide valuable insights into the dynamics of the Swiss Stock Index. The conclusions and methods discussed in this study provide a strong basis for further research, enhancing our capacity to predict market movements and make wise choices in a volatile financial environment. This study highlights the significance of accurately and meticulously simulating stock market behavior in addition to adding to the corpus of knowledge in financial econometrics. By using sophisticated GARCH models and doing thorough statistical analyses, we have been able to gain important insights into the workings of the Switzerland stock markets, which have helped us to better, comprehend the complex field of stock market volatility prediction.



REFERENCES

1. Badarla, S., Nathwani, B., Trivedi, J., Spulbar, C., Birau, R., Hawaldar, I.T., Minea, E.L. (2021) Estimating fluctuating volatility time series returns for a cluster of international stock markets: A case study for Switzerland, Austria, China and Hong Kong, *Physics AUC (Annals of the University of Craiova, Physics)*, vol. 31, 43-52.
2. Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* , 74, 3–30.
3. Birau, R., Spulbar, C., Trivedi, J., & Florescu, I. (2021) Modeling volatility in the stock markets of Spain and Hong Kong using GARCH family models in the context of COVID - 19 pandemic, *Revista de Științe Politice. Revue des Sciences Politiques*, 72, 3 – 21.
4. Birau, R., Trivedi, J., Baid, R., Florescu, I., & Simion, M. L. (2023). Estimating volatility patterns using GARCH models: A case study on Swedish stock market. *Revista de Științe Politice. Revue des Sciences Politiques* , 78, 50-59.
5. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* , 31 (3), 307–327.
6. Bonga, W. G. (2019). Stock Market Volatility Analysis using GARCH Family Models: Evidence from Zimbabwe Stock Exchange. *Munich Personal RePEc Archive* , 2-13.
7. Choudhry, T., & Wu, H. (2008). Forecasting ability of GARCH vs kalman filter method: evidence from daily UK time-varying beta. *Journal of Forecasting* , 27, 670–689.
8. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of American Statistical Association* , 74 (366), 427–31.
9. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* , 50 (4), 987–1007.
10. Kim, H. Y., & Won, C. H. (2018). Forecasting the Volatility of Stock Price Index: A Hybrid Model Integrating LSTM with Multiple GARCH-Type Models. *Expert Systems With Applications* , 1-33.
11. Kumar, S., Anand, A., Birau, R., Meher, B. K., Kumar, S., & Ion, F. (2023a). Temporal Analysis of Mexico Stock Market Index Volatility using GJR-GARCH model. *Revista de Științe Politice. Revue des Sciences Politiques* , 79, 46-56.
12. Kumar, S., Meher, B.K., Birau, R., Simion, M.L., Abhishek, A., & Manohar, S. (2023b) Quantifying Long-Term Volatility for Developed Stock Markets: An Empirical Case Study Using PGARCH Model on Toronto Stock Exchange (TSX), *Annals of “Dunarea de Jos” University of Galati Fascicle I. Economics and Applied Informatics Years XXIX – no2/2023*, DOI <https://doi.org/10.35219/eai15840409338>, ISSN-L 1584-0409, ISSN-Online 2344-441X, 61-68.
13. Kumar, S., Meher, B. K., Birau, R., Simion, M. L., Anand, A., & Kumar, S. (2023c). Long-term volatility forecasting of Brazilian stock index behavior using suitable GARCH family models. *Revista de Științe Politice. Revue des Sciences Politiques* , 79, 9-24.
14. Leite, A. L., & Lima, M. V. (2023). A GARCH Model to Understand the Volatility of the Electricity Spot Price in Brazil. *International Journal of Energy Economics and Policy* , 13 (5), 332-338.
15. Maqsood, A., Safdar, S., Shafi, R., & Lelit, N. J. (2017). Modeling Stock Market Volatility Using GARCH Models: A Case Study of Nairobi Securities Exchange (NSE). *Open Journal of Statistics* , 7, 369-381.
16. Meher, B. K., Hawaldar, I. T., Mohapatra, L., Spulbar, C., & Birau, R. (2020). The Effects of Environment, Society and Governance Scores on Investme Investment Returns and Stock Market Volatility. *International Journal of Energy Economics and policy* , 10 (4), 234-239.
17. Phillips, P. C., & Perron, P. (1988) Testing for a Unit Root in Time Series Regression. ' *Biometrika* , 75 (2), 335-346, Published By: Oxford University Press.
18. Sokpo, J. T., Iorember, P. T., & Usar, T. (2017). Inflation and Stock Market Returns Volatility: Evidence from the Nigerian Stock Exchange 1995Q1-2016Q4: An E-GARCH Approach. *Munich Personal RePEc Archive* , 1-19.
19. Spulbar, C., Birau, R., & Imran, Z. A. (2020). Analyzing Short Term Momentum Effect on Stock Market of Hong Kong. An Empirical Case Study,. “*Ovidius” University Annals, Economic Sciences Series* , XIX (2/2019), 889-894.
20. Spulbar, C., Birau, R., Trivedi, J., Hawaldar, I. T., & Minea, E. L. (2022). Testing volatility spillovers using GARCH models in the Japanese stock market during COVID-19, *Investment Management and Financial Innovations* , 19 (1), 262-273.
21. Spulbar, C., Birau, R., Trivedi, J., Simion, M.L., Baid, R. (2023) Assessing Volatility Patterns using GARCH Family Models: A Comparative Analysis Between the Developed Stock Markets in Italy and Poland, *Annals of*



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22. Sun, H., & Yu, B. (2019). Forecasting Financial Returns Volatility: A GARCH-SVR Model. *Computational Economics* .
 23. Vedat, A. (1989). Conditional heteroskedasticity in time series models of stock returns: Evidence and forecasts. *Journal of Business* , 62, 55–80.