The Relationship Analysis and Volatility Modelling of Selected Major Global Indices

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ABSTRACT: *ARCH and GARCH models are significant in time series analysis, especially in finance. These models help analyse and predict volatility. The research examines worldwide index volatility. The time series data selected for the study was from May 2012 to July 2022, totalling 123 observations. This research reveals that GARCH (1,1) is the best model for capturing volatility in key global Indices Budapest SE, Hang Sheng, MOEX, Nifty 50, Nikkei 225, S&P 500 and Tadawul using Akaike, Schwarz, and Hannan-Quinn InformationCriteria. Variance and forecast graph using GARCH Model. This paper aims to examine the relationship between major global indices. It also attempts to estimate the volatility of the indices.*

KEYWORDS*: ARCH, GARCH, Return, Volatility.*

INTRODUCTION:

In recent years, modelling and predicting the volatility of a financial time series has been a popular study topic. Volatility is significant for many economic and financial applications, such as portfolio optimization, risk management, and asset pricing. Volatility is the relative pace at which stock prices rise and fall. Suliman, Ahmed. The most well-known and often used models for this volatility are heteroscedastic models. The fundamental goal of constructing these models is to predict future volatility, which will assist with portfolio allocation, risk management, and derivative pricing accuracy.

Engle's ARCH model and Bollerslev's GARCH model were the first to be published. They're popular because analysts can estimate a series' variation at a given period. Since then, various empirical time series variance models have been created.

ARCH models were established to tackle stock price growth (or decline) difficulties. GARCH extends ARCH by using previous squared returns and historical variances to describe the present variance of financial data at time t.

In this study, an attempt has been made to understand the relationship between the selected indices Budapest SE, Hang Sheng, MOEX, Nifty 50, Nikkei 225, S&P 500 and Tadawul. ARCH and GARCH Modelsare used to estimate the volatility of the indices.

LITERATURE REVIEW:

Volatility affects trade volume. Most research says stock price volatility discourages local and international business by increasing risk and uncertainty. Engle and Ng recommend VAR. Volatility affects outcomes.

Campbell et al. suggested using continuous volatility measurements while the series changes is nonsensical and inefficient. Major errors are followed by additional big errors and small errors by microscopic inaccuracies in financial data. Linear time series predict uncorrelated, but not necessarily independent, identically distributed shocks. Non-linear time series: shocks should be independent and identically distributed, but they aren't.

Rydberg argued neither ARCH nor GARCH have asymmetry or leverage (the fact that past returns correlate with future volatility). GARCH (p,q) models operate well for most equity-return dynamics but can't anticipate stock volatility since they require a symmetric volatility-return relationship.

Floros estimated MCRR using out-of-sample data. Riskier short trades need more funds. They used ARCH and GARCH.

Soumya Ganguly (2021), BRICS growth will exceed G-6. In 2020, BRICS broke this tendency. Few studies examine BRICS stock market volatility and linkages since 2020. We tracked volatility and BRICS stock market performance from November 18, 2019 through May 7, 2021. GARCH and ARDL are tested. GARCH sees volatile markets in Russia and India. EGARCH shows India's leverage. ARDL test confirms Russia-India stock market links.

ARDL test indicates short-run relationships between India, Brazil, and South Africa, and India and South Africa. Investors from BRICS countries should hedge.

Bhowmik (2020) databases Snowballing. GARCH stock return and volatility are studied. Stocks "barometer" the economy. Risk is volatility. GARCH analyses return and volatility. This evaluates 2008-2019 returns and volatility. Most academics support stock markets.

Vo xuan (2020), 2008-2018 IVOL and Vietnam stock returns are compared. IVOL's stock is evaluated using Fama-Macbeth and portfolio sorting (portfolio-level analysis). CAPM, Fama-French, and Carhart model IVOL. IVOL amps alpha samples. Negative alpha and full-sample don't correspond. contradiction This research advises buying alpha subsample stocks.

AbonongoJohn (2016), Volatility affects investments and financial stability. This article modelled Ghana Stock Exchange volatility and risk-return using three distributional assumptions. Investors anticipated market gains. Volatility. Investors were rewarded for riskier assets, indicating a positive risk premium. Equilibrium models indicate equity leverage. It's TGARCH-M (1,1).

Dimitrios Dimitriou (2011) compares stock returns and volatility in 12 EMU and 5 international markets. 1992-2007, or until the current financial crisis. Mean-variance tradeoff evidence is mixed. Parametric GARCH predicts modest market returns and volatility. A flexible semi-parametric specification for conditional variance shows a negative association in virtually all markets. Most markets have a negative asymmetry in volatility's response to positive and negative stock return shocks.

Mike (2010), The research examined India and China's developing stock markets from January 2005 to May 2009. ARCH-LM discovers conditional heteroscedasticity, whereas BDSL finds nonlinearity. According to these results, the GARCH (1,1) model captures nonlinearity and volatility clustering. Chinese stock market volatility is greater than Indian, says the report.

Glosten (1993), To predict conditional variance, a modified GARCH-M model accounts for seasonal volatility, positive and negative return innovations, and nominal interest rates. Using a modified GARCH-M model, they show that monthly conditional volatility may be short-lived. Unexpected returns reduce conditional volatility and vice versa. Asset evaluation has traditionally emphasised risk-return trade-off. This research compares risk-to-return ratios across asset kinds and periods.

Nelson (1991) used GARCH models to characterise conditional variance and asset risk premia. Three difficulties plague asset pricing methods. Since Black, scholars have shown a negative correlation between current and future volatility (1976). GARCH models skip it. (ii) GARCH models restrict conditional variance dynamics by setting parameter limitations. Estimated coefficients aren't always correct. Inconsistent persistence criteria make it hard to tell whether GARCH conditional variance shocks "persist." ARCH solves these problems. This method estimates 1962-1987 CRSP Value-Weighted Market Index risk premium.

THEORETICAL BACKGROUND:

Volatility: A securities or market index's volatility may be measured statistically as the dispersion of returns for that particular asset or index. When it comes to the vast majority of situations, a security's level of risk increases in direct proportion to its level of volatility. Volatility is often assessed using either the standard deviation or the variation between returns on the same securities or market index.

Return: Return is the variation in the price of the asset, investment, or project over time, which may be expressed as a price change or a percentage change. A positive return signifies a profit, whereas a negative return reflects a loss.

Returns are often annualised for reasons of comparison, but a holding period return evaluates the gain or loss throughout the whole holding period. The real return takes into account the impacts of inflation and other external variables, while the nominal return is simply concerned with the price change.

RESEARCH METHODOLOGY:

These findings are based on the monthly closing prices of major global indices, and the time series data covers almost ten years, starting from May 2012 and closing in July 2022 including 123 observations.

According to the findings of this study, the monthly closing prices of the major global indices are higher than zero, which indicates that Pi is greater than 0. The return that one receives for holding such an asset (stock), is given by

$Ri = P_i / P_{i-1}$, Cryer and Kung

Where is the return for the current month, Pi represents the price at which the current month's trading session ended, and P_{i-1} represents the price at which the previous month's trading session ended. The grand mean of the monthly returns may be calculated using:

$$\bar{R} = \frac{\sum_{i=1}^{n} R_i}{N}$$

Let $Zi = Ri - \bar{R}$

$Zi^2 = [Ri - R]^2$ (3)

Zi^2 is a measure of volatility for $i = 1,2,3, \ldots, N$

GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTIC (GARCH) MODEL

The conditional variance, t2, was made more generic by allowing it to build on the foundation of previous conditional variances. This generalisation was achieved by adjusting the ARCH model to produce the GARCH model. This situation may be described by the GARCH (p, q) model, where p is the order of the GARCH terms in $\sigma 2$ and q is the order of the ARCH terms in z2:

$Zt = \varepsilon t \sigma t2, \varepsilon t \sim N\ 0{,}1,\ t = 1{,}2, \ldots, n$

$\sigma t2 = \omega + \alpha 1Zt-1\ 2 + \alpha 2Zt-2\ 2 + \cdots + \alpha qZt-q\ 2 + \beta 1\sigma t-1\ 2 + \beta 2\sigma t-2\ 2 + \cdots + \beta p\sigma t-p\ 2$

where $\omega>0$, $\alpha i \geq 0$, $\beta j \geq 0$, $i=1, 2, \ldots q$, $j=1, 2, \ldots . p$, $Zt / It \sim N\ (0, \sigma t2)$.

Zt represents the dependent variable, εt represents the error terms, It represents the information set at time t, and $\alpha i and \beta j$ represents the unknown parameter coefficients. Specifically, when p=0, the process simplifies to the ARCH (q) process, and when p=q=0, εt is equivalent to a white noise.

DATA ANALYSIS AND FINDINGS

5.1 Descriptive Analysis

Indices	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Sum Sq. Dev.
BUDAPEST SE	0.008	0.006	0.202	-0.182	0.054	-0.091	5.551	0.353
HANG SHENG	0.002	0.005	0.130	-0.117	0.047	-0.212	2.936	0.273
MOEX	0.008	0.010	0.246	-0.342	0.084	-0.153	5.310	0.785
NIFTY	0.011	0.009	0.147	-0.233	0.048	-0.734	7.231	0.284
NIKKEI 225	0.010	0.015	0.150	-0.105	0.049	-0.289	3.258	0.292
TADAWUL	0.005	0.012	0.164	-0.173	0.055	-0.465	3.930	0.373
S&P 500	0.010	0.017	0.127	-0.125	0.040	-0.459	4.189	0.198

Table 5.1: Descriptive Analysis of Major Global Indices

The basic descriptive statistics analysis findings are presented in the above table 5.1. The mean values of all the indices are positive and close to zero. Returns are positive in nature and indices made positive returns or profits. Kurtosis value for all the indices except HangSheng is greater than 3, Compared to a normal distribution, the dataset has larger tails. The kurtosis value of HangSheng is2.936 i.e., less than 3 but it is almost close to 3. Hence the data is normally distributed.

All of the indices have a negative skewness value, which indicates that the left-hand tail of the distribution is more extreme than the right-hand tail.

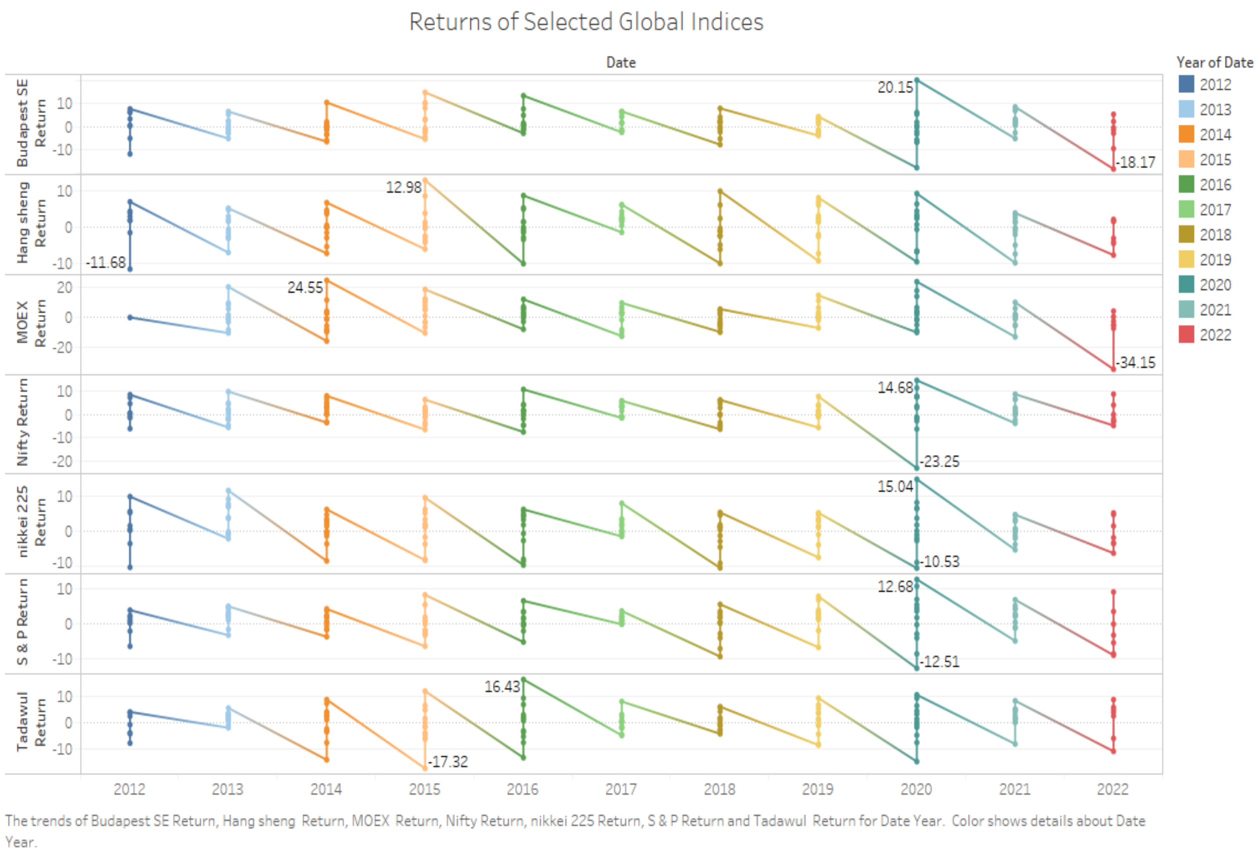
5.2 Unit Root Test

		At Level					
Return	**Method/ Parameter**	**No intercept and Trend**		**Individual Intercept**		**Individual Intercept and Trend**	
		Statistic	**Prob.****	**Statistic**	**Prob.****	**Statistic**	**Prob.****
	Levin, Lin & Chu t*	-30.09	0.00	-34.63	0.00	-39.12	0.00
	ADF - Fisher Chi-square	1823.55	0.00	525.30	0.00	492.35	0.00
	PP - Fisher Chi-square	1820.41	0.00	526.56	0.00	493.91	0.00
	Im, Pesaran and Shin W-stat	---	---	-31.58	0.00	-33.09	0.00
	Breitung t-stat	---	---	---	---	-12.54	0.00

Table 5.2: Unit Root Test Results of Major Global Indices.

Unit Root Test Results of Major Global Indices are presented in the above table 5.2. From the Levin, Lin & Chu t* and Augmented Dickey-Fuller Group Unit Root Test. All the indices are stationary at level.

Return Analysis



Graph 5.1: Returns of Global Indices

The returns of all selected Indices for the studyare shown in graph 5.1. The minimum return for Budapest SE is in the year 2022 and the maximumis in the year 2020. The minimum return for Hang Sheng is in the year 2012 and the maximumis in the year 2015. The minimum return for MOEX is in the year 2022 and the maximum is in the year 2014. The minimum and maximum returns of Nifty, Nikkei 225 and S&P Indices made in the year 2020. The Tadawal made minimum returns in the year 2015 and maximum returns in the year 2016.

Correlation Analysis

Correlation	TADAWUL	S&P 500	NIKKEI 225	NIFTY	MOEX	HANG SHENG	BUDAPEST SE
TADAWUL	1.00						
S&P 500	0.44	1.00					
NIKKEI 225	0.33	0.66	1.00				
NIFTY	0.31	0.60	0.48	1.00			
MOEX	0.22	0.42	0.22	0.25	1.00		
HANG SHENG	0.29	0.47	0.42	0.42	0.32	1.00	
BUDAPEST SE	-0.01	-0.07	-0.01	-0.08	-0.13	0.00	1.00

Table 5.3: Correlation Results of Major Global Indices.

The correlation test results for Selected Indices are presented in Table 5.3. Nifty 50 is strongly positively correlated with S&P 500. Nikkei 225 is strongly positively correlated with S&P 500. Except Budapest SE all other Indices shows slightly positively correlation (negligible) with other indices.

Granger Causality Test

Lags: 2			
Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
TADAWUL --->MOEX		3.66899	0.03
TADAWUL --->BUDAPEST SE		7.74855	0.00
S&P 500 --->BUDAPEST SE		16.1439	0.00
NIKKEI 225 --->BUDAPEST SE		13.25	0.00
NIFTY --->BUDAPEST SE		18.501	0.00
MOEX --->BUDAPEST SE		11.0156	0.00
HANG SHENG --->BUDAPEST SE		14.8045	0.00

Table 5.4 Pairwise Granger Causality Test

Table 5.4 shows the results of the Pairwise Granger Causality Test of Indices. The Tadamul Index shows the short-term relationship between MOEX and Budapest SE. Nifty shows a short-term association with Budapest SE. Hang Sheng, MOEX, Nifty 50, Nikkei 225, Tadwul and S&P 500 show short-term relationships with Budapest SE.

Cointegration Test

Series: TADAWUL__RETURN S___P_RETURN NIKKEI_225_RETURN NIFTY_RETURN MOEX__RETURN HANG_SHENG__RETURN BUDAPEST_SE_RETURN								
Lags interval (in first differences): 1 to 1								
Cointegration Rank Test (Trace)					**Cointegration Rank Test (Maximum Eigenvalue)**			
Hypothesized		**Trace**	**0.05**		**Hypothesized**	**Max-Eigen**	**0.05**	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.570211	397.6361	111.7805	0	0.570211	93.73518	42.77219	0
At most 1 *	0.47494	303.9009	83.93712	0	0.47494	71.51098	36.63019	0
At most 2 *	0.421893	232.3899	60.06141	0	0.421893	60.82767	30.43961	0
At most 3 *	0.409454	171.5623	40.17493	0	0.409454	58.4646	24.15921	0
At most 4 *	0.336852	113.0977	24.27596	0	0.336852	45.59398	17.7973	0
At most 5 *	0.28073	67.50369	12.3209	0	0.28073	36.57653	11.2248	0
At most 6 *	0.243175	30.92716	4.129906	0	0.243175	30.92716	4.129906	0

Table 5.5 Cointegration Test

Table 5.5 shows the results of the Cointegration Test of Indices. The cointegration results show- that the indices have a long-term association with each other. As the p-significant value is less than .05 which means the null hypothesis is rejected. Hence, they have long-term association with other indices.

Heteroskedasticity Test: To Test ARCH Effect

Heteroskedasticity Test: ARCH

Indices	F stat	Prob. F (1,120)	Obs* R-squared	Chi-square p-value	Hypothesis Result
Budapest SE	0.043	0.836	0.044	0.834	Null Hypothesis Accepted
Hang Sheng	2.911	0.091	2.889	0.089	Null Hypothesis Accepted
MOEX	0.441	0.508	0.447	0.504	Null Hypothesis Accepted
Nifty 50	11.080	0.001	10.312	0.001	Null Hypothesis Rejected
Nikkei 225	0.605	0.438	0.612	0.434	Null Hypothesis Accepted
S&P 500	20.921	0.000	18.112	0.000	Null Hypothesis Rejected
Tadawul	0.060	0.807	0.061	0.805	Null Hypothesis Accepted

Table 5.6 Heteroskedasticity Test: ARCH Effect

Table 5.6 shows the Heteroskedasticity ARCH Test of the selected indices. The Chi-square p significance value is less than .05 for Nifty 50 and S& P 500. Hence, the null hypothesis is rejected. There is arch effect for both Nifty 50 and S & P 500. For other indices there is no arch effect.

The ARCH Model can be estimated only for Nifty 50 and S & P 500 indices.

ARCH Model

	Models Identified	**Information criteria**		
Indices	**GARCH(p,q)**	**AIC**	**SIC**	**HQ**
Nifty 50	(5,0)	-3.2735	-3.11346	-3.208493
	(1,1)	**-3.30975**	**-3.2183**	**-3.272605**
S & P 500	(5,0)	-3.64999	-3.48995	-3.584984
	(1,1)	-3.67697	-3.58552	-3.639826

Table 5.7 Heteroskedasticity Test: ARCH Model Test

Table 5.7 shows the Heteroskedasticity Test: ARCH Model Test of Nifty 50 and S&P 500. Akaike info criterion, Schwarz criterion and Hannan-Quinn criterion for GARCH (1,1) are less than the model GARCH (5,0). Hence the model is estimated further using GARCH (1,1)

GARCH Model Fit for Nifty 50 and S & P 500:

	Models Identified	**Parameters**		
Indices	**GARCH(p,q)**	**C**	**RESID(-1)^2**	**GARCH(-1)**
Nifty 50	GARCH(1,1)	0.002045	0.473935	-0.316595
S & P 500	GARCH(1,1)	0.000281	0.283687	0.561842

Table 5.8 GARCH Model Fit for Nifty 50 and S&P 500 Indices

GARCH model fit summary for the two indices Nifty 50 and S & P 500 with their parameters are shown in table 5.8.

The estimated model parameters and their equation is as follows:

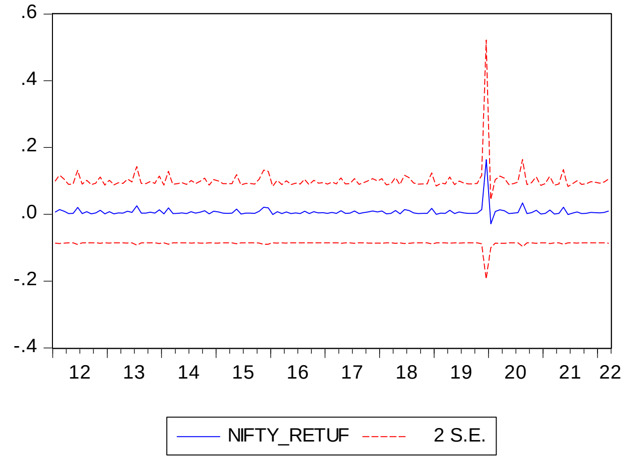
Nifty 50

The volatility model identified for Nifty 50 Index is

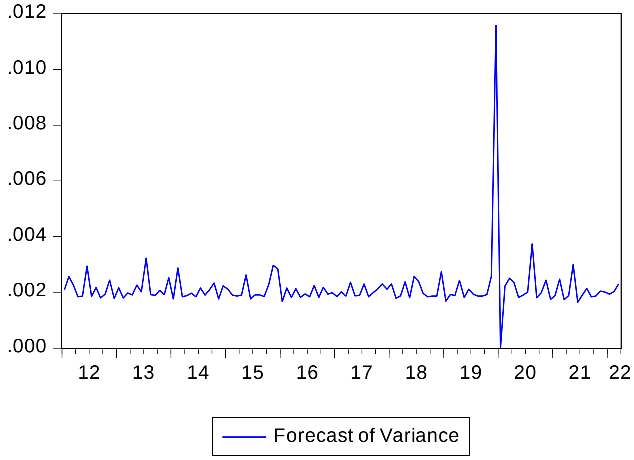
Estimation Equation:

NIFTY_RETURN = 0.0127300414366

GARCH = 0.00204460859878 + 0.473934662678*RESID(-1)^2 - 0.316595420221 * GARCH(-1)



Forecast: NIFTY_RETUF	
Actual: NIFTY_RETURN	
Forecast sample: 2012M01 2022M03	
Included observations: 123	
Root Mean Squared Error	0.046535
Mean Absolute Error	0.034624
Mean Abs. Percent Error	153.1875
Theil Inequality Coefficient	0.699730
Bias Proportion	0.005555
Variance Proportion	0.487069
Covariance Proportion	0.507376
Theil U2 Coefficient	0.989541
Symmetric MAPE	159.6105



Graph 5.2: Forecast Graph and data of Nifty 50

Graph 5.2 shows the Forecast Graph and data of Nifty 50. The variance portion is .4870 Bias Proportion is .0055 which is very less. The model is fit.

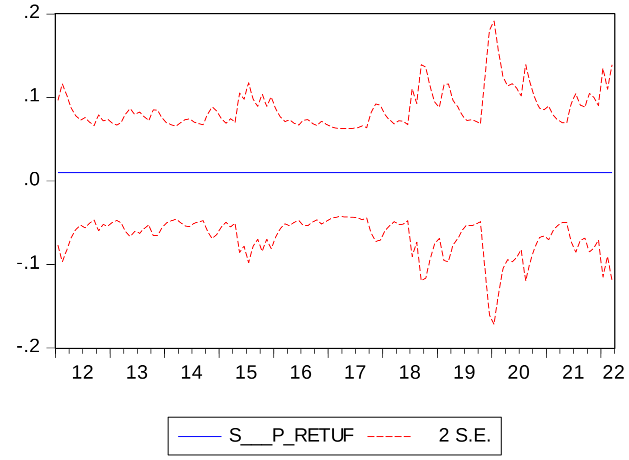
S&P 500:

The volatility model identified for S&P 500 Index is

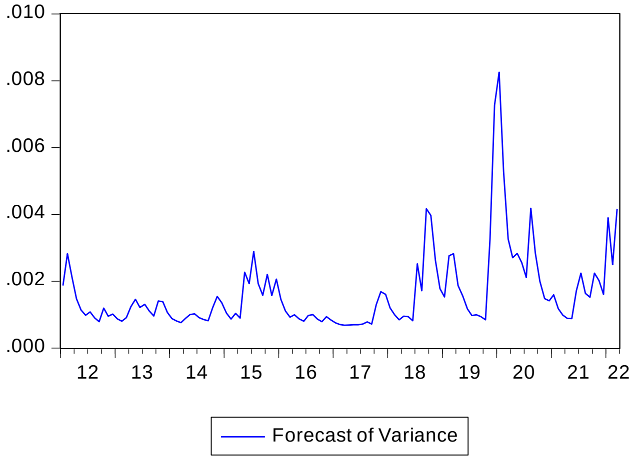
Estimation Equation:

SP_RETURN = 0.00974460043704

GARCH = 0.000280726569029 + 0.28368730816* RESID(-1)^2 + 0.561842478414* GARCH(-1)



Forecast: S___P_RETUF	
Actual: S___P_RETURN	
Forecast sample: 2012M01 2022M03	
Included observations: 123	
Root Mean Squared Error	0.040162
Mean Absolute Error	0.029544
Mean Abs. Percent Error	244.5001
Theil Inequality Coefficient	0.786703
Bias Proportion	0.000005
Variance Proportion	0.999993
Covariance Proportion	0.000002
Theil U2 Coefficient	1.113707
Symmetric MAPE	128.0201



Graph 5.3: Forecast Graph and data of S&P 500

Graph 5.3 shows the Forecast Graph and data for S&P 500. Variance proportion is .99999 and Bias Proportion is .000005 which is very less. The Model is fit.

CONCLUSION

The purpose of this study is to analyse the relationship and the volatility of the main global indexes that have been chosen. The minimum return for Budapest SE is in 2022 and the highest is in 2020. The minimum Hang Sheng return is in 2012, highest is in 2015. MOEX returns are lowest in 2022 and highest in 2014. Nifty, Nikkei 225, and S&P minimum and maximum returns in 2020. Tadawal made the lowest returns in the year 2015, while 2016 was the best. S&P 500 and Nifty 50 are strongly positively correlated. Nikkei 225 and S&P 500 are correlated. Short-term relationships exist between Hang Sheng, MOEX, Nifty 50, Nikkei 225, Tadwul, and S&P 500 and Budapest SE. There is long term relationship between the indices.

According to the findings of the research, GARCH (1,1) models are better than other models when it comes to the analysis of financial data since they provide lower information requirements for AIC, SIC, and HQ. In future the detailed study can be conducted on sectoral indices. The relationship, association and VAR Model can be implemented. Advanced tools and tests can be used for further study.

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