Volatility Models for World Stock Indices and Behaviour of All Share Price Index

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Abstract— *The purpose of the study is to model the volatility of the world stock indices. The word volatility is derived as the results of unequal variances of the error terms of the return series. The technical term used here is Heteroscedasticity. The investors in financial market consider the movement of the volatility of several locations for the risk management, derivatives pricing and hedging, market making, portfolio and for the different financial aims .The volatility modelling and forecasting is not very common in the Sri Lankan aspect. Volatility modelling with great emphasize on Sri Lanka is a very noteworthy attempt. The identification of the volatility models for the stock indices of Colombo stock exchange and stock markets of United States, India and United Kingdom are highly useful to the investors. The purpose of modelling the volatility of these selected stock indices is that Investors try to invest in several stock markets to diversify the risk. To capture the characteristics of volatility in the stock price series, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models have been used. Many GARCH family models were considered in this study. All Share Price Index of Colombo stock exchanges (ASPI), S & P 500 index of New York stock exchange, FTSE 100 of the London stock exchange and BSE SENSEX index of Bombe stock exchange have been considered in this study and the study period is from 1st January 2004 to 1st January 2014. GARCH (1, 1) model was identified as the best model for the ASPI return series, EGARCH (1,1) model was identified as the best model for both the FTSE 100 and BSESENSEX indices return series and while S & P 500 return series is best expressed by EGARCH (2,1) model. The model adequacy of the selected models have been tested using the ARCH LM test, Correlogram of squared returns and Correlogram of standardized residuals, while Q-Q plot was applied to check the error distribution. After the investigation of the numerical accuracy of the model estimated, the models have been used to forecast future volatility.*

Keywords— *Volatility, GARCH Family Models, Stock Index*

I. INTRODUCTION

Capital markets which consist of stock markets and bonds markets, commodity markets, money markets and Insurance markets are the main components of the financial market. When we look at the term “financial market” the stock exchange is an important part of it. Analysis of the stock indices and forecasting the future values are very noteworthy attempt. The stakeholders of the financial market are getting the advantage of it. The selected stock indices are the stock indices of the top trade countries of Sri Lanka in recent past. Therefore, most probably, investors try to invest in theses stock exchanges. In the case of analysis of different stock indices, it’s very important that log return series or return series should be taken in to the account, because direct statistical analysis of financial prices is difficult. The reason for this fact is very important. Consecutive price or price indices are highly correlated and the variances of prices often change with the time. On the other hand, log stock return is the log difference between the current closing price and the previous closing price. Many studies have pointed out that the returns of the financial markets are not independent; therefore they cannot be model using the independent and identically distributed process like moving average models. If the variances of the error terms are not equal then the error terms will be large for some parts or the range of the data, then the data series is suffer from the heteroscedasticity. Many financial data consist of Heteroscedasticity behaviour.

In the case of heteroscedasticity or error terms which have a characteristics size or variance, modelling or analysis should be different from the normal process. These characteristics of the financial data will help to develop the Volatility clustering. Volatility clustering occurs when large stock price changes are followed by large price change, of either sign, and small price changes are followed by periods of small price changes. To over-come this problem for modelling and forecasting, it is important to focus on special technique. In this research, the different stock price indices will be investigated to analysis the time varying errors. Bollerslev and Mikkelsen (1996) pointed out the special characteristics of the financial data which has volatility.

The characteristics are long memory, excess Kurtosis, fat tail, leverage effects, volatility clustering and spill over effect. This is the background for this study about volatility modelling. The main objective of this research is to identify the behaviour of the stock price indices which consists of heteroscedasticity and how to forecast stock prices volatility under the condition of volatility clustering.

II. LITERATURE REVIEW

Many researchers have studied about the volatility behaviour of the stock prices in various angles. Volatility of assert has been documented in a various papers like Fama (1965) and ARCH literature developed by Engle (1982). As mentioned in Bollerslev and Wright (2001).Emenike (2010) pointed out that modelling volatility is an important element in pricing Equity, risk management and portfolio management and not only that Emenike (2010) noted that volatility clustering makes investors more averse to holding stocks due to uncertainty. The study of financial asset volatility is very important to academics, policymakers, and financial market participants for several reasons as said by the Goudarzi and Ramanaragana (2010). Many researches like Modelling Sudan stock market volatility by Suliman and Ahmed (2011), Modelling American market S & P 500 by Kun (2011), Modelling Johanneburg stock exchange by Niyitegeka and Tewari (2013) and etc pointed out that the application of the GARCH models for stock market volatility analysis and the highlighted thing in those areas .The researchers initially considered the various type of GARCH models to capture the hidden information of the volatility or the series and finally concluded the study with the best fitting GARCH model.

III. METHODOLOGY

To achieve the main objectives of this thesis, following methodologies will be used.

A. Calculate the stock returns

Subtracting result of time $(t+1)^{th}$ stock price value from the t^{th} stock price value will create the stock return value for the particular time period. If the calculated value is positive value, it illustrates that the increment of the stock price value and decline if otherwise.

B. Logarithmic return

Logarithmic returns build up with the difference between the log price value of the particular day and the log price values of the previous day.

C. Volatility

Volatility is a statistical measure used in various type of time series analysis. However, in financial angle (Stock price analysis) it is a measurement derived from the dispersion of returns of any stock price index. Volatility can be measured by considering the variance or standard deviation of the returns. In the case of the financial market, it is referred to as the spread of assert returns. In other words, volatility can be referred as the amount of uncertainty about the size of dispersion in a stock value. If the stock values will significantly spread out over a massive range of values, then the high volatility may exist. This will suggest that the stock prices can largely change over a short or medium time period (either direction). If the stock price values does not fluctuate dramatically in a particular time period, then it will suggest that the low volatility.

1) *Volatility Clustering:* Volatility clustering can be explained as follows. In particular time series of stock prices, it is observed that the variances of returns or log-prices returns are high for some periods and also low for some periods. This property of time series can be called the 'volatility clusters' and is usually considered by modelling the price series with an ARCH family model.

D. ARCH Models

ARCH (p) process captures the conditional heteroscedasticity of returns. According to the seminal paper by Engle (1982). We shall refers to all discrete time stochastic processesϵt to the form,

$$\epsilon t = Z_t . \sigma_t$$

$Z_t \sim iid E(Z_t) = 0 \; var(Z_t) = 1 \sigma_t$ = time varying positive & measurable function of the time t-1 information set

The serial correlation in squared returns or conditional heteroscedasticity (volatility clustering) can be modelled using a simple autoregressive (AR) process for squared residuals. To do that first of all, Financial returns can be modelled using the AR processes, Y_t denoted that the finacial returns and it's a stationary time series, Y_t can be expressed as it mean plus a white noice if there is no significant autocorrelation in $Y_t$itself.

$$Y_t = C + \epsilon t$$

C is the mean ofY_t, and ϵt is iid with mean zero.

To allow for the volatility clustering *or* conditional heteroscedasticity, we should assume that $Var_{t-1}(\epsilon_t^2) = \sigma_t^2$ with Var_{t-1} (.) denoting the variance conditional on information at time t-1. After that the today's conditional variance is a weighted average of past squared unexpected returns.

$$\sigma_t^2 = \infty_0 + \infty_1 . \epsilon_{t-1}^2 + \infty_2 . \epsilon_{t-2}^2 + \dots\dots\dots + \infty_p . \epsilon_{t-p}^2$$

ϵ_t = iid process with 0 mean and constant variance.

P = Number of Lags.

E. GARCH models

Although the ARCH and GARCH models can be used to treat the heteroscedasticity, ARCH models are not often used in the financial markets because the simple GARCH models perform so much better. The GARCH means Generalized Autoregressive Conditional Heteroscedasticity. GARCH model consist of the two equations

Conditional means Equation: The mean equation is written as a function of constant with an error term normally, However, the mean equation can be anything. A simple liner regression can provide a model for the conditional mean of a return process.

$$r_t = \mu + \epsilon_t$$

r_t = Return Values. μ = mean value ϵ_t = Error term

Conditional variance equation: The conditional variance equation will describe the evolution of the conditional variance of the unexpected returns.

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \beta \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha \cdot \epsilon_{t-i}^2$$

α_0 = Constant term, ϵ_t = Error term t= time period β and α are coefficients.

The time varying nature of the volatility of residuals which are generated from the mean equation is modelled by the conditional variance. That means prediction can be done by forming a weighted averages of a long term average (The constant), the forecast variance from last period (The GARCH term) and the information about the volatility observed in the previous period (ARCH terms)

F. EGARCH Model

The background thinking of the Exponential Generalized Autoregressive Conditional Heteroscedasticity model is based on Volatility. That means the volatility is more likely to be high at time t if it was also high at time t−1. On the other hand, it is described as the volatility is more likely to be low at time t if it was also low at time t−1.

The main advantage of the EGARCH model is the parameter restriction is not required because, it takes log-variance Therefore, and positive variance condition in the Left-hand-side (LHS) of equation is automatically satisfied.

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \cdot \log \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \cdot \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$$

σ_t^2 = Conditional variance at time t.

β_j = Coefficent of the autoregressive GARCH terms.(j=1 , 2…q)

α_i = Coefficent of the autoregressive ARCH terms (i = 1,2 ……p)

γ_k = Asymmetric order at lag K.

ε_{t-i} = Residual from the mean equation at lag i.

ω = A constant term.

A. Diagnostics Tests

1) Residual Diagnostics Test – Correlogram – Q Statistics: Correlation of Standardized residual up to any specified numbers of lags are displayed by the Correlogram of the Q-Statistics. The Idea behind the Correlogram of the standardized residuals is to check the remaining serial correlation in the mean equation. In other words, this theory is used to check the autoregressive conditional heteroscedasticity (ARCH) in the residuals. If the mean equation is correctly specified, if all the Q Statistics are not significance, then it will create a path to accept the mean equation correctly.

2) Correlogram of Squared Residuals: This test displays the correlogram (autocorrelations and partial autocorrelations) of the squared standardized residuals. This test can be used to test the remaining ARCH in the variance equation and to confirm the correction of the variance equation. If the variance equation is correctly specified all the Q statistics should be in-significance

3) *ARCH LM Test*: The null hypothesis here is the equality in variance or homoskedasticity. The acceptance of the null hypothesis here is the acceptance of homoskedasticity or no ARCH effect under process series. In other words, there are no time varying variances in the data or no volatility clustering.

The ARCH model can be written as the AR model using the squared residuals. This is a regression of the squared residuals based on the constant and lagged squared residuals up to order q. The following model can be considered as the regression model that will help to develop ARCH LM test

$$\varepsilon_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s \cdot \varepsilon_{t-s}^2\right) + v_t$$

ε = Residuals. And v_t = Regression error term.

The ARCH LM test is carries out the Lagrange-multiplies test to test whether the standardized residuals exhibit additional ARCH Under the Null hypothesis, The LM test statistics is asymmetrically follow chi-squared distribution with q degree of freedom.

(Observations * R-squared calculated from equation above) $\sim \chi_q^2$

IV DATA AND PRELIMINARY ANALYSIS

A. Data for Analysis

Data for the study is based on the four countries in the world including Sri Lanka, United State, India and United Kingdom. The selected countries excluding Sri Lanka are the top trade partners of Sri Lanka with in recent past. They are United Kingdom, United States of America, and India. Colombo stock exchange (All Share Price Index), Newyork stock exchange(S & P 500 Index), London Stock exchanges (FTSE 100 Index) & Bombe Stock Exchange (S&P BSE SENSEX Index) are used as the selected Stock market and stock price indices. The data are daily data from first of January 2004 to first of January 2014.

B. Advantage of Daily Data over the Monthly and weekly data.

Daily data is preferred as it is able to capture all the possible interaction and information .However weekly or monthly data will not be able to capture interaction that last for only a few days. Daily data is superior for short term or medium tactical forecasting, Days of the week have difference patterns, that's means the news is quickly & efficiently incorporate into stock prices. Information generated yesterday is obviously more important in explaining the prices today than the information generated last week or before. The stock market prices are heavily affected by the impact of lot of macro economy variables such as interest rate & exchange rates and also the stock price changes heavily depend on the current situation of country, declaration of war, changes of the oil prices, various announcements such as portfolio forecasts and etc

C. Initial Analysis of the Selected Stock series

Table 1. Initial Analysis

Statistics	ASPI	FTSE100	S&P 500	BSE SENSEX
Mean	0.00071	0.00015	0.00020	0.00050
Maximum	0.07299	0.09384	0.10957	0.15990
Minimum	0.11135	0.09264	0.09469	0.11809
Std.Dev	0.01142	0.01192	0.01287	0.01633
Skewness	0.75938	0.15702	0.32729	0.05913
Kurtosis	15.4082	12.0258	14.0373	10.9722
Jarqueberra	15594.5	8866.82	12816.0	6553.14
Probability	0.00000	0.00000	0.00000	0.0000
Sum sq.dev	0.31237	0.37092	0.41711	0.66003
Observation	2395	2609	2516	2474

The highest mean return is related to the ASPI series and the lowest is related to the FTSE 100 return series. All the four series indicates the negative skewness that means all the four series consist of most of decreases than the increases. The Jarque-berra statistics of all the return series are highly significance. It rejects the null hypothesis equals the return are normally distributed. And this result finally indicates that the returns of the all series are not normally distributed. The skewness, Kurtosis and the Jarque-berra statistics indicates that the deviation of the returns from the normal distribution. The above kind of statistics assure the reliability of the predictions based on the standard deviation.

D. Q-Q Plot

The Quantiles and Quantiles diagrams illustrate that how the each returns series from selected four stock exchanges deviate from the normal distribution graphically. If the sample is perfectly normally distributed the points should all fall on the 45 degree line or on other words if the data is normally distributed then the quantiles will lie on a straight line. When we looking at the Indian BSE SENSEX series, it somewhat lends to behave like a normal distribution. However Sri Lankans' ASPI and the USA S&P 500 highly deviate from the normal distribution.

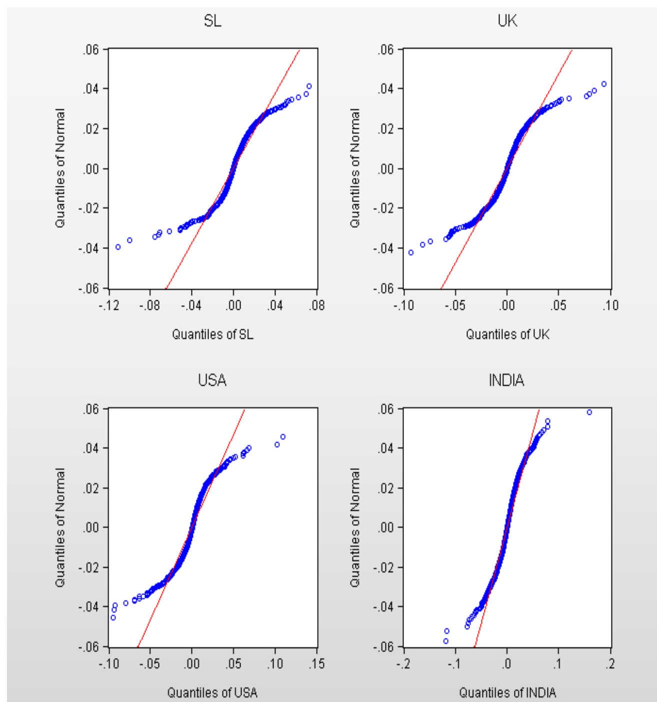

Figure5. Q-Q Plot for Stock returns series

D. Identify the linkage and relationship of selected series

Table 2. Identify the Granger-Causality to ASPI

	Test 1	Test 2	Test 3
	BSE SENSEX	S & P 500	FTSE 100
F -Test	3.837	15.03	2.6399
P-value	0.0217	3×10^{-6}	0.0716

Three test has done to identify the Granger Causality to ASPI of Colombo Stock Exchange. P-value is significant for the test 1 and 2.That means acceptance of the GANGER causality to the ASPI.USA S & P 500 series and Indian BSE SENSEX series are shown the highly significance Causes behaviour for the ASPI of Sri lanka. However other series don't illustrate any kind of significant causes to the ASPI.

V. ADVANCED ANALYSIS

Volatility clustering implies a strong autocorrelation in squared return. Therefore a simple method for detecting the volatility clusters is to calculate the Box-Pierce LM test using the 1st order autocorrelation in squared returns. The test results implies that there is significant volatility clusters in all the four return series and after that it is necessary to identify the asymmetric behaviour of the volatility clusters. The Asymmetric of the volatility is happened when volatility increases more when the stock prices were falling than when it was rising by the same amount. This has been test using a separate test statistics and the help of the chi-square distribution. The results show ASPI series illustrate the symmetric Volatility clusters and all other selected series illustrate Asymmetric volatility clusters. For symmetric series can be modelled using the symmetric type GARCH models and others can be modelled by Asymmetric GARCH models.

A. The Best GARCH Model for All-Share-Price Index (ASPI)

The best model has done a great for clearly model and forecast the volatility. However identification of the best fitted model has number of steps and at the end of these steps, the best fitted model can be summarised as follows.

The mean equation.

$r_t = c + r_{t-1} + \epsilon_t$

$r_t = 0.000491 + 0.236029 r_{t-1}$

The variance equation.

$\sigma_t^2 = \alpha_0 + \beta\sigma_{t-1}^2 + \alpha.\epsilon_{t-1}^2$

$\sigma_t^2 = 8.82 \times 10^{-6} + 0.67334.\sigma_{t-1}^2 + 0.28003.\epsilon_{t-1}^2$

$\alpha_0 > 0$ And $\alpha \& \beta \geq 0$, $\epsilon_t =$ Error term

Zivot (2008) pointed out that the constraint α + β <1 confirmed that the covariance stationary of the return process. According to this statement, the constraint related to here is (0.28003 + (0.67334) < 1 that's mean eventually the volatility will settle down to a long run level or to the long run steady state level.

After fitting the GARCH models, it is important to investigate the actual and fitted volatility using a specific descriptive method. The actual volatility can't be observed. However, there is no problem to use the squared retuned as the proxy for the actual volatility and Awartani and Corradi (2005) used the squared returns as the proxy to the actual volatility

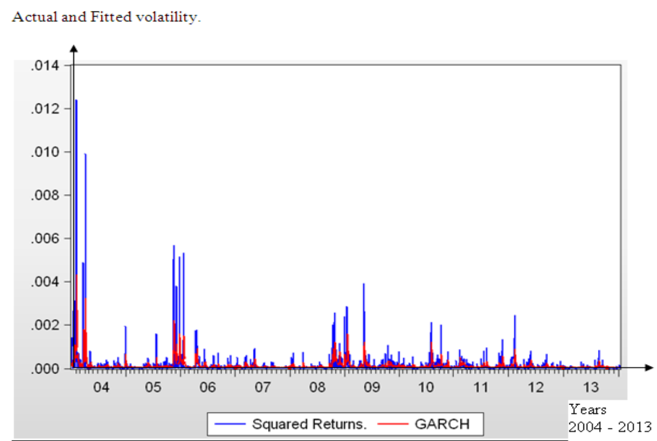

Figure 2. Compare Actual and the Fitted Volatility

B. Diagnostics test for the ASPI of Colombo Stock Exchange.

Heteroskedasticity Test: ARCH

F-statistic	0.004658	Prob. F(1,2391)	0.9456
Obs*R-squared	0.004661	Prob. Chi-Square(1)	0.9456

Figure 3: Output Results of the ARCH LM Test

1) ARCH LM Test: The above results are obtained from the E-Views software. According to that, The ARCH LM test statistic is highly not significance. That means that accept the null hypothesis which is "There is no heteroscedasticity in the standardized residuals".

2) The correlogram of the squared residuals and correlogram –Q Statistics: The correlogram of the squared residuals consists of the highly in-significance Q - Statistics values from lag 1 to 36. This will confirm that the selected variance equation is highly accepted to describe the error variance of the mean equation. Meanwhile, the correlogram –Q Statistics is in-significant for initial lags. That's mean the mean equation is correctly specified.

3) Q-Q Plot: Using the Q-Q- plot below, it can be seen that the residuals are much closed to the straight line. As the result of this, a selected assumption of t-distribution is valid.

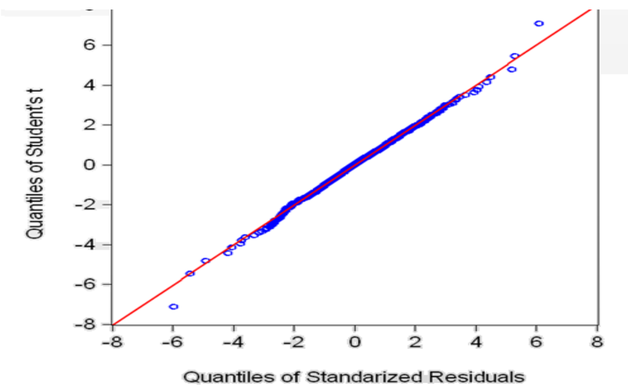

Figure 4: Q-Q Plot for test the error distribution

C. Forecasting using the fitted GARCH model

The following diagram will illustrate the trading days Volatility forecasting values from 2/1/2014 to 13/1/2014

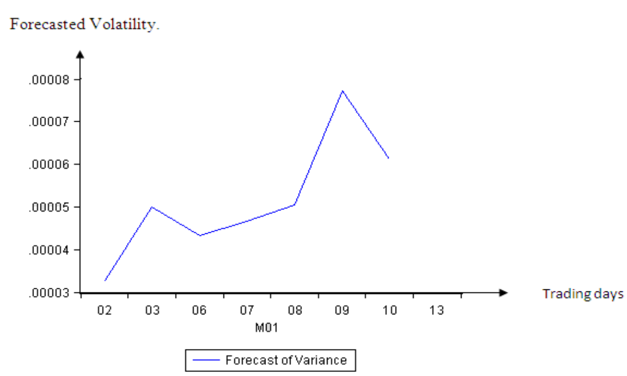

Figure 5: Forecasting results for future period.

D. Fitting the GARCH Models for Other Selected stock prices

The best model has done a great service to clearly model and forecast the volatility. However identification of the best fitted model has number of steps and at the end of these steps, the best fitted model can be summarised as follows.

Fitted Model for S & P 500 series

The Mean Equation.

$r_t = c + \gamma_{t-1} + \epsilon_t$

$r_t = 0.000484 - 0.053444\ \gamma_{t-1}$

The Variance equation.

$$\log(\sigma_t^2) = c + \beta.\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma.\left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| + \alpha.\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \delta.\log(\sigma_{t-1}^2)$$

$$\log(\sigma_t^2) = -0.282057 - 0.113734.\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.251082\left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| - 0.151531.\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) - 0.981404\log(\sigma_{t-1}^2)$$

$\omega, \alpha, \gamma, \delta \geq 0$

Fitted Model for S & P BSESENSEX series

The Mean Equation.

$r_t = c + \gamma_{t-1} + \epsilon_t$

$r_t = 0.000698 + 0.073515\ \gamma_{t-1}$

The Variance equation.

$$\log(\sigma_t^2) = c + \beta.\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + + \gamma.\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \alpha.\log(\sigma_{t-1}^2)$$

$$\log(\sigma_t^2) = -0.403693 + 0.198333.\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.118984.\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + 0.971117\log(\sigma_{t-1}^2)$$

$\alpha, \gamma, \beta \geq 0$

Fitted Model for FTSE 100 series

The mean equation.

$r_t = c + \gamma_{t-1} + \epsilon_t$

$r_t = 0.000336 - 0.042500\ \gamma_{t-1}$

The variance equation.

$$\log(\sigma_t^2) = c + \gamma.\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \omega.\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \alpha.\log(\sigma_{t-1}^2)$$

$$\log(\sigma_t^2) = -0.232296 + 0.115636.\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.122982.\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + 0.984926.\log(\sigma_{t-1}^2)$$

$\omega, \alpha, \gamma \geq 0$

E. Diagnostics Test for fitted GARCH models for S & P 500, S& P BSE SENSEX & FTSE 100 stock price series

1) Correlogram of Squared residuals and Correlogram – Q Statistics: For every fitted model for selected stock markets, the correlogram of the squared residuals consists of the highly in-significance Q statistics values from lag 1 to 36. This will confirm the selected variance equation for each and every series is highly accepted to describe the variance of the mean equation. Meanwhile, the correlogram –Q Statistics are in-significant for all the lags up to 36. That's mean the mean equation of each and every model is correctly specified.

Table 3. ARCH LM Test results

Series	Test Statistics	P-Values	Comments
S & P 500	0.1287	0.7198	Test In-Significant
S&P BSESENSEX	0.4792	0.488	Test In-Significant
FTSE 100	2.066	0.1505	Test In-Significant

2) ARCH LM test: The ARCH LM test statistics is highly not significance. That means accept the null hypothesis that the There is no heteroscedasticity in the standardized residuals

The selected assumption of t-distribution for the entire model fitting process was checked using the Q-Q plot. The assumptions of the error distribution have been confirmed by the Q-Q Plot.

F. Forecasting using the selected best model

The forecasting has been done for the future periods using the selected models of S & P 500, S & P BSESENSEX and FTSE 100 series. The best GARCH models for describe the volatility of the each and every stock prices give the most accuracy forecasting with minimum root mean square errors when compare to the non-best models for each series.

G. Numerical Accuracy of the Best model

Zivot (2008) suggest that the numerical accuracy of model estimated can be examined by comparing the volatility estimates of GARCH (1, 1) Model with the volatility estimates from the ARCH (P) model. After completing the model building or selecting process it is necessary to test the numerical accuracy of the estimates to assure that the estimated model is efficient for volatility clustering. The reason for this step is to reduce spurious inference.In-appropriate coefficent estimates can induse spurious inference. According to the Zivot (2008), the comparisons have done with the selected best models and the ARCH (p) model. The comparisons have done graphically. The graphical method has the best and common process to test the numerical accuracy. All the selected best models for describe the selected series volatility have satisfied the numerical accuracy. The following figure shows the results of the test that has done for check the numerical accuracy of selected EGARCH (2,1) Model for S & P 500 series with GARCH(1,0) (This is an ARCH (P) Model) model to assure that the estimated model is efficient for volatility clustering.

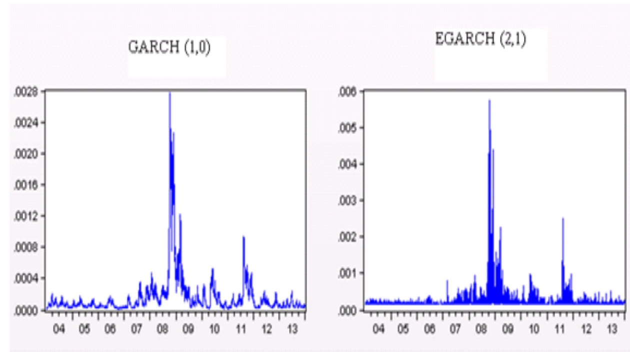

Figure 6: Graphical Test for Numerical Accuracy of the selected best model for S&P 500

VI. GENERAL DISCUSSION AND CONCLUSION

All four stock price indices contain the Volatility and volatility clusters and ASPI of Colombo Stock Exchange illustrates the symmetric volatility clusters and other three series have Asymmetric volatility clusters. GARCH (1,1) model has been fitted for ASPI , EGARCH(1,1) model has been fitted for BSE SENSEX and FTSE 100 and EGARCH (2,1) has been fitted for S & P 500 series. Forecasting of the volatility can be done using the fitted models and there are significance influences or causes from the BSE SENSEX & S & P 500 series to ASPI of Colombo stock exchange during the selected period for this research. These forecasting values are more important for investors who are willing to invest in difference stock exchanges for decision makings. The starting values, Optimization algorithm choice, Convergence criteria and the use of numerical derivatives will influence the numerical estimates of GARCH parameters from difference software. To assure that the estimated model is efficient for volatility clusters the numerical accuracy test has been tested. The suggested improvements for future research are many macro-economic factors are needed to analysis the behaviour of the All Share Price Index more accurately. Many variables and factors are helpful to improve the forecasting results from the selected GARCH models. Specially, the period of global financial crisis should be removed or avoided to improve the forecasting values of S & P 500 and FTSE 100.There are some suggestions for further research. It is better to identify the volatility spill over among the Colombo stock exchange and the world stock exchanges for the period of the pre and post war period of Sri Lanka. However some advanced and sophisticated software packages are needed to identify the volatility spill over among Colombo stock exchange and world stock exchanges. The multivariate GARCH models are very complex models and these models require some advanced computational codes to analysis and some software packages is needed to analysis the advanced GARCH models.

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