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Evaluating the Forecasting Performance of Symmetric and Asymmetric GARCH Models across Stock Markets: Stock Market Returns and Macroeconomic Variables

By N. Chitra Devi

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I. Introduction

Over the last two decades, a large number of researchers have turned their attention to figure out the sensitivity of asset returns to the volatility of macroeconomic fundamentals. The stock market is highly volatile and complex in nature. The volatility of stock market returns has gained significance among the researchers and become a fertile area in which application of various econometric tools on the financial time series facilitates to examine the disperse of returns over certain period. Hence, volatility measurement is the signal to know the performance of a stock market.

The ordinary least square method is the superior model in predicting the stock market prices under the Gauss Markov assumptions. In the presence of heteroskedasticity, the application of Ordinary Least Square method on the financial time series yields spurious regression. Consequently, a model namely ARCH (Autoregressive Conditional Heteroskedasticity) was developed by Engle (1982) to capture the volatility under the condition of heteroskedasticity. Following the model of ARCH, an extended model of ARCH was proposed by Bollerslev (1986) to capture the symmetric volatility of any financial time series data under the assumption of heteroskedasticity.

After the introduction of GARCH model, many researchers have focused their attention to extend the GARCH models under various specifications. The GARCH models such as T-GARCH proposed by Nelson (1991) E-GARCH developed by Glosten, Jagannathan, and Runkle (1993) capture the asymmetric volatility of any financial time series. Along with the T-GARCH and E-GARCH models, many researchers have developed other GARCH family models such as IGARCH, AGARCH, GARCH-M, FIGARCH under various specifications. There is no conclusion on the GARCH model that is superior to capture the volatility of a financial time series. But the performance of a model differs across markets due to distinguished characteristics of each stock market and time period. In general, the selection of the best model is based on the error measurement of the GARCH model.

In this study, we have considered USA and UK stock market returns to examine the unforeseen relationship with the macroeconomic variables over the period from 1991 to 2014. Apart from examining the relationship between stock market returns and macroeconomic variables, an attempt has been taken to analyze the performance of the model by using the error measurement techniques such as Mean Squared Error, Root Mean Squared Error and Mean Absolute Percentage Error. Subsequently, the results of the error measurement approaches are compared and ranked to find out the superior model that explains the interrelationship between stock market returns and selected key macroeconomic variables.

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II. Literature Review

A large number of studies documented the relationship between macroeconomic variables and stock market returns, but, very few studies evaluated the superior model in explaining the stock market returns. The empirical identification of the macroeconomic variables affecting the stock market returns by employing ARCH/GARCH models has focused mainly on developed and emerging stock markets. El-Nader and Alraimony (2012) investigated the relationship between stock market returns and macroeconomic variables and documented that the ARCH (1) model performs well and therefore, the extension of GARCH (1, 1) model is not necessary. Alberg, Shalit, and Yosef (2008) compared the forecasting performance of several GARCH models with different distributions and found that EGARCH under student-t distribution is the most promising model explaining the dynamic behavior of stock market returns. Ahmed and Suliman (2011) has employed both symmetric and asymmetric GARCH models and found that asymmetric GARCH models are fit than the symmetric GARCH model. Subsequently it reveals that the stock market behavior is asymmetric and it implies that negative news have more impact than the positive news.

Kirui, Wawire, and Onono (2014) evaluated the relationship using TGARCH model and observed that the impact of news is asymmetric and confirmed the presence of leverage effects in Nairobi stock market. Wei-Chong, See-Nie, and Ung (2011) compared the GARCH models with Adhoc models on Japanese stock market and documented that GJR GARCH model is superior to the simple GARCH (1, 1) model. Lim and Sek (2013) have used symmetric and asymmetric models to capture the volatility of stock returns in Malaysia and found that symmetric GARCH models outperform well in the pre and post crisis period, whereas, in the crisis period, asymmetric GARCH models outperform well. Atoi (2014) employed first order symmetric and asymmetric GARCH models under normal and student 't' distribution and found that the power GARCH (1, 1, 1) in student-t distribution is the best predictive model based on the error measurement approaches of Root Mean Square Error (RMSE). Al Freedi, Shamiri, and Isa (2011) examined the volatility of Saudi stock market prices using Symmetric and Asymmetric GARCH models and found that the GJRGARCH model outperforms in the pre-crisis period, whereas the Simple GARCH model performs better in the post crisis period. Miron and Tudor (2010) examined the presence of leverage effects in Romanian and US daily stock market returns by employing EGARCH, PGARCH and TGARCH models and documented that the EGARCH model exhibit lower forecast error comparing with the other asymmetric GARCH models.

Marcucci (2005) compared different GARCH models in forecasting ability of US stock market returns and found than Markov Regime Switching GARCH models outperform well in forecasting ability at shorter horizon, whereas, in the longer horizon Standard asymmetric GARCH models performed well. Hansen and Lunde (2005) reported that GARCH (1, 1) model is not inferior to other model in terms of their ability to forecast the conditional variance. The review of comparison of GARCH family models gives a notion that the performance of GARCH models differs across markets. This study is isolated from the previous literature by comparing the performance of GARCH models across stock markets using error measurement approaches such as Mean Squared Error, Root Mean Squared Error, and Mean Absolute Percentage Error.

III. Data and Methodology

The aim of the study is to evaluate the forecasting performance of the symmetric and asymmetric GARCH models in examining the linkage between macroeconomic variables and stock market returns. Thus, NYSE Composite Index from USA and FTSE 100 index from UK are selected as the dependent variable and Inflation, Interest rate, Money supply, Industrial Production Index, and exchange rate considered as the independent variables. The data used in the study consist of monthly time series observations covering the period of January 1991 to December 2014. Monthly closing price index of NYSE (New York Stock Exchange) composite and FTSE (Financial Times Stock Exchange) 100 are collected from Yahoo finance, whereas the other macroeconomic variables influencing the stock market returns are mainly collected from the Organization for Economic Co-operation Development (http://stats.oecd.org/). Three months Treasury bill rate has been collected from http://www.bankofengland.co.uk, http://www.federalreserve.gov/releases/h15/ data.htm and ACWI (All country World Index) of MSCI has been collected from https://www.msci.com websites

a) Macroeconomic Variables and Transformations

i. *Stock Market Returns*

Stock market returns depicts the pulse of an economic condition and the ups and downs of the stock price movements reveals the volatility of the market. Monthly average closing price of NYSE composite Index and FTSE 100 index are taken and converted into logarithmic returns using the following formula.

$$DLNSMR = Ln\ SMR_t - Ln\ SMR_{t-1}$$

ii. *Industrial Production*

Index of industrial production is a proxy used for real economic output of the economy. An increase in economic activity increases the profit of companies and in turn it raises the stock prices to go up. Many previous literatures have used industrial production index as a proxy for representing the economic conditions of a country. Moreover, the industrial production reveals the true picture of an industrial economic growth of a country. Chen, Roll, and Ross (1986) produced evidence that current stock prices are positively influencing the future level of economic activity. Therefore, increases in industrial production positively impact the stock prices and decreases in industrial production make an opposite effect on stock prices. It is expected from the study that there is a positive relationship exists between industrial production and Stock returns. Industrial production is transformed as,

$$DLNIP = Ln\ IPt - Ln\ IPt\text{-}1$$

iii. *Interest Rate*

Investors use interest rate as the barometer for earning profit or facing loss from investment in an efficient capital market. A rise or fall in interest rate influence the investment decision of the investors as they consider the interest is the minimum rate of return or the risk free rate of return expected from investment. An increase or decrease in interest rate obviously has a negative or positive impact on stock returns as investors motivated to change the portfolio structure in favor of or against the bonds. Therefore, Inverse relationship is expected between interest rate and stock market returns .(El-Nader & Alraimony, 2012); Fifield, Power, and Sinclair (2002) found that there is a significant relationship exists between stock market prices and interest rate, whereas, Quadir (2012) found that there is insignificant relationship between stock market prices and interest rate. 3 month Treasury bill rate is used to represent interest rate. The transformation of interest rate is given as,

$$DLNIR = Ln\ IR_t - Ln\ IR_{t-1}$$

iv. *Inflation*

A high inflation reduces the purchasing power of each unit of currency that spent to purchase goods and services and raises the disposable income and reduces the savings. Therefore, investment in stock market may considerably be reduced when inflation influences the stock market returns negatively. However, there is an ongoing debate on the impact of inflation on stock returns; the influence depends on various factors and time period. Hence the inflation is an unpredictable factor. It has given contradictory results in the previous literature. Fama (1981) concluded that there is a positive relationship between inflation and stock returns but, Mukherjee and Naka (1995) reported negative relationship between stock returns and inflation. Consumer price index is considered as a proxy to represent inflation rate. The inflation is transformed using the following formula.

$$DLNIF = Ln\ LIF_t – Ln\ LIF_{t-1}$$

v. *Money Supply (M3)*

Money supply represented by M3 is the broad money supply index including money with public, demand deposit of banks and demand deposit of Apex bank. The downturn of stock market price is substantially influenced by the liquidity of money supply. A high liquidity of money supply strengthens the stock market price of an economy. On the other hand, decrease in money supply tends to decreases the stock market returns. Fama (1981) documented that there is a negative relationship between inflation and stock market prices because of increasing money supply tends to increase the discount rate and lowers the stock market prices. On contrary to the result of Fama, Mukherjee and Naka (1995) found that there is a positive relationship between money supply and stock market returns as a result of increasing cash flows increases the investment in stock market. The money supply has been transformed using the following formula.

$$DLNMS = Ln\ M3_t - Ln\ M3_{t-1}$$

vi. *Exchange Rate*

Depreciation of domestic currency against foreign currencies creates a favorable pitch for the growth of an economy by attracting more portfolio investment from foreign investors and augmenting exports to foreign countries. Hence the capital flows from foreign countries would increase the stock returns and it creates a positive impact on stock market prices. On the other hand, Appreciation of domestic currency takes away the foreign capital flows and makes imports cheaper and it creates negative impact on stock market prices. Therefore the stock market prices are highly sensitive to the foreign exchange rate of a country and the impact of exchange rate and stock prices has conceived more importance in the literature. Nnenna (2012) found that there is a significant and positive impact on Nigeria stock market volatility. On contrary to Nnenna, El-Nader and Alraimony (2012) found negative relationship between real exchange rate and Amman Stock market returns. The relationship between exchange rate and stock market prices produced conflicting results and the magnitude of relationship differs from country to country. The exchange rate used for the study are US dollar against SDR currency and UK Pound Sterling(₤) against Per US dollar($). The transformation of exchange rate is done using the following equation.

$$DLNER = Ln\ ER_t - Ln\ ER_{t-1}$$

vii. *MSCI World*

The integration among the countries in the decade of 1990s became a major challenge for investors to understand the domestic stock market to the external shocks arising out of global equity markets volatility. The MSCI world index is used as a proxy to represent the global equity prices. This variable is included in the study to assess the impact of world stock market returns on domestic stock market returns. The following equation is applied to calculate world stock market returns.

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DLNWSR = Ln WSRt - Ln WSRt-1

b) Methodology

i. *Ordinary Least Square Estimation*

The OLS estimation is the conventional and superior model in explaining the cause and effect relationship between variables. The application of OLS is superior where the data is free from the problem of autocorrelation, non-stationary and heteroskedasticity. Therefore, as the initial attempt, OLS method is selected to examine the relationship between stock market returns and macroeconomic variables.

The basic mean equation model of Regression is given as

$$DL = \theta 0 \quad + \theta 1 DLNIPt \ + \theta 2 DLNIRt \ + \theta 3 DLNIFt \ + \theta 4 DLNMSt \quad + \theta 5 DLNERt \ + \theta 6 DLNWSRt\mu t \tag{1}$$

D denotes the first differences of the stock returns and key macroeconomic variables. Where LN denotes natural logarithm, $\theta 0$ denotes constant or intercept of the regression model $\theta_1\, \theta_2\, \theta_3\, \theta_4\, \theta_5\, \theta_6$ are the coefficients of the independent variables, μt is the white noise error term. Here, IP, IR, IF, MS, ER, and WSR are the independent variables and SMR is the dependent variable.

ii. *Arch- Lm Test of Heteroskedasticity*

The Autoregressive conditional heteroskedasticity Lagrange multiplier test is used to model observed time series data. In the conventional econometrics, the variance of the error terms is assumed as constant over time. Otherwise it is considered as the series is homeskedastic. If the error variance is not constant, it is called heteroskedastic. The ARCH model assume the variance of the current error term or innovation is the function of the previous time periods error terms. Such models are often called ARCH model and it was developed by Engle. 1982. It is found out by applying the following equation.

$$\hat{\varepsilon}^2_t = \hat{\alpha}_0 \ + \sum_{i=1}^{q} \hat{}_i \alpha \varepsilon^2_{t-i} \tag{2}$$

$\hat{\varepsilon}^2_t$ Denotes the squared error at lag t. $\hat{\alpha}_0$ is the constant. $\hat{\boldsymbol{\alpha}}$ indicates the coefficient of lagged squared residuals.

c) GARCH (1.1) Generalized Autoregressive Conditional Heteroskedasticity

The application of ordinary least square method on the time series data where the conditional variance of the error terms is not constant will produce spurious regression results. To overcome the problem of heteoskedasticity, ARCH model has come into solve the problem arising out of error terms. In particular ARCH models assume the variance of the current error term or innovation to be a function of the previous time periods error terms or innovation. In simple, the current error term is related with the square of the previous innovations. The Generalized Auto Regressive Conditional Heteroskedasticity proposed by Bollerserv in 1986 captures the volatility clustering and unconditional return distribution. This study adopts the standard ARCH/GARCH (1.1) model using the following equations.

i. *Mean Equation*

$$DLNSMR_t = \theta_0 \ + \theta_1 DLNIP_t \ + \theta_2 DLNIR_t \ + \theta_3 DLNIF_t \ + \theta_4 DLNMS_t \ + \theta_5 DLNER_t \quad + \theta_6 DLNWSR_t + \mu_t \tag{3}$$

ii. *Variance Equation*

$$\mathrm{h}^2_{\mathrm{t}} = \theta_0 + \lambda_1 \mu^2_{t-1} \ + \phi_1\, h^2_{t-1} \tag{4}$$

where θ_0 is the intercept, $\boldsymbol{\lambda 1}$. and $\boldsymbol{\phi 1}$ are the ARCH and GARCH coefficients and $\mathrm{h}^2_{\mathrm{t}}$ is the conditional stock return volatility

d) TGARCH (Threshold Generalized Autoregressive Conditional Heteroskdasticity)

One of the major weaknesses of the GARCH model is that the GARCH model assumes that error terms irrespective of the sign have similar magnitude of change on the volatility of stock market returns. To overcome the problem of symmetric effect, the TGARCH model was proposed by Zakoian and Runkle. In particular, the bad news creates more impact on the stock market returns than the degree of variations created by Good news. The TGARCH model divides the distribution of the innovations into two disjoint intervals and approximate a piecewise linear function for the conditional standard deviation. The Threshold GARCH(1,1) model is applied with the following equations.

i. *Mean Equation*

$$DLNSMR_t = \theta_0 + \theta_1 DLNIP_t + \theta_2 DLNIR_t + \theta_3 DLNIF_t + \theta_4 DLNMS_t + \theta_5 DLNER_t + \theta_6 DLNWSR_t + \mu_t \quad (5)$$

ii. *Variance Equation*

$$h_t^2 = \theta_0 + \lambda_1 \mu_{t-1}^2 + \phi_1 h_{t-1}^2 + \gamma_1 \mu_{t-1}^2 d_{t-1} \quad (6)$$

$\lambda 1.\ \phi 1$ and $\gamma 1$ are the ARCH . GARCH and TGARCH co-efficients, h^2 is the conditional stock return volatility, Ω_{t-1} is the set of all information available at time $_{t-1}$, $d_{t-1} = \{\mu_{t-1} \begin{smallmatrix} < 0 \\ \geq 0 \end{smallmatrix}\}$ < 0 indicates that bad news news ≥ 0 shows positive news volatility to the positive and negative error variance. Neither ARCH nor the GARCH capture the asymmetry effect on the volatility of stock market returns. The equation of E-GARCH (1,1, 1) is given below.

e) EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity)

The EGARCH model was put forward by Nelson in 1991 to examine the asymmetry effect of stock market

i. *Mean Equation*

$$DLNSM = \theta 0 + \theta 1 DLNIPt + \theta 2 DLNIRt + \theta 3 DLNIFt + \theta 4 DLNMSt + \theta 5 DLNERt + \theta 6 DLNWSRt + \mu t \quad (7)$$

ii. *Variance Equation*

$$\log(h_t^2) = \alpha + \delta \left|\frac{\mu_{t-1}}{h_{t-1}}\right| \gamma \frac{\mu_{t-1}}{h_{t-1}} + \beta \log(h_t^2) \quad (8)$$

In the variance equation,, α *is the intercept*, $\delta\ \beta\ \gamma\ a$ re the co-efficients estimated in EGARCH model.

f) Error Measurement Approaches for Model Evaluation

The GARCH family models are evaluated using three error measurement approaches such as mean squared error (MSE) root means squared error (RMSE) and mean absolute percentage error (MAPE).

i. *Mean Squared Errors (MSE)*

Mean square error is the important error measurement approach which is commonly used to evaluate the performance of the model and it measures the average of the squares of the errors. Based on the average of the squares of the errors of each model, the forecasting performance of the symmetric and asymmetric GARCH models are compared and ranked to find out the most appropriate model to determine that the model that avoid large errors. The mean square error is estimated by

$$MSE = \sum_t^n \frac{\varepsilon t^2}{n} \quad (9)$$

ε_t^2 is the squared value of $Y_t - \hat{Y}_t$ Where, Y_t is the actual observed value and $\hat{Y}_t$ is the forecasted value at time t.

ii. *Root Mean Squared Error (RMSE)*

RMSE is the common error measurement approaches which amplifies and penalize the large errors to distinguish and compare the performance of the models. It is estimated as

$$RMSE = \sqrt{\sum_t^n \frac{\varepsilon_t^2}{n}} \quad (10)$$

ε_t^2 is the squared value of $Y_t - \hat{Y}_t$ Where, Y_t is the actual observed value and $\hat{Y}_t$ is the forecasted value at time t.

g) Mean Absolute Percentage Error (MAPE)

The MAPE is estimated as

$$MAPE = \sum_t^n \left|\frac{\left(\frac{\varepsilon_t}{Y_t}\right) * 100}{n}\right|$$

ε_t is the value of $Y_t - \hat{Y}_t$ Where, Y_t is the actual observed value and $\hat{Y}_t$ is the forecasted value at time t.

IV. Results and Interpretations

The macroeconomic variables such as Stock Market Returns (SMR), Industrial Production index in natural log (LIF), Interest rate in Log (LIR), Inflation in natural log (LIF) Money Supply in natural log (LMS), Exchange Rate in log (LER), World stock Market returns (WSR), are considered to analyze the basic statistical features of the data. The table 1 summarizes the descriptive statistics such as mean, minimum, maximum values, standard deviation, kurtosis, skewness and the Jarque-Bera Test. The Jarque-Bera test, a test for normality, is used to examine the randomness of the macroeconomic variables considered for the study. Based on the probability values of Jarque-Bera test, the null hypothesis of normally distributed can be rejected.

The average stock price of New York Stock Exchange Composite index and MSCI composite Index are 8.63 and 5.51 respectively. The standard deviation of USA Stock Index is 0.46 and the MSCI world standard deviation is 0.35.Therefore, it can be concluded from the table 4.1 that the US market is highly volatile comparing with the world market as the standard deviation of stock returns is low. While in UK, the standard deviation is 0.30 which is lower than USA and MSCI world indicates the volatility of stock market returns is comparatively low. The stock market indices, Industrial production index, Interest rate, Inflation in USA, Money supply in UK and Exchange rate in UK are negatively skewed and it indicates that these variables have long left tails. Few macroeconomic variables such as Money supply in USA, Exchange rate in USA and Inflation in UK are positively skewed and it shows the long right tails of the distribution. . The kurtosis value of all variables is less than 3 and it indicates that the distribution is platykurtic. The probability values associated with the jarque bera test, a test for normality, reveals that the stock returns and macroeconomic variables are deviated from the normal distribution. Based on the Jarque bera statistics and p-values, the null hypothesis of normally distributed is strongly rejected at 5% significance level. The descriptive statistics indicates that the data are not normally distributed and therefore, there is no randomness in the data.

Table 1: Descriptive statistics on Macroeconomic Variables

	SMR	LIP	LIR	LIF	LMS	LER	WSR	SMR	LIP	LIR	LIF	LMS	LER
				U.S.A			C.V				U.K		
Mean	8.63	4.55	0.20	4.43	29.37	-0.37	5.51	8.46	4.64	1.04	4.45	27.75	-0.50
Max.	9.31	4.77	1.83	4.69	30.08	-0.22	6.07	8.84	4.73	2.56	4.72	28.51	-0.34
Mini.	7.59	4.20	-4.61	4.12	28.82	-0.49	4.77	7.68	4.55	-1.49	4.16	26.87	-0.73
S.Dev.	0.46	0.15	1.83	0.17	0.40	0.06	0.35	0.30	0.06	1.17	0.14	0.56	0.09
Skew.	-0.70	-0.90	-1.07	-0.08	0.16	0.31	-0.47	-0.78	-0.33	-1.04	0.27	-0.04	-0.66
Kurto.	2.32	2.58	2.66	1.75	1.71	2.25	2.21	2.46	1.55	2.40	2.16	1.63	2.72
J-B	29.32	40.66	56.65	19.03	21.23	11.48	18.29	32.54	30.72	55.71	11.99	22.67	21.84
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs.	288	288	288	288	288	288	288	288	288	288	288	288	288

a) *Unit Root Test on Macroeconomic Variables*

Before examining the impact of macroeconomic variables on stock returns, it is necessary to find out whether the data is suffering from the problem of unit root or not. If the series has unit root or non-stationary, transformation of series from level data to differenced data is mandatory. The widely used tests for unit root are the augmented Dickey- Fuller (1979) (ADF) unit root test and Phillips-Perron (1988) (PP) test. The first step to examine the long run relationship between the stock market returns and macroeconomic variables is to know the order of integration of all variables. Augmented Dickey-Fuller test is applied on US stock market returns and macroeconomic variables to examine if there is a unit root in the time series of the variables. The Augmented Dickey-Fuller test applied on each macroeconomic variables of including stock market returns is presented in the table 2.

Table 2: ADF unit root test results on macroeconomic variables

	Variables	I	I&T	I(Ist Difference)	I&T(Ist Difference)
USA	SMR	-1.77	-2.03	-15.45	-15.45
	LIP	-1.70	-2.21	-4.38	-4.43
	LIR	-0.34	-1.79	-13.75	-13.78
	LIF	-1.47	-2.45	-10.80	-10.89
	LMS	2.44	-3.62	-5.23	-7.26
	LER	-2.19	-2.77	-12.24	-12.22
C.V	WSR	1.58	-2.18	-15.41	-15.39
UK	SMR	-2.35	-2.28	-16.60	-16.61
	LIP	-1.20	-1.53	-20.97	-21.14
	LIR	-0.60	-1.66	-10.89	-10.88
	LIF	1.21	-1.71	-4.40	-3.82
	LMS	-1.32	0.52	-16.14	-16.23
	LER	-3.37	-3.44	-12.17	-12.16
CRITICAL VALUES					
	1%	-3.453072	-3.990470	-3.453072	-3.990470
	5%	-2.871438	-3.425616	-2.871438	-3.425616
	10%	-2.572116	-3.135961	-2.572116	-3.135961

C.V indicates common Variable I stand for Intercept, I&T stands for Intercept and Trend

b) Hypothesis of the model

Ho: $\delta = 0$ the time series has unit root or is a non-stationary

H1: $\delta \neq 1$ the time series has no unit root or is a stationary

The Augmented Dickey-Fuller test is applied to examine whether data at level or the differenced are stationary or not. The results of the test gives support that all the variables in time series are not stationary in their levels except money supply in USA and exchange rate in UK at five percent level of significance. Therefore, the null hypothesis of non-stationary is accepted at level data. It means that there is a unit root at level data. But all the individual time series become stationary in their first differences. Consequently, Null hypothesis of non stationary is rejected in the first differences of the data.

The Asterisk*** shows the rejection of the null hypothesis of non-stationary at the 1% level of significance, ** indicates rejection of null hypothesis at 5% percent level of significance and * shows the rejection of unit root at 10% level of significance. The Mackinnon (1996) critical values are used for the models with intercept and with intercept and trend of Augmented Dickey-Fuller test. The computed ADF test-statistic at first difference data is smaller than the critical values - "tau" statistics or critical values, the Null hypothesis of non- stationary is rejected.

c) Impact of macroeconomic variables on stock market returns

The Augmented Dickey Fuller test shows that all the macroeconomic variables are stationary at first difference. Hence, the first difference of all the macroeconomic variables are selected to examine the impact of macroeconomic variables on stock market returns by employing the Ordinary Least Square method. The result of the analysis is presented in the table 3.

The table 3 shows the regression co-efficient of macroeconomic variables including stock market returns. The SMR is the USA stock market returns which are used as the dependent variable whereas, the production index, Interest rate, Inflation, Money supply, exchange rate and MSCI world index are considered as the independent variables explaining the stock market returns in USA. Based on the regression results, it is understand that the macroeconomic variables considered for the study are influencing the stock market returns positively except the production index. As contrary to the expectations, the production index has negative impact on stock market returns and it indicates when industrial production falls down, the stock market prices may go up.

Table 3: Results of the Regression Analysis – USA

Dependent Variable: SMR

Variables	Coefficient	Std.Error	Z-Statistics	Probability
Intercept	0.000562	0.001579	0.355890	0.7222
DLNIP	-0.024042	0.136884	-0.175634	0.8607
DLNIR	0.000554	0.003581	0.154596	0.8773
DLNIF	0.073282	0.268040	0.273397	0.7847
DLNMS	0.287962	0.244999	1.175362	0.2408
DLNER	0.194850	0.075220	2.590400	0.0101
DLNWSR	0.910337	0.020427	44.56539	0.0000
R-Squared	0.883142	Akaike Information Criterion		-5.599189
Adj R-Squared	0.880637	Schwarz Criterion		-5.509933
F-Statistic	352.6769	Hannan-Quinn Criterion		-5.563417
Prsob(F-statistic)	0.000000	Durbin Watson Statistic		1.937898

It is surprised to note that the index of industrial production reveals a detrimental effect which do not support the postulates presented by Chen et al. (1986) But still in line with the previous studies, the impact of industrial production on stock returns is ambiguous. The world stock return is the most significant factor influencing the stock market return at 5% significance level. The Durbin Watson statistics which is closer to two reveals that there is no auto or serial correlation in the data. The Adjusted R-square, the co-efficient of determination, is 88.06% which indicates that the 88.06% of the stock market return variations are explained by the independent variables.

Table 4: Result of the Regression Analysis - UK

Dependent Variable: DLNSMR

Variables	Coefficient	Std.Error	Z-Statistics	Probability
Intercept	-0.001083	0.001603	-0.675471	0.4999
DLNIP	0.028166	0.141027	0.199722	0.8418
DLNIR	-0.030050	0.013285	-2.262006	0.0245
DLNIF	0.024037	0.305178	0.078764	0.9373
DLNMS	0.089891	0.125411	0.716772	0.4741
DLNER	0.484769	0.058266	8.319892	0.0000
DLNWSR	0.828724	0.029626	27.97277	0.0000
R-Squared	0.743363	Akaike Information Criterion		-4.872292
Adj R-Squared	0.737864	Schwarz Criterion		-4.783037
F-Statistic	135.1728	Hannan-Quinn Criterion		-4.836520
Prob(F-statistic)	0.000000	Durbin Watson Statistic		2.176994

The results of the Regression analysis reveals that the macroeconomic variables, interest rate, exchange rate and world stock market returns are influencing the stock market returns significantly while other macroeconomic variables have insignificant impact on the stock market returns. The production index, as expected influence the stock market returns positively. If industrial production is higher, the stock market returns will also be higher. But the interest rate which is significantly negative shows that increasing interest rate decreases the stock market returns in UK. The adjusted R-Square value is 73.78%. It denotes that 73.78% of the stock market returns variations are explained by the independent variables. Moreover, the Durbin Watson statistics reveals that there is no auto or serial correlation in the data. However, the application of Ordinary Least Square method becomes BLUE when there is no auto correlation and free from the problem of Heteroskedasticity. Therefore Residuals of Regression model are extracted and applied the ARCH LM test of Heteroskedasticity to know whether the model applied is the appropriate one in explaining the variations of stock market returns.

d) ARCH –LM Test of Heteroskedasticity

For computing ARCH LM test, the ordinary least square method is used to compute the residuals and Resid^2 is used as the dependent variable and Resid^2(-1) is used as an independent variable. The result is presented in the table 5. The Arch test highly rejects the null hypothesis of no arch effect in the time series data. The result shows the data is suffering from the problem of heteroskedasticity. The p value of Chi-Square is 0.0002 in USA and 0.044 in UK. The probability values are lower than the critical value of 0.05. The residual squared at lag one coefficient are with a significant p value of 0.00 and 0.04. The table 5 shows that the error variance is not constant over the time period taken for the study.

Table 5: ARCH LM TEST of Heteroskedasticity on Regression Residuals

Country	Intercept	Resid	Chi-Square Value	Prob.	F-Statistics	Obs.R Squared
USA	0.000162	0.21754	0.0002	0.0002	14.09915	13.52690
UK	0.000375	0.118952	0.0444	0.0443	4.075626	4.046260

Hence, it is concluded from the results that ARCH effect is present in the data which proves the presence of heteroskedasticity. The presence of ARCH effect indicates that the application of OLS method is not the true representation of the relationship between macroeconomic variables and stock market returns. Therefore, Symmetric and asymmetric GARCH models have been applied to investigate the relationship between stock market returns and macroeconomic variables in USA and UK. After examining the relationship, the symmetric and asymmetric GARCH models have been evaluated and ranked using the error measurement approaches such as Mean Squared Error, Root Mean Squared Error and Mean Absolute Percentage Error.

e) Model Evaluation using out of Sample Analysis

The out of sample forecasting performance of symmetric and asymmetric GARCH models are evaluated and compared with the Mean squared Error(MSE), Root Mean Squared Error(RMSE) and Mean Absolute Percentage Error(MAPE) and the result of the analysis applied on USA is presented in the table 6.

Table 6: Comparison of Symmetric and Asymmetric GARCH Models in USA

MODELS	MSE	RANK	RMSE	RANK	MAPE	RANK
Symmetric Garch	0.010242	1	0.014651	2	116.4482	2
Asymmetric T-Garch	0.010246	3	0.014654	3	116.5536	3
Asymmetric E-Garch	0.010245	2	0.014643	1	115.9785	1

The different error measurement approaches have given different results to evaluate the forecasting accuracy of symmetric and asymmetric GARCH models applied in USA. The MSE shows that the symmetric E-GARCH model outperform well than the other asymmetric GARCH models while the RMSE reveals that Asymmetric E-GARCH model is the most accurate forecasting model comparing the values of T-GARCH and E-GARCH models. The MAPE indicates that the E-GARCH model is the best accurate forecasting model in USA. The GARCH and E-GARCH models are the worst performing model in forecasting the stock market returns in USA. Therefore, the majority of the error measurement approaches indicate that the Asymmetric E-GARCH model outperform well than the T-GARCH and GARCH models. The result is consistent with the results produced by Miron and Tudor (2010).

Table 7: Comparison of Symmetric and Asymmetric GARCH Models in UK

MODELS	MSE	RANK	RMSE	RANK	MAPE	RANK
Symmetric Garch	0.015680	3	0.2075	1	127.2060	2
Asymmetric T-Garch	0.015653	2	0.2077	3	127.5035	3
Asymmetric E-Garch	0.015631	1	0.2077	2	126.9936	1

Based on the values of Mean Square Error, it is understood that the forecasting accuracy of E- GARCH model is the best performing model while the RMSE produced that the symmetric GARCH model is the best performing model. The MSE and RMSE show differences in evaluating the model but the MAPE indicates that E-GARCH is the appropriate model in forecasting the stock market returns in UK. The application of GARCH models in different stock markets is analyzed and the results are presented in the table 8.

Table 8: Comparison of Symmetric and Asymmetric GARCH Models in USA and UK Stock Markets

Country	Symmetric GARCH	RANK	Asymmetric T-GARCH	RANK	Asymmetric E-GARCH	RANK
COMPARISION BASED ON MSE						
USA	0.010242	1	0.010246	1	0.010245	1
UK	0.015680	2	0.015653	2	0.015631	2
COMPARISION BASED ON RMSE						
USA	0.014651	1	0.014654	1	0.014643	1
UK	0.20753	2	0.20771	2	0.20770	2
COMPARISION BASED ON MAPE						
USA	116.4482	1	116.5536	1	115.9785	1
UK	127.2060	2	127.5035	2	126.9936	2

The forecasting accuracy of symmetric and asymmetric GARCH models are evaluated and ranked based on the lowest to highest error values. The model which shows lowest error carries the first rank and subsequent ranks are given to following models. The MSE, RMSE and MAPE values indicate that the Symmetric and Asymmetric GARCH model holds the first rank when comparing the error measurement values of UK. The error measurement techniques indicate that the GARCH models perform well in USA while comparing the error measurement values of UK.

V. Conclusion

The study evaluates the application of different symmetric and asymmetric GARCH models in USA and UK using the monthly observations of January 1991 to December 2014. The Augmented Dickey Fuller test applied on macroeconomic variables shows that the all the variables except exchange rate and money supply at level are non-stationary and became stationary at first difference.

Therefore the first difference logarithmic data are considered for application of ordinary least square method to find out the nexus between stock market returns and macroeconomic variables. But the application of regression is not the appropriate method due to the existence of conditional heteroskedasticity. The presence of conditional heteroskedasticity is confirmed with the help of ARCH LM test of heteoskedasticity.

Hence, Symmetric and Asymmetric GARCH models are applied to find out the linkage between stock market returns and macroecnomic variables and their performance are evaluated and ranked based on the error measurement approaches such as Mean Square Error, Root Mean Square error and Mean Absolute Percentage Error.

The results indicate that the Asymmetric E-GARCH model outperforms well than the other models such as Asymmetric T-GARCH and symmetric GARCH models in both USA and UK stock markets. While comparing the performance of GARCH type models across stock markets, the forecasting accuracy of symmetric and asymmetric GARCH type models are superior to USA than the application of GARCH in UK.

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