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Predicting the volatility in stock return of emerging economy: An empirical approach

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Abstract. *Investors become jittery when they do not earn return on their hard earned money. In the same time, they want to make their investment in safe place rather than losing it. For better return, they also want to estimate the volatility in stock market. The basic purpose of the present study is to forecast the volatility in stock return of emerging economies. For the same, the adjusted daily closing price of eleven countries is considered for five years. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) has been applied to predict the stock return of these countries. The different orders of GARCH have been applied in predicting the volatility. It is found that the volatility of every stock return can be forecasted.*

Keywords: emerging countries, stock return, GARCH.

JEL Classification: C22, G12, L11.

Introduction

Financial markets are being characterized by their stochastic nature that involves the precarious movement of prices of securities in both directions. Financial market volatility is vital barometer of dynamic inconstancy of the stock markets (Raja and Selvam, 2011). Variability in the returns that is caused due to changes in prices of the securities is specified as volatility which is measured by the standard deviation or variance. It is defined as extent of fluctuations in the prices of variable i.e. stock prices that could move up and down. Ups and down are the normal phenomenon in the markets but if their price oscillation is sharp and steep, then it becomes complicated for the investors to forecast and plan their strategies. Investors invest in the market for the gain of risk premium. High fluctuations in the market augments the ambiguity in the market regarding the future returns and hence increases the risk. Inconsistent performance of the markets creates further dubious condition for returns creating difficulty for investors to predict the market. Excessive fluctuations makes the financial planning a challenging task. Researchers and academicians are delving deep into this topic to gain useful insights for modeling and forecasting patterns of volatility.

Emerging markets are witnessing high volatility as compared to developed countries, making it an interesting areas for the researchers (Santis and Imrohoroglu, 1997). This could be due to information asymmetry in these types of the markets. Emerging markets are becoming hot new option for investors to enhance their wealth. Emerging markets are being characterized by high volatility (Cohen, 2001). High volatility could lead to huge gains as well as huge losses. These financial markets in emerging countries are harboring high attention from economists, practitioners and researchers from all over the world. Emerging markets are on the path to growth and development. Economic growth is on rise and is driven by uncertain upswings and downswings.

In such highly volatile markets, it becomes hard for the companies to raise funds in the capital markets. Investors lose their confidence in these types of situations. Excessive fluctuations cause losses to risk averse investors creating unfavorable impact (Premaratne and Balasubramanyam, 2011). These are accumulated to further aggravate the situation that could lead to crashes in the market. Accurate estimation of volatility is crucial for risk management practices. Investors are interested in studying the volatility so that they can apply this knowledge in maximizing returns and minimizing risk. They can analyze the impacts of volatility on their investment assets. Fluctuations in the market could be attributed to various macroeconomic factors like inflation, exchange rate, interest rate and certain institutional factors like market performance (Islam, 2013). Investment philosophy of investors also plays an important role in maintaining the stability in the market. Retail investors usually gets involved in rat race creating disturbances in the market. High variations in the market are caused by lack of proper skills and knowledge of investors.

Estimating volatility is the key factor to be analyzed in taking the financial decisions. Financial strategies are framed after due investigation of financial market volatility. Appropriate investment and leverage decision are taken after considering the volatility variable. Normal volatility is favorable for active and healthy stock market (Lin, 2018). Generally securities markets face serious issues regarding variability. Modeling volatility is also required in derivative pricing, risk management and portfolio management. So appropriate model has to be selected that can estimate and forecast volatility of financial time series accurately as financial markets are stochastic in nature. Stock prices are not constant and same is the case with volatility. Some periods show calmness in the markets and some are characterized by high movements. In statistical terms, it is defined as heteroskedastic property. It implies that volatility changes with the time horizon. Various time series models have been developed to capture this characteristic in modeling volatility of the series.

Volatility could be measured in two ways one is historical volatility that is calculated on the past data and the other is implied volatility that is derived from market price of traded security. There are different volatility models i.e. traditional estimators, extreme value estimators and conditional models. Traditional econometric models assumes volatility to be constant in describing the volatility of stock market return. These are the oldest ones that measures unconditional volatility through simple standard deviation. It is calculated as close to close estimated volatility. With the knowledge and awareness that in the financial markets volatility is time varying and showing serial correlations, these models lost their importance and conditional models came into picture. Extensive studies have been conducted to show that these traditional estimators are incapable of explaining the financial data precisely. Other one is extreme value estimator which calculates volatility on the basis of extreme values (high and low prices) in the stock market. Then came the conditional models that take into consideration time-varying nature of the volatility.

Usual characteristics being found in financial time series are volatility clustering and leptokurtosis (Mandelbrot, 1963). There has been exceptional progress in advancement of the econometric models which have been able to apprehend distinctive characteristics in the financial time series. One of the model that has the ability to model conditional volatility or variance after incorporating these characteristics is Generalized Autoregressive Conditional Heteroskedasticity (GARCH) which was proposed by Bollerslev (1986). It has ability to annotate the common characteristics being present in financial series like leptokurtosis, volatility clustering and asymmetric or leverage effects. It is an extension of Autoregressive conditional heteroscasdicity (ARCH) that was given by Engle in 1982. It provides a more flexible approach to capture dynamic structures of conditional variance (Chou, 1988). ARCH model was initially developed to study the temporal nature of stock returns volatility. It proved to be effective model however in order to capture dynamic order of conditional variance higher order ARCH is required. GARCH cured this problem and completed the requirement as it make its base on infinite ARCH specification by which parameters are reduced from infinity to two. GARCH models explained today's volatility as the function of the constant term plus alpha times the yesterday squared residuals and beta times the yesterday variance. There are two parameters that is one ARCH term and one GARCH term.

Further extensions of ARCH and GARCH models have also been developed to grab the other distinctive effects like leverage and asymmetric effect. EGARCH was propounded by Nelson in 1991, TGARCH was developed by Zakoinin in 1994, GJR-GARCH by Glosten, Jganathan and Runkle in 1993. GARCH models are appropriate for high frequency financial data like stock returns that witness conditional variance. GARCH is used frequently to model the volatility/variance which depends upon past residual squared observation and past variance of the series.

In this paper, focus is on forecasting and modeling volatility of emerging countries using GARCH(1,1) technique. This would enable the investors to make sound decisions. They would be familiarized with movement of stock indices among the countries. The paper is organized as follows Section 2 discusses the related works section 3 explains GARCH modeling. Section 4 presents analysis and discussion. Section 5 concludes the paper with summary and future directions.

Review of literature

GARCH models have been frequently used by many researchers to model the volatility. Various empirical studies have been conducted for estimating and forecasting financial volatility.

Chou (1988) investigated the persistence of volatility and risk premium scenario in the US Market from 1962 to 1985 with the help of GARCH model. US markets have witnessed changing equity premiums with a point of risk estimate aversion of 4:5. Uncertainty was there in 1974, that causes the markets to plunge causing increase in volatility by 26%. Lamourex and Lastrapes (1990) in their study contributed to the empirical evidence in usage of ARCH to capture the heteroskedasticity in stock returns. Conclusions found to be valid in the cases of analyzed stocks and this study further paved the way for the employment of ARCH and GACH models in studying behavior of asset prices.

Pandey (2005) analyzed the estimation and forecasting ability of three different traditional estimators, four extreme value estimators, and two conditional volatility models. Realized volatility estimates were used as benchmarks for the purpose of comparison. High frequency data was analyzed from the Jan 1999 to Dec 2001. Three time periods were used i.e. 1 day, 5 day and 1 month. Indexes have shown the characteristics of high frequency financial time series. GARCH(1,1), GARCH(1,1)-Rolling and EGARCH models were applied under conditional models If bias terms are talked about conditional volatility models have performed better than extreme value estimators. In terms of predictive power of models extreme value estimators have performed better than conditional models in providing 5 day and 1 month ahead volatility forecasts. Frimpng and Abaiye (2006) employed random walk, GARCH(1,1), EGARCH(1,1) and TAGRCH(1,1) to forecast and model conditional variance in Ghana stock exchange. Index studied was Databank Stock Index (DSI) for 10 years. AIC and LL criteria was used to measure and compare the performance. DSI index rejected the hypothesis of random walk hypothesis. One can predict and forecast the market. Assuming the normal distribution of the series, GARCH(1,1) model has outperformed the other models.

Floros (2008) selected two Middle East indices Egypt (CMA General Index) and Israeli (TASE-100 index) and studied their patterns of volatility and market risk. Daily data for the time period 1997-2007 was taken and symmetric GARCH models were applied and they were successful in capturing dynamics of the series. Insignificant results came out regarding relationship between expected returns and risk. GARCH-M model concluded that higher expected risk does not necessarily leads to high returns. In the series of estimating volatilities using symmetric models, Islam (2013) in their paper applied two symmetric models GARCH(1,1) and GARCH-M(1,1). Sample was of three Asian markets namely Kuala Lumpur Composite Index (KLCI) of Malaysia, Jakarta Stock Exchange Composite Index (JKSE) of Indonesia and Straits Times Index (STI) of Singapore. Daily observations were analyzed for the time period of five years. GARCH-M model tested the hypothesis between expected returns and risk. Results stated that GARCH models have superior ability in capturing volatility clustering and leptokurtosis. Coefficient of risk premium was significant in case of Indonesian markets as it tends to be more volatile.

Alberg, Shalit and Yosef (2008) employed asymmetric models to forecast two major Tel-Aviv Stock Exchange (TASE) indices: TA100 and TA25. Different density functions are used to compare the forecasting performance of both symmetric as well non-symmetric models namely GARCH, EGARCH, GJR and APARCH models together. E GARCH models have outperformed the other three models while using students t distribution. EGARCH has better risk management ability for this exchange returns as per the study. Eminike (2010) analysed the behavior of stock returns of Nigerian stock exchange using GARCH(1,1) and GJR-GARCH(1,1). General error distribution method was used in calculating the volatility. Monthly data of indices were taken from 1999 to 2008. Evidences of volatility clustering, fat tailed distribution and leverage effects were present in the series for the study. GARCH models were successful in capturing the conditional volatility of the series.

In modeling and forecasting of Malaysian stock market proxy KLCI was done by Angabini and Wasiuzzaman (2012). In their study, an attempt was made to study the impact of financial crisis of 2007-2008 on volatility of Kuala Lampur Stock Exchange (KLCI) in Malaysian stock market. Two study period were taken one including the crisis other one excluding the crisis. AR(4) was finally selected as fit model for conditional mean and for conditional variance GARCH(1,1) EGARCH(1,1) and GJR-GARCH was finalized. Impact of global financial crisis could be stated with significant increase in volatility and presence of leverage effect is detected with a small drop in the persistency. Another study regarding Malaysian stock market was by Shamiri and Zaidi in 2009 applied GARCH, EGARCH and NGARCH models. These Models were applied and their performance was compared using different error distributions. Indexes depicted the characteristics of volatility clustering and leptokurtosis. Choice of error distribution has played an important role that the choice of models during the measurement of performance.

Lim and Sek (2013) in their paper employed both symmetric and asymmetric to analyze the Malaysian stock market volatility. Three time periods are used for analysis -pre-crisis 1997, during crisis and post-crisis 1997. Mean squared error, Root mean squared error and the mean absolute percentage error are the error statistical tools to compare the performance of GARCH models. Crisis period favored asymmetric models and symmetric models were preferred during pre and post crisis period. Impact of exogenous variables named exchange rate and crude oil prices was significant only in pre and post crisis period.

Oberholzer and Venter (2015) investigated the impact of financial crisis of 2007-09 on the behavior of volatility. The study period was divided into three sub periods. Daily volatility of 5 indices of Johennserberg Stock exchange were studied and their changes were analyzed using various extensions. GARCH(1,1), GJR-GARCH(1,1) and EGARCH(1,1) models were the selected ones and their performance were analysed with the help of various error statistical tools. GJR-GARCH(1,1) came out to be the best model for all indices except FTSE top 40 index. With the inclusion of impact of the financial crisis, E-GARCH became the best model.

Lin (2018) analysed forecasting performance of various extensions of GARCH models. SSE Composite index was the subject of the study. Significant time-varying and volatility clustering features were prevalent in the volatility of Shanghai composite index. Good estimation was observed in both symmetric as well as asymmetric models. Best performing model was found to be EGARCH model. Awalludin, Ulfa and Soro (2018) modeled the stock price return volatility in Indonesian stock market. GARCH(1,1) was employed to estimate the volatility and it showed the evidences of volatility clustering in few stocks. GARCH(1,1) a linear model captures volatility clustering successfully. Maximum Likelihood estimation method was used to estimate the parameters. Volatility series was fitted using natural cubic spline function.

Data and research methodology

Data consist of daily 5 year observations of 11 emerging countries. Their major stock indexes are taken and values are obtained from yahoo.finance.com from 1st January 2014 to 31st December 2018. R studio software is employed to estimate and forecast conditional stock returns.

Studies of Mandebrot (1963), Fama (1965) and Black (1976) focused on the distinctive features of stock returns that is volatility clustering, leptokurtosis and asymmetric or leverage effects. Conditional heteroskedastic models incorporate these time-varying characteristics of second moments of distribution notably. They are not like traditional and extreme value estimators whose assumption is regarding unconditional variance. In 1982 Engle proposed Autoregressive conditional heteroscedasticity model that processes lagged disturbances if forecasted variance is on the basis of variance of the error terms known as ARCH effect. ARCH(1) model states Time varying variance as the function of b_0 (constant term) and $b_1e^2_{t-1}$ (squared error of previous term one lagged period.).Under this Volatility is modeled by relating the conditional variance of error terms to the linear combination of the squared disturbances in the recent past.

Further research concluded that in order to apportion the potent nature of conditional variance, higher order ARCH is needed. So this condition was fulfilled and Generalized ARCH (GARCH) was introduced by Bollerslev in 1986. Both ARCH and GARCH models became prominent and were employed intensively in various empirical studies. If forecasted variance is on the basis of variance of the error terms and past value of the terms it is known as GARCH(1,1).It helps to model the volatility or variance which is dependent upon past residual squared observations and past variance of the series. There are both symmetric as well as non-symmetric GARCH models. Linear and non linear extensions have been developed by another academicians. In this paper GARCH(1,1) model is used to estimate and forecast the volatility of stock returns of emerging countries. Conditional mean equation for the stock return is defined as constant term plus residuals.

$r_t = \theta + u_t$

The basic and widespread GARCH(1,1) model can be presented as:

$\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 \sigma^2_{t-1}$
σ^2_t – current day variance or volatility;
α_0 – omega or constant;
u^2_{t-1} – previous squared error residuals, known as ARCH term;
σ^2_{t-1} – yesterday variance or volatility, known as GARCH term.

All parameters α_0, α_1 and α_2 are non-negative. In order to ensure weakly stationarity of the GARCH process, $\alpha_1 + \alpha_2 < 1$ this condition should be fulfilled. α_1 depicts the short run persistency of the shocks and α_2 indicates the long run persistency of the shocks. GARCH(1,1) is the linear model and models the symmetric in the series.

Two basic conditions for applying GARCH model:
1. Volatility Clustering: Large changes are succeeded by large changes, small changes are being followed by small changes. It is the behaviour of the assets in which prices tends to cluster in the group.
2. ARCH effect: The presence of the autocorrelation in squared residuals of the series is known as Arch effect. It is known as heteroskedasticity also known as non-constant variance.

Framework for GARCH(1,1) model:

After the fulfillment of above two conditions, GARCH(1,1) is applied in the stock returns. Volatility clustering is checked by the time series plot of the returns series. Arch LM test is applied to detect the presence of autocorrelation. Then GARCH(1,1) is applied and coefficients are generated along with their p-values.

Data analysis

Descriptive statistics

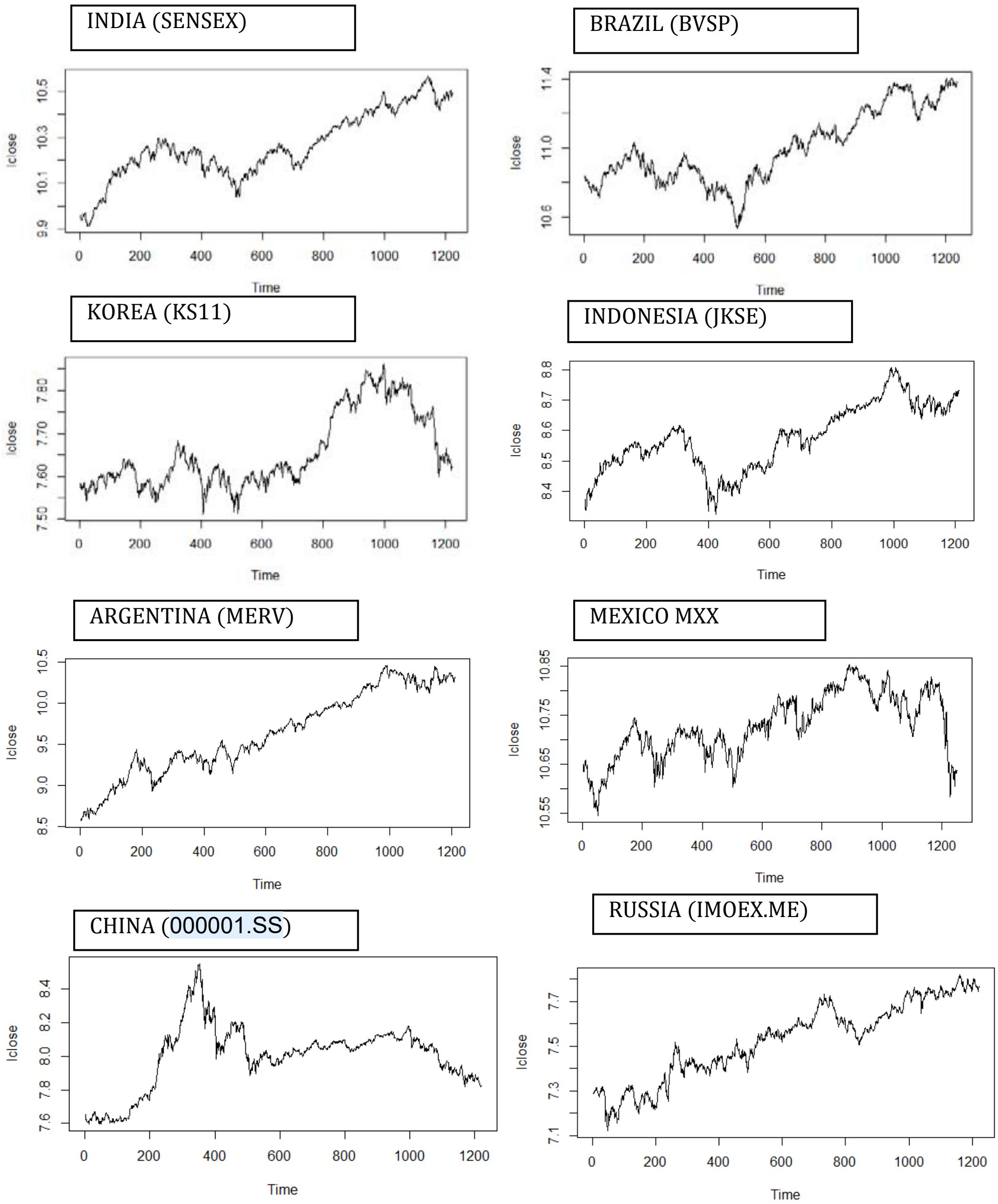
On the basis of availability of data, 11 emerging countries are identified. Closing prices of these indexes are taken into consideration for 5 years. Table 1 provides descriptive statistics depicting mean, minimum, maximum, standard deviation, skewness and kurtosis of indices of these selected emerging countries. Figure 1 depicts the change in log of daily closing prices of indices of selected emerging eleven countries. Figure 2 represents change in returns of daily closing prices that is volatility clustering.

Table 1. *Descriptive statistics of selected indices of these emerging countries*

Country	Index symbol	N	Min	Max	Mean	Std dev	Skew	Kurt
India	Sensex	1223	-0.061197	0.033236	0.000437	0.008399	-0.491976	6.014365
Brazil	iBovespa (Bvsp)	1236	-0.092107	0.063887	0.000451	0.014734	-0.076022	4.854293
Korea	KS11	1221	-0.045411	0.034728	3.02E-05	0.007504	-0.489692	5.582291
Indonesia	JKSE	1211	-0.040884	0.044514	0.000296	0.008963	-0.434803	5.682779
Argentina	MERV	1210	-0.106400	0.090651	0.001437	0.021956	-0.271899	5.266557
Mexico	MXX	1251	-0.059884	0.035251	-1.05E-05	0.008546	-0.529666	7.233409

Country	Index symbol	N	Min	Max	Mean	Std dev	Skew	Kurt
China	000001.SS	1219	-0.088732	0.056036	0.000137	0.015044	-1.224012	10.00030
Russia	IMOEX.ME	1221	-0.114189	0.093670	0.000391	0.011725	-0.593853	16.31261
Philippines	PSEi	1214	-0.069391	0.035762	0.000182	0.009678	-0.345535	5.776407
Turkey	XU100	791	-0.102597	0.088424	0.000668	0.013700	-0.254488	10.64279
Chile	Ipsa	1237	-0.060343	0.066691	0.000262	0.007480	0.228051	11.92841

Figure 1. *Time plot of change in log of closing price indices of emerging countries*



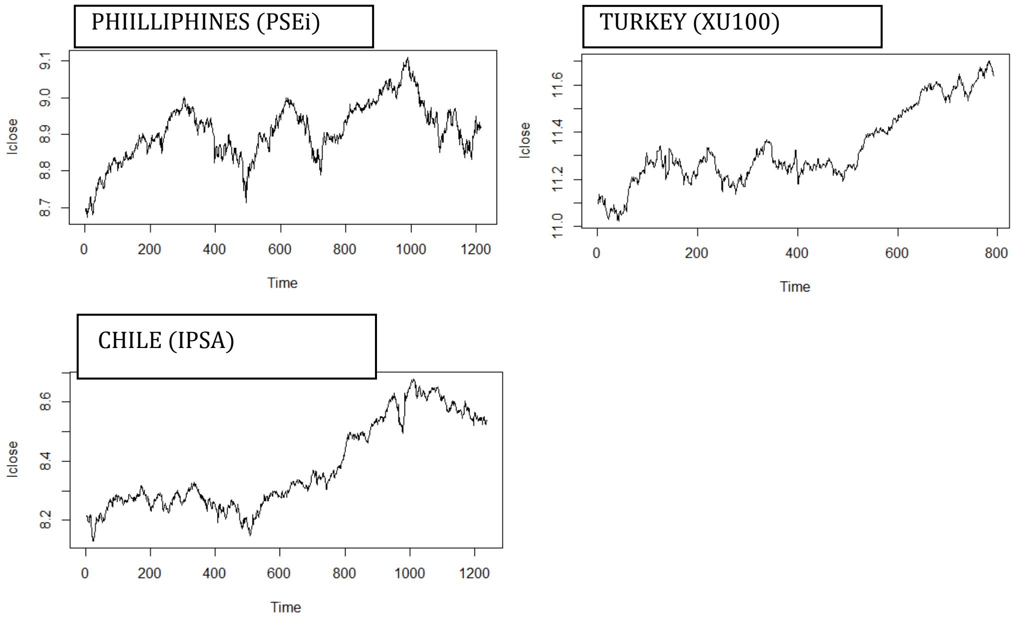
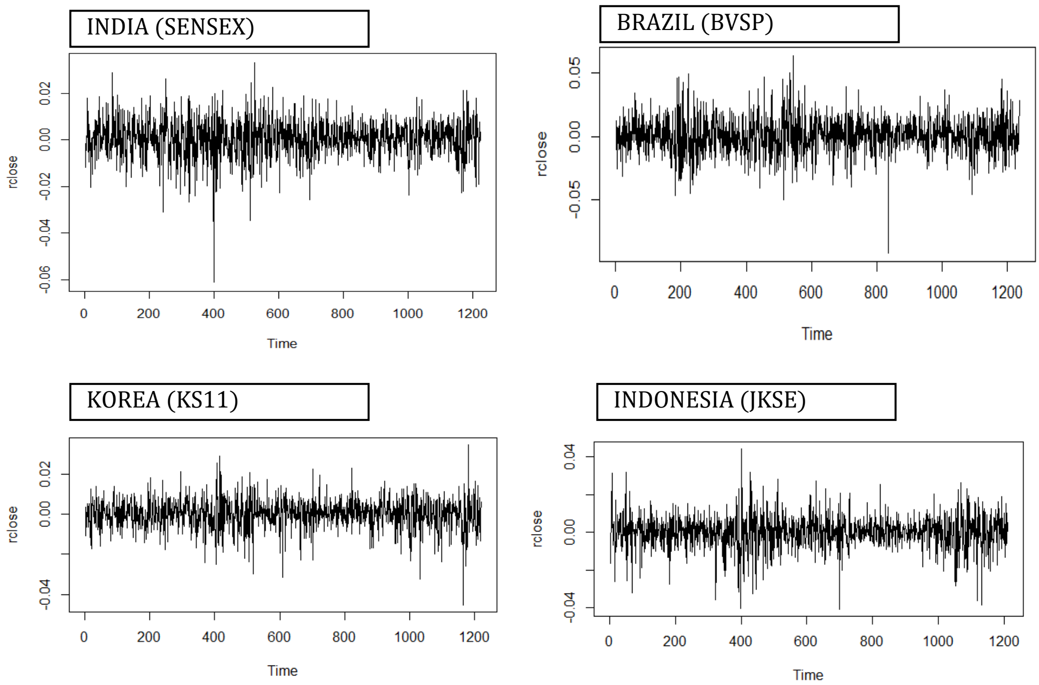
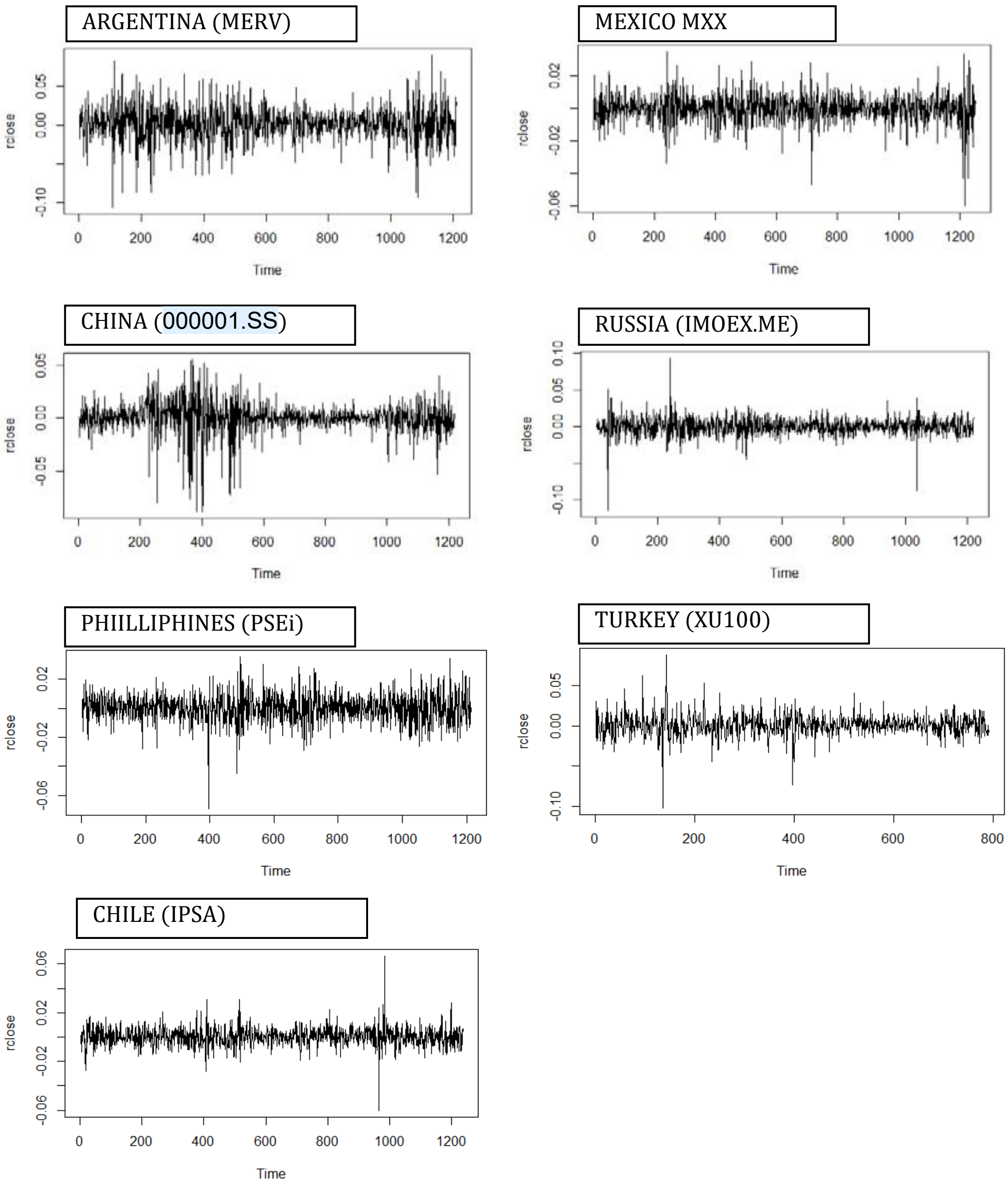


Figure 2. *Time plot of change in stock returns of closing price indices of emerging countries (volatility clustering)*





Application of GARCH model

Every return series is found stationary. Augment dicker Fuller test was applied for detecting the presence of unit root. Graphs of return series are showing volatility clustering as shown in Figure 2. All financial time series are highly leptokurtic having fat tails. Table 2 presents results of Arch Test. p vale is less than 5% thus rejecting null hypothesis of having ARCH effect. Every indices is showing presence of Arch effect which is prerequisite for applying GARCH models. Table 3 is showing output of GARCH estimation.

Table 2. *ARCH LM Test*

Country	Returns Data	Chi-squared	df	p-value
India	Sensex	43.755	12	1.681e-05
Brazil	iBovespa (Bvsp)	42.831	12	2.411e-05
Korea	KS11	63.545	12	5.058e-09
Indonesia	JKSE	86.164	12	2.718e-13
Argentina	MERV	122.96	12	2.2e-16
Mexico	MXX	172.35	12	2.2e-16
China	000001.SS	203.8	12	2.2e-16
Russia	IMOEX.ME	34.641	12	0.000534
Philippines	PSEi	39.3	12	9.392e-05
Turkey	XU100	102.6	12	2.2e-16
Chile	Ipsa	40.214	12	6.626e-05

Table 3. *GARCH(1,1) output*

Country	Returns data	w	A_1	A_2	$A_{1+} A_2$
India	Sensex	0.000001	0.052015 (0.002035)	0.932767 (0.000000)	0.984782
Brazil	iBovespa (Bvsp)	0.000007	0.053707 (0.000000)	0.914147 (0.000000)	0.967854
Korea	KS11	0.000004	0.077164 (0.000000)	0.858457 (0.000000)	0.935621
Indonesia	JKSE	0.000001	0.047484 (0.062221)	0.938231 (0.000000)	0.985715
Argentina	MERV	0.000027	0.179525 (0.000000)	0.777671 (0.000000)	0.957516
Mexico	MXX	0.000004	0.112321 (0.000345)	0.839955 (0.000000)	0.952276
China	000001.SS	0.000001	0.069240 (0.000026)	0.929758 (0.000000)	0.998998
Russia	IMOEX.ME	0.000018	0.156461 (0.000313)	0.727802 (0.000000)	0.884263
Philippines	PSEi	0.000004	0.070236 (0.000000)	0.889333 (0.000000)	0.959569
Turkey	XU100	0.000001	0.023788 (0.000000)	0.972067 (0.000000)	0.995855
Chile	Ipsa	0.000010	0.221234 (0.000000)	0.615812 (0.000000)	0.837046

Conclusions

The basic objective of the present study is to examine and forecast the volatility of the stock exchanges of emerging countries. It is found that the volatility of every stock return can be forecasted. Both ARCH and GARCH terms are significant in all the cases. Their sum of the coefficients are large enough to denote the persistence of the volatility. The overall persistency of shock is largest in China's stock return and lowest in case of Chile's stock exchange as their parameters sum is highest and lowest respectively. The sum of α_1 & α_2 is less than one ($\alpha_1 + \alpha_2 < 1$) implies the mean reverting GARCH model. Comparing the result of short run and long run shock persistency, it is found that long run shock is more persistent than short run as their α_2 is larger than α_1.

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