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Stock Return Autocorrelation and Volatility in Emerging Nations

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ABSTRACT

This research has been conducted to estimate the Value at Risk of nations and volatility of returns of indices by using GARCH based models in the emerging equity markets of the world.

For the study six emerging markets were taken into consideration viz. china, India, turkey, Mexico, Indonesia, Russia, and Brazil. The data these emerging stock indices of the world have been taken for the research purpose. Different GARCH (auto regressive) based models were applied to estimate the volatility in markets , further different Garch based models were compared for best fit and VaR was calculated to estimate the risk. The results of Garch (1,1) model shows that there is no serial correlation in Brazil and Mexico and for India, China, Russia and Turkey there exist positive serial correlation. E-garch which is superior model than garch reported that there is no serial correlation in Brazil, china, Mexico and Russia but for India and Turkey there exist positive serial correlation. Further a stronger garch model that is Pgarch was applied which showed that there is positive serial correlation in all the Emerging equity markets viz. India, China, Russia and Turkey. The generalized results can be of positive correlation between India, China, Russia and Turkey markets.

Keywords: Volatility, Risk Estimation, Garch Based estimation, Emerging Nation, Autocorrelation

1.0 Introduction

The paper comprises of detailed understanding of GARCH models viz. IGARCH, EGARCH, FIEGARCH and GARCH (p, q) model. The GARCH estimation was used for estimating volatility and VaR estimation for measuring risk of investment in these nations. This research was conducted to estimate the VAR by using different GARCH based models. The following section shows the understanding of VAR and different GARCH based models used in our study.

Value-At-Risk

Choudhry (2001) described in his book VaR as a measure of market risk. It is the maximum loss which can occur with set percentage confidence over a holding period of n days. It is the measure of probability of risk present in the portfolio i.e. the expected loss in the portfolio. It was introduced in October1994 when JP Morgan launched RiskMetrics. The VAR may be calculated in number of ways, using a statistical model or by computer simulation. VaR is calculated within a given confidence interval, typically 95%or 99%; it seeks to measure the possible losses from a position or portfolio under “normal” circumstances.

The most commonly used VaR models assume that the prices of assets in the financial markets follow a normal distribution. To implement VaR, all of a firm’s positions data must be gathered into one centralized database. Once this is complete the overall risk has to be calculated by aggregating the risks from individual instruments across the entire portfolio. The potential move in each instrument (that is, each risk factor) has to be inferred from past daily price movements over a given observation period. Hence the data on which VaR estimates are based should capture all relevant daily market moves over the previous year. The VAR estimation captures only those risks which can be measured in quantitative terms.

2.0 Literature Review

Koksal and Orhan (2012) studied about the market risk of both developed and developing countries during the global financial crises. The results indicated that the performance of VaR as a measure of risk is better in developing nations than in developed nations and the possible reason could be deeper impact of global financial crisis on developed countries than emerging markets.

Azizan *et al*. (2012) forecasted in his study portfolio risk estimation by using GARCH and Var Methods because portfolio risk management is part of their decision-making process. According to Hull (2006), VaR is widely used by fund managers "to provide a single number summarizing the total risk in a portfolio of financial assets." Based on this assumption they conducted an analysis to compare the effectiveness of VaR analysis and GARCH method in forecasting risk estimation. The results indicated that VaR is considered better in predicting the risk as it gives the percentage and rank of risk level.

Singh, Allen and Powell (2011) estimated Value at Risk Using Extreme Value Theory. They demonstrated that EVT can be successfully applied to Australian stock market return series for the purpose of predicting next day VaR by using GARCH (1,1) based dynamic EVT approach. They also showed that with back testing results EVT method performed better than GARCH (1,1) and Risk Metrics based forecasts.

Oskooe and Shamsavari (2011) provided results indicating there is no asymmetric effect in the changing volatility. The results also showed that the empirical results from estimating asymmetric GARCH models (TARCH, EGARCH and PARCH) do not confirm the asymmetric volatility in Iran stock market.

Kourouma *et al*. (2011) estimated in his paper Extreme Value at Risk and Expected Shortfall during Financial Crisis. They took the data of CAC 40, S&P 500, Wheat and Crude Oil indexes during the 2008 financial crisis. They have shown an underestimation of the risk of loss for the unconditional VaR models as compared with the conditional models. This underestimation is stronger using the historical VaR approach than when using the extreme values theory VaR model. Even in 2008 financial crisis, the conditional EVT model was more accurate and reliable for predicting the asset risk losses.

Ünal (2011) evaluated in his study Value-at-risk forecasts. In his paper he has compared the performance of various value-at-risks (VaR) forecast models viz. historical simulation, Risk Metrics and models based on extreme value theory.

McMillan and Thupayagale (2010) evaluated Stock Index Return Value-at-Risk Estimates in South *Africa* by taking in account broader selection of GARCH-based models, which includes a variety of asymmetric and long memory models. The results suggest that models having both asymmetric and long memory attributes surpass other methods in estimating VaR which are similar to the volatility forecasting.

Dimitris *et al*. (2010) assessed Value at risk models for volatile emerging markets equity portfolios. The results indicated that although there were documented differences between emerging and developed markets, VaR models are more successful and common for both.

McAleer *and Oxley* (2010) reviewed in his paper robust risk management strategy to the Global Financial Crisis (GFC) to estimate Value-at-Risk (VaR) forecast. The paper further provided evidence on the suitability of the median as a GFC-robust strategy by the use of additional set of new extreme value forecasting models which do not include DPOT and Conditional EVT.

Gnamassou (2010) evaluated in his paper Value-at-risk prediction to compare alternative techniques applied to a large sample of individual stock data. The results show that Historical Simulation, Risk-Metrics, GARCH and GJR-GARCH-based models techniques showed poor performance except when used with Student distribution.

Andjeli , Djaković and *Radišić* (2010) reviewed in his paper Application of VaR in emerging markets. They investigated the relative performance of Value at Risk (VaR) methods with the daily returns series of four different emerging markets viz Slovenian (SBI20), Croatian (CROBEX), Serbian (BELEX line) and Hungarian (BUX) stock indices. They conducted this research to determine the possibility of application of the HS and Delta normal VaR with 95% and 99% confidence level in investment processes on the emerging markets of the selected Central and Eastern European countries. Analyses, synthesis and statistical/mathematical methods were applied. The results indicated that methods shown to afford accurate VaR estimates in developed markets do not necessarily have application on the emerging markets.

Thupayagale (2010) applied GARCH-based models in value-at-risk estimation by forecasting performance of a range of volatility models by using stock index return of emerging markets in context of the basel regulatory framework in Value-at-Risk estimation. Their results suggested that models with long term effects are important in providing improved VaR estimates that minimise occasions when the minimum capital requirement identified would have fallen short of actual trading losses. Along with that, the results highlighted the relevance Basel regulatory framework, and using out-of-sample forecast evaluation methods for identifying forecasting models that provide accurate VaR estimates.

Ergen (2010) studied in his paper VaR Prediction for Emerging Stock Markets. he took the stock index data of long time series by comparing the performance of ten different market risk models of 12 emerging market by predicting one day ahead Value-at-Risk and back testing these predictions. He uses two-step estimation in his study, which ensures unbiased parameter estimates for the GARCH process. He has also implemented classical single step joint estimation which shows that the two-step methodology provides better backtesting performance.

Xiao and Koenker (2009) estimated conditional quantile for GARCH models by using quantile regression because it is very nonlinear. They have studied asymptotic properties of the sieve approximation, the minimum distance estimators, and the nalquantile regression estimators employing generated regressors. They also used Monte Carlo and empirical application which resulted that the proposed estimation methods perform better than some existing conditional quantile estimation methods.

Roy (2009) estimated the Value at Risk for the Indian capital market. He took the data of Indian capital market (BSE-SENSEX and NSE-NIFTY) with other global indicators and its own volatility using daily returns covering the period 2003 to 2009. The paper estimates VaR of return in the Indian capital market on the basis of two composite methods i.e. (a) using univariate GARCH and (b) using ARMA for mean equation. The results indicated that after comparison it was found that VaR of return in the Indian capital market estimated based on GARCH with suitable mean specification performs better than the ARMA-GARCH method.

Kang and Yoon (2009) examined value-at-risk (VaR) analysis performance in the Context of the market volatility of five Asian emerging stock markets. They found that the skewed Student's t APARCH model is the best for incorporating the skewness and excess kurtosis of stock returns, and the appropriate assumption of return distribution can provide more accurate VaR models. Which helps portfolio managers of trading positions in Asian stock markets can build optimal margin levels.

Carchano *et al*. (2009) forecasted VaR in Spot and Futures Equity Markets in his research. They took the data of three stock indices - S&P 500, DAX 30, and Nikkei 225 - for the period December 14, 2004 to December 31, 2008 and presented evidence for the validity of the ARMA-GARCH model with tempered stable innovations to estimate one-day-ahead VaR in the cash and futures markets of the same. They also tested whether adding trading volume to the classical tempered stable model improves the forecasting ability of the model. And finally they also compared the number of times the market data drop below the corresponding one-day-ahead VaR estimations for both spot and futures equity markets in CTS with and without models including trading volume.

Žiković and Aktan (2009) investigated in their paper Global financial crisis and VaR performance in emerging markets. They analyzed relative performance of a wide array of Value at Risk (VaR) models with the daily returns of Turkish (XU100) and Croatian (CROBEX) stock index prior to and during the ongoing financial crisis. Along with this they also studied the behaviour of conditional and unconditional extreme value theory (EVT) and hybrid historical simulation (HHS) models to generate 95, 99 and 99.5% confidence level estimates. The results showed that at the time of crises all tested VaR model except EVT and HHS models seriously under predict the true level of risk, with EVT mode doing so at a higher cost of capital compared to HHS model.

Kasman (2009) estimated in his paper Value-at-Risk for the Turkish Stock Index Futures by using the FIGARCH(1,d,1) model with three different distributions: Normal, Student-t, and skewed Student-t. The results indicated that the evidence of long memory in volatility shows uncertainty or risk is an important determinant of the behaviour of daily futures prices in the Turkish futures market. Further empirical results showed that based on the Kupiec LR failure rate test the FIGARCH (1, d, 1) models with skewed Student-t distribution perform better than the results generated by normal distribution.

Altăr and Iorgulescu (2008) analyzed in their paper Value at Risk measure for a portfolio consisting of three stocks traded at Bucharest Stock Exchange by using different model viz. historical volatility, EWMA volatility model, and GARCH type models for the volatility of the stocks and of the portfolio and a dynamic conditional correlation (DCC) model. The result indicated that using conditional volatility models and distributional tools which accounts for the non-normality of the returns leads to a better VaR-based risk management. VaR computed on the basis of a GARCH (1,1) model for the volatility of the portfolio returns seems to be the best compromise between precision, capital coverage levels and the required amount of calculations.

Janak and Sarat (2008) investigated the financial integration of India’s stock market with that of global and major regional markets. They have used six stock price indices i.e. the 200-scrip index of BSE of India to represent domestic market, stock price indices of Singapore and Hong Kong to represent the regional markets and three stock price indices of U.S., U.K. and Japan to represent the global markets. Based on daily as well as weekly data covering end-March 2003 to end- January 2008 they found that Indian market’s dependence on global markets, such as U.S. and U.K., was substantially higher than on regional markets such as Singapore and Hong Kong, while Japanese market had weak influence on Indian market.

Floros (2008) modelled Volatility using GARCH Models. He took the daily data from Egypt (CMA General Index) and Israel (TASE-100 index). He applied various time series methods, including the simple, exponential, threshold, asymmetric component, the component and the power GARCH model. The results indicated that increased risk will not mandatorily lead to a rise in the returns. It was also found that the most volatile series is CMA index from Egypt, because of the uncertainty in prices.

Morimoto (2008) estimated VaR by comparing GARCH models. The comparison was made to evaluate the applicability of such models by using high resolution intraday data for analysing intraday risk. Using transformation data they determined one step ahead VaR and the performance of five multivariate GARCH models were compared on the basis of frequency that the estimated VaR exceeded observed data. It was thus found that for risk management in intraday framework the existing GARCH model could be applied by simply transforming the irregularity spaced data into regular time series. As per the results the dynamic conditional correlation model was considered favourable for risk management.

Benavides and México (2007) analysed in their paper GARCH Processes and Value at Risk for Mexican Interest Rates Futures. Their analysis was carried out for several time-horizons, which has trading at the Mexican Derivatives Exchange. The GARCH process was applied to determine the VaR with time horizons of more than one trading day Real-World Densities (RWD). As per the results GARCH models are relatively accurate for time horizons of one trading day. But the volatility diligence captured by these models is reflected with relatively high VaR estimates for longer time horizons. These results have also implications for short-term interest rate forecasts given that RWD are estimated.

Mike and Philip (2006) conducted the Empirical analysis of GARCH models in estimating VAR by using several GARCH models which included risk metrics and two long memory GARCH models of both long and short positions. They took the data of 12 market indices and four foreign exchange rates. As per their results that both stationary and fractionally integrated GARCH models performed better than

Risk Metrics in estimating 1% VaR. The results also indicated that taking a fat-tailed error model for estimating VAR is important. It was found that the t-error models are better than normal-error models in long position. No such asymmetry was observed in the exchange rate data.

Dimitris *et al*. (2006) estimated VAR for long and short trading positions of Athens Stock Exchange and three stocks exchange of Greek companies which are listed in ASE. Their paper provides estimates of various models of ARCH which are based on skewed student distribution. The results lead to the conclusion that the skewed Student APARCH model performs better than all other requirement modelling VAR for long or short positions.

Assaf (2006) reviewed in his paper extreme Observations in the MENA Stock Markets and Their Implication for VaR measures. In the paper they have used the extreme value theory to analyze four emerging financial markets which belongs to MEENA region including Egypt, Jordan, Morocco, and Turkey. They found that the VaR estimates based on the tail-index were higher than those based on a normal distribution for all markets, and thus proper risk assessment should not neglect the tail behaviour in these markets, as that can lead to an improper evaluation of market risk.

Rampersad and Watson (2005) studied the efficacy of Value at Risk models in Caribbean Equity Markets and also make recommendations on how existing VaR models may be enhanced to increase their usefulness within the Caribbean context. Their results provides evidence that the most effective VaR models is the parametric VaR in equity markets.it also indicated that these VaR models utilizing the assumption of time varying volatility were more effective in the Jamaica and Trinidad & Tobago equity markets than in the Barbados and Eastern Caribbean equity markets.

Kuester *et al*. (2005) predicted the Value–at–Risk for Comparing Alternative Strategies. For predicting value at risk they have compared the out-of-sample performance of existing methods and some new models by taking 30 years data of NASDAQ. The results indicated that most approaches perform inadequately, except a hybrid method, combining a heavy-tailed GARCH filter with an extreme value theory-based approach which performed best overall.

Eksi, Irem and Kasirg .(2005) applied several tests to test a variety of VaR models. Their results indicated that EVT is theoretically more appropriate for calculating risk measures. Also all other models were found equivalent according to Lopez backtest results whereas EVT is found to be superior to GARCH model according to another test named Kupiec test.

Rombouts and Verbeek (2004) evaluated Portfolio Value-at-Risk using Semi-Parametric GARCH Models. They estimated various alternative multivariate GARCH models for daily returns on the S&P 500 and NASDAQ indexes. They also examined the economic value of multivariate GARCH models. The results indicated that the semi parametric models performed uniformly while parametric models gave unacceptable failure rates. It was also found that the semi parametric models are superior and robust.

Bao *et al*. (2004) compared the predictive power of alternative VaR models in terms of the empirical coverage probability and the predictive quantile loss for the stock markets of five Asian economies. There results showed that Risk metrics model behaves reasonably well before and after the crisis, except some EVT models which behave better in the crisis period. There experiment also demonstrated that risk forecasting during the crisis period is more difficult and yields poorer results than during still periods.

Fabozzi, Tunaru and Wu (2004) modelled Volatility for the Chinese Equity Markets. They took a wide series of GARCH models for investigating the volatility of the Chinese equity data from the Shenzhen and Shanghai markets. In contrary to previous studies they had found empirical evidence of volatility clustering. Each market containing several GARCH models were used to test spill-over effect between the two Chinese markets. Their results suggested that there is no volatility transmission between the two markets.

Gencay and Selcuk (2004) estimated in their paper the relative performance of the nine emerging markets by using Extreme value theory and Value-at-Risk. They concluded that the risk and reward are not equally similar in given economies.

Angelidis et al. (2003) took perfectly diversified portfolios of five stock indices and evaluated the performance of an extensive family of ARCH models in modelling daily Value- at- Risk (VaR), using a number of distributional assumptions and sample sizes. They found that leptokurtic distributions are able to produce better one-step-ahead VaR forecasts and for the accuracy of the forecast the choice of sample size is very important, whereas the specification of the conditional mean is indifferent.

Fernandez (2003) used a sample comprised of the United States, Europe, Asia, and Latin America. Their findings suggested that (i) on an average; EVT gives the most accurate estimates of value at risk. (ii), tail dependence decreases when filtering out heteroscedasticity and serial correlation by multivariate GARCH models.

Chen, Hae and Hsieh (2003) forecasted Value at Risk (VAR) in the futures market using Hybrid method of Neural Networks and GARCH model. They took the data of NASDAQ 100 and Dow Jones futures index market. The results indicated that the hybrid method has outperformed the conventional method in estimating VAR. it was among all other methods the hybrid method was considered to be the best.

Burns (2002) took the long history of S&P 500 to compare these estimators with several other common approaches to value at risk estimation. The derived results shown that among all other methods GARCH estimates are in terms of the accuracy and consistency of the probability level. He found that weighting recent observations when fitting the GARCH model was beneficial.

Tagliafichi (2002) applied in his paper the Arch models in the selection of as best Portfolio. It was found that the presence of GARCH effects in the model used for calculating the values of Beta, permit to enforce the idea of obtaining a best coefficients, with minimum variance.

Chan *et al*. (2001) used two methods namely the normal approximation and the data tilting method, for the purpose of constructing confidence intervals for the conditional VaR estimator and to assess their accuracies by applying simulation studies. They also applied the proposed approach to an energy market data set. The results indicated that Monte Carlo simulation if studied with the GARCH models along with Student-t innovations will yield valid confidence intervals for the VaR estimator whereas the normal approximation has a slightly higher coverage probability.

Berkowitz and Brien (2001) measured the accuracy of VaR models in commercial banks. They provided descriptive statistics on the trading revenues and the associated Value-at-Risk forecasts internally estimated by banks. For a sample of large bank holding companies, they evaluated the performance of banks' trading risk models by examining the statistical accuracy of the VaR forecasts. This article was the first to provide a detailed analysis of the performance of models actually in use.

Giot and Laurent (2001) modelled in this paper daily value-at-risk using realized volatility and arch type models. They took the data of CAC40 and SP500 for their study. This paper also indicated that daily returns standardized by the square root of the one-day-ahead forecast of the daily realized volatility are not normally distributed.

Danielsson and De Vries (2000) proposed a semi-parametric method for unconditional Value-at-Risk (VaR) evaluation. In which largest risks are modelled parametrically and smaller risks are captured by the non-parametric empirical distribution function. The resulted depicted that at the 5 % level the Risk Metrics analysis is best, but for predictions of low probability, it strongly under predicts the VaR while the semi-parametric method is the most accurate.

Aggarval *et al*. (1999) analyzed in their paper in Emerging Stock Markets in which cause of major shifts in emerging markets' volatility. The analysis of risk was based on volatility models. They found that there are dissimilar developed markets and large changes in volatility appear to be related to country-specific events.

Mecagni and Sourial (1999) examined in their paper the behaviour of stock returns in the Egyptian stock exchange, pricing securities efficiency, and the relationship of returns and conditional volatility. They used GARCH (p,q)-M models to estimate the daily indices indicating significant departures from the efficient market hypothesis. The results also showed a significant positive link between risk and returns, which thereby significantly affected during the market downturn.

Goorbergh and Vlaar (1999) analyzed the Value-at-Risk Analysis of Stock Returns in his paper by applying various Value-at-Risk techniques to the Dutch stock market index. The main conclusions of the research are: (1) while modelling value-at-risk changing volatility is the most important characteristic of stock returns and this can be modelled by means of GAARCH; (2) By using t-distribution the fat tails of the distribution can be modelled for low confidence levels; (3) Due to not coping up with the volatility clustering phenomenon the tail index estimators are not up to the mark.

Bekaert and Harvey (1997) analyzed emerging equity market volatility. They showed that the volatilities are significantly negatively correlated, with each market's volatility Granger causing volatility on the other market. International investors can therefore diversify better their portfolios by including such emerging markets. The benefit of diversification on emerging markets is also extensively discussed by them.

Alexendar and Lieh (1997) they examined the performance of the forecasting methods viz. equally weighted average, exponentially weighted average and GARCH. Along with this they showed how long covariance matrices are important for global risk management systems. The results indicated that the EWMA are better in predicting long term return distributions. The estimates produced by GARCH model are more conservative reflecting 1% value at risk measure.

Baillie *et al*. (1996) projected the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model by generalizing the IGARCH model to allow for persistence in the conditional variance. The results indicated that it is advisable to investigate whether long memory property of volatility in financial time series can affect the measurement of market risk or not.

Based on the above literature, the objectives of the research were set.

3.0 Objectives

1. To estimate volatility based on different GARCH based models for emerging nation's viz. China, India, Turkey, Mexico, Indonesia, Russia, and Brazil.
2. To find out best fit GARCH model for estimation of volatility.
3. To find out the Value at Risk for emerging nation's viz. China, India, Turkey, Mexico, Indonesia, Russia, and Brazil.

4.0 Research Methodology

For the study purpose a sample of six emerging stock markets was taken and the data for the same (index returns) was taken from the year 2000 to 2012. Individual stock exchange (representative) of each nation during the study period acted as a sample element for evaluating GARCH based model in VaR estimation. Purposive sampling technique was used for study purpose. Secondary data sources were used to collect the data regarding closing stock prices of each index.

After collecting the data, following tools were applied for analysis purpose;

1) Checking for normality through Jarque Bera.
2) Stationary of data will be checked by using ADF and PP.

Following GARCH models were evaluated;

- GARCH (p,q) model

$h_t = \omega + \alpha(L)\, \varepsilon_t^2 + \beta\,(L)\, h_t$

- EGARCH(p,q) model

$h_t = \omega + [\,1 - \beta\,(L)]^{-1}[1 + \alpha(L)]\, g(\eta_{t-1})$

- IGARCH (p,q) Model

$\varphi(L)(1-L)\varepsilon_t^2 = \omega + [1-\beta(L)]v_t$

- FIEGARCH (p, d, q) model

$h_t = \omega + \varphi(L)^{-1}(1-L)^{-d}[1+\varsigma(L)]g(\eta_{t-i})$

VaR was estimated using the below given formula;

VaR=$N_a\sigma 3V$

The following are an indication of the steps involved in implementing the Engle-Granger (E.G) test, details descriptions of each steps will follow in the subsequent sections:

1. First step is to follow the presence of a unit root in each variable in data under investigation, using Augmented Dickey-Fuller (ADF) and test the variables by Phillips- Perron (PP).
2. Differencing the data in the presence of unit root and conduct the (ADF) test again on the differenced data.
3. Exclude the variables where one of the variables is non stationary and other is stationary.
4. Calculated the log returns to apply the GARCH further as it is mandatory.

5.0 Testing for Unit Root

The data series of index returns for China, India, Turkey, Mexico, Indonesia, Russia, and Brazil were checked for stationary by using ADF test. The results of the same are summarized below in Table 1.

<TABLE 1 HERE>

The ADF and PP unit root test are applied to data. Both unit root test indicates that null hypothesis is rejected at level, thus further tests at level were applied. From results we can conclude that data is stationary of order I (0). T-statistic value is more than critical value shows that data is stationer.

6.0 Descriptive Statistics

Descriptive statistics results for all 6emerging market under study namely, Brazil, China, India, Mexico, Turkey and Russia are summarized in the Table 2.

<TABLE 2 HERE>

The descriptive statistics results for all six emerging market under study namely, Brazil, China, India, Mexico, Turkey and Russia shows that the S.D for Brazil and Mexico is significantly low. As mean of Brazil and Mexico is -0.115780 and S.D is 0.988058. Mean of China, India, Turkey and Russia is-0.351083,-0.320585,-0.452892 and -0.066997 respectively and S.D. is 1.068014, 1.035493, 1.055038 and 1.031289 respectively. This shows that there is moderate variability in these markets.

The value of skewness for all the emerging markets is negative which shows that the data is not normally distributed. This implies that the negative variables had extreme values during the study.

From the Table 2 it is determined that the distribution for all the markets is LEPTOKURTIC as all the values are more than 3 for all the emerging markets. If the values would have been less than 3 then the distribution would be PLATYKURTIC.

The Jarque Bera test is applied to measure the difference of skewness and kurtosis of the data series with those from the normal distribution.

Autocorrelation Functions (ACFs) and Partial-autocorrelation Functions (PACFs)

The autocorrelation function (ACF) is a set of correlation coefficients between the series and lags of itself over time. The partial autocorrelation function (PACF) is the partial correlation coefficients between the series and lags of itself over time. The index return data for all the nations is tested for autocorrelation (see Tables 3 to 8). We test the presence of autocorrelation in log returns using the ACF, PACF.

- Q statistic tests the null hypothesis of no auto correlation for China. The Table 3 shows there is no auto correlation at lag 1.
- Q statistic tests the null hypothesis of no auto correlation for Brazil. The Table 4 shows there is no auto correlation at lag 1.
- Q statistic tests the null hypothesis of no auto correlation for India. The Table 5 shows there is auto correlation at all the lag.
- Q statistic tests the null hypothesis of no auto correlation for Mexico. The Table 6 shows there is no auto correlation at lag 1.
- Q statistic tests the null hypothesis of no auto correlation Russia. The Table 7 shows there is auto correlation at all the lag.
- Q statistic tests the null hypothesis of no auto correlation Turkey. The Table 8 shows there is auto correlation at all the lag.

7.0 ARCH LM Test

This is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). This particular specification of heteroskedasticity was motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals. ARCH in itself does not invalidate standard LS inference. However, ignoring ARCH effects may result in loss of efficiency.

The Obs*R-squared statistic is Engle's LM test statistic, computed as the number of observations times the from the test regression. The arch lm test, test's the null hypothesis of no arch effect present. The table 9 shows that there is presence of Arch effect or not:

The Table 9 shows that there is Arch effect present in all the emerging equity markets viz. India, Brazil, Mexico, Russia and Turkey except for China. Since there are ARCH effects in the stock return data, we can proceed with estimation of GARCH models. We estimate the following symmetric GARCH models: the GARCH (1,1) model with normal and Student's *t*-distribution and the GARCH-M model as well as the following asymmetric GARCH models: the EGARCH (1,1) model with normal and Student's *t*-distribution distribution, the GARCH-GJR model and the APARCH model.

8.0 Models of Changing Variance

Thupayagale in his paper talked about the seminal contributions of Engel (1982) and Bollerslev (1986) in modelling of financial asset returns has been cast in the generalized autoregressive conditional heteroskedasticity. For asset returns, the GARCH class of models involves the estimation of an equation for asset returns and a conditional variance □ ht□specification. The dynamics of ht for a wide range of financial asset returns has been found to be adequately modelled as a GARCH(1,1) process.

8.1 GARCH (p,q) Model

The standard GARCH (p, q) model forecasts of volatility. The GARCH (1,1) model is estimated for the given time series and results of the same are discussed in the Table 9. The stationarity of GARCH(1,1) is checked by $\alpha 1 + \beta 1 < 1$. From the table 10 it can be seen that GARCH model is stationary for all the cases. EViews reports the Durbin-Watson (DW) statistic as a part of the standard regression output. The Durbin-Watson statistic is a test for first-order serial correlation. More formally, the DW statistic measures the linear association between adjacent residuals from a regression model. The Durbin-Watson is a test of the hypothesis in the specification.

The Table 10 shows that there is no serial correlation in Brazil and Mexico as value of Durbin Watson statistic is around 2. Except these in all other Emerging equity markets viz. India, China, Russia and Turkey there exist positive serial correlation as the Durbin Watson static is below 2.

8.2 E-GARCH Test

Formally, an EGARCH(p,q):

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2$$

where $g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|))$, σ_t^2 is the conditional variance, ω, β, α, θ and λ are coefficients. Z_t may be a standard normal variable or come from a generalized error distribution. The formulation for $g(Z_t)$ allows the sign and the magnitude of Z_t to have separate effects on the volatility.

The EGARCH model has a number of advantages over the GARCH *(p,q)* model. The most important one is its logarithmic specification, which allows for relaxation of the positive constraints among the parameters. Another advantage of the EGARCH model is that it incorporates the asymmetries in stock return volatilities. Another advantage of the EGARCH model is that it successfully captures the persistence of volatility shocks. Based on these advantages, we apply the EGARCH model for estimating the volatility of the Emerging equity market.

Table 11 and 12: Here the null hypothesis states that coefficients are not significant. From the above two tables it can be seen that all Coefficient are significant for India, China, Mexico and Turkey. For Brazil it is not significant up to lag 5 as the probability values are more than 5 %. For Russia it is significant at all levels except at lag 3.

The above tables also show that there is no serial correlation in Brazil, china, Mexico and Russia as value of Durbin Watson statistic is around 2. While for rest of the Emerging equity markets viz. India and Turkey there exist positive serial correlation as the Durbin Watson static is below 2.

8.3 P-GARCH

In the Power ARCH model, the power parameter δ of the standard deviation can be estimated rather than imposed.

Table 13 and 14: The above table shows that there is positive serial correlation in all the Emerging equity markets viz. India, China, Russia and Turkey as the Durbin Watson static is below 2 for all.

As per the observation of above table the coefficient is significant for India at all Lags. For Brazil it is not significant at any lag except at lag 5. For China coefficient is significant only at lag 1 and 2. Mexico's coefficient value is not significant till lag 4; it becomes significant at lag 5. For Russia it is significant at all lags except at lag1. And for turkey coefficient is significant at lag 1, 2 and 5.

8.4 Comparison of Best Fit Model

The comparison of the GARCH models are made in terms of their Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) values in the estimation stage and forecast performances in the forecasting stage.

It can be concluded from table 15 that both the AIC and SIC values from EGARCH model are smaller than that from GARCH (1,1) and PARCH models. Therefore, it shows that EGARCH is a better model than GARCH (1,1) and PARCH for estimating daily stock indices of emerging equity markets.

9.0 Value at Risk

An important and topical strand of recent empirical research has focused on the calculation of value-at-risk (VaR) in these markets. VaR models were developed to estimate the exposure of a portfolio to market risk (Jorion, 2007). VaR has also emerged as standard quantitative measure of market risk within most financial institutions; moreover, this method also forms the basis for a host of risk controls (e.g., position limits and margin requirements) (IMF, 2007). There are various methods, or approaches, to measure VaR. Differences among these approaches arise from the model applied to the estimation of the expected changes in prices. Table 16 in annexure presents the VaR failure rates for the emerging equity markets, reported at the 95 percent probability levels.

On the basis of above table we can compare the VaR of the emerging equity markets of India, Brazil, China, Mexico, Russia and Turkey. The lower VaR value signifies lower failure rate in stock market. Thus on the basis of observation of above table Russia has a VaR value -2043939.735 which signifies that it has lowest failure rate of all other emerging equity markets.

10.0 Conclusion

This research has been developed to estimate the VaR of the stock returns in the selected nations (emerging equity markets). Ten years data of six emerging equity markets namely Brazil, china, India, Mexico, turkey and Russia has been taken for study purpose. VaR is calculated to estimate the probability of risk in the portfolio of these nations. Initially for data checking purpose, ADF and PP tests were applied to check the stationary of data, the result of which indicated that the data was stationary at level. Further descriptive statistics were applied to check the normality of data. This included Skweness, kurtosis and Jarque Bera. The ARCH (LM) test i.e. Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity in residuals was applied. The data was normally distributed. The arch effect was found in all the emerging equity markets which implied that there was impact of previous day's returns on the present returns.

The ARCH effect was found and thus the basic condition for the GARCH testing was satisfied and furthers the GARCH models were applied for volatility testing. The GARCH model considered for the testing were GARCH (1,1), EGARCH and PGARCH. For the given data series, EGARCH model was found to be best fit as the value of AIC and SC is lowest for this model. VaR has been calculated to estimate the market risk associated with these models. This was done by using historical method of calculating VaR. It was found that the Russia has least market risk or least failure rate as the value of VaR was lowest. The reason for this could be lesser impact of global financial crises in Russia. The another reason could be Investors in the Russian stock market misprice consumer sector shares and this is a big buying opportunity, according to Russian strategists and Wealthy households are also more prevalent in Russia; 15% of them have income above $50,000 compared with 5% in Brazil, 2% in China and 1% in India. Similar researches has been conducted by Azizan *et al*. (2012), Kourouma *et al*. (2011), Dimitrakopoulos *et al*. (2010), Thupayagale (2010), etc. on the similar topics. Similar results were obtained by Gnamassou et al in 2010 which showed that Historical Simulation, GARCH models techniques showed poor performance except when used with Student distribution.

The serial correlation is often (though incorrectly) associated with market inefficiencies, implying a violation of the Random Walk Hypothesis and the presence of predictability in returns. The serial correlation is associated with illiquidity too.

Positive serial correlation means that positive returns tend to follow positive returns (a momentum type of property). Negative serial correlation means that positive returns tend to be followed by negative returns (a reversal or "correction" property). Both Conrad and Kaul (1988) and Lo and MacKinlay (1988) examine weekly returns of NYSE stocks and find positive serial correlation over short horizons.

Although short- to intermediate-horizon returns suggest momentum in stock market prices, studies of long-horizon returns (i.e., returns over multiyear periods) by Fama and French (1988) and Poterba and Summers (1988) indicate pronounced negative long-term serial correlation in the performance of the aggregate market. The latter result has given rise to a "fads hypothesis," which asserts that the stock market might overreact to relevant news. Such overreaction leads to positive serial correlation (momentum) over short time horizons. Subsequent correction of the overreaction leads to poor performance following good performance and vice versa. The corrections mean that a run of positive returns eventually will tend to be followed by negative returns, leading to negative serial correlation over longer horizons. These episodes of apparent overshooting followed by correction give the stock market the appearance of fluctuating around its fair value (as per a chapter in highered mcgrawhill.com)

The non-existence of serial correlation in returns for Brazil and Mexico show that the day returns is independent of history. Predicting the future trends of returns in such markets is a difficult task. But for India, Turkey and China, with (positive) serial correlation, the probability of a "+"following a "+" is greater than following a "-".

As per an article published at pages.stern.nyu.edu, stating the viewpoint of investment strategy, serial correlations can sometimes be exploited to earn excess returns. A positive serial correlation would be exploited by a strategy of buying after periods with positive returns and selling after periods with negative returns. A negative serial correlation would suggest a strategy of buying after periods with negative returns and selling after periods with positive returns. Since these strategies generate transactions costs, the correlations have to be large enough to allow investors to generate profits to cover these costs. It is therefore entirely possible that there be serial correlation in returns, without any opportunity to earn excess returns for most investors.

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(Tables & Figures)

Table 1: Unit root testing

Variables	ADF Test			PP Test			Order of Integr-ation
	H0: Variable is nonstationary			*H0: Variable is nonstationary*			
Exogenous	**Constant**	**Constant, Linear Trend**	**None**	**Constant**	**Constant, Linear Trend**	**None**	
INDIA	-14.30651	-14.33401	-8.828596	-63.35959	-63.31803	-70.41372	**I(0)**
BRAZIL	-17.75470	-18.31283	-17.11781	-63.26332	-61.89770	-65.06997	
MEXICO	-17.71642	-18.31773	-17.05070	-63.38477	-61.97070	-65.23971	**I(0)**
CHINA	-11.58462	-11.67822	-7.775729	-69.96653	-69.29921	-78.60912	
TURKEY	-8.739749	-11.05677	-5.888221	-69.29599	-68.36446	-76.11992	**I(0)**
RUSSIA	-17.91972	-17.94657	-12.41631	-63.31589	-63.25268	-63.60358	
Asymptotic critical values							
	-2.88	-3.44	-1.94	-2.88	-3.44	-1.94	
	-2.58	-3.14	-1.61	-2.57	-3.14	-1.61	
****** implies significant at I O% level, ** implies significant at 5% level and * implies significant at 10% level.***							

Table 2: Descriptive statistics

	BRAZIL	CHINA	INDIA	MEXICO	TURKEY	RUSSIA
Mean	-0.115780	-0.351083	-0.320585	-0.115780	-0.452892	-0.066997
Std.Dev.	0.988058	1.068014	1.035493	0.988058	1.055038	1.031289
Skewness	-1.101618	-1.206101	-1.107833	-1.101618	-1.161277	-1.063925
Kurtosis	4.882480	5.550387	5.231928	4.882480	6.077385	5.348105
Jarque-Bera	1102.934	1618.446	1298.975	1102.934	1952.212	1284.455
Prob.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table3: Correlogram of Daily Stock Returns of China

Lag	AC	PAC	Q-Stat	Prob
1	0.027	0.027	2.4035	0.121
2	0.134	0.134	61.294	0.000
3	0.115	0.110	104.27	0.000
4	0.114	0.095	146.68	0.000
5	0.089	0.060	172.37	0.000
6	0.106	0.071	209.17	0.000
7	0.100	0.064	241.72	0.000
8	0.128	0.089	295.72	0.000
9	0.081	0.037	317.09	0.000
10	0.116	0.064	361.48	0.000
11	0.098	0.048	392.79	0.000

12	0.107	0.051	430.08	0.000
13	0.074	0.017	448.21	0.000
14	0.075	0.011	466.69	0.000
15	0.076	0.016	485.54	0.000
16	0.107	0.050	522.87	0.000
17	0.082	0.030	545.17	0.000
18	0.101	0.041	578.88	0.000
19	0.065	0.005	592.82	0.000
20	0.095	0.030	622.38	0.000
21	0.066	0.009	636.75	0.000
22	0.065	0.001	650.50	0.000
23	0.077	0.017	669.75	0.000
24	0.046	-0.015	676.85	0.000
25	0.087	0.031	701.75	0.000
26	0.094	0.042	730.83	0.000
27	0.062	0.008	743.54	0.000
28	0.055	-0.010	753.33	0.000
29	0.043	-0.018	759.47	0.000
30	0.126	0.076	811.79	0.000
31	0.078	0.037	831.60	0.000
32	0.085	0.030	855.52	0.000
33	0.054	-0.009	865.16	0.000
34	0.052	-0.015	874.15	0.000
35	0.081	0.026	895.74	0.000
36	0.047	-0.009	902.91	0.000

Table 4: Correlogram of Daily Stock Returns of Brazil

Lag	AC	PAC	Q-Stat	Prob
1	-0.006	-0.006	0.1251	0.724
2	0.084	0.084	22.172	0.000
3	0.058	0.059	32.627	0.000
4	0.092	0.087	59.289	0.000
5	0.064	0.057	72.105	0.000
6	0.095	0.082	100.89	0.000
7	0.039	0.024	105.78	0.000
8	0.053	0.029	114.79	0.000
9	0.059	0.038	125.73	0.000
10	0.089	0.066	150.52	0.000
11	0.048	0.028	157.80	0.000
12	0.059	0.031	169.01	0.000
13	0.035	0.009	172.79	0.000
14	0.064	0.033	185.75	0.000
15	0.070	0.045	201.31	0.000
16	0.032	0.002	204.56	0.000
17	0.077	0.049	223.54	0.000
18	0.049	0.023	231.17	0.000
19	0.040	0.008	236.27	0.000
20	0.059	0.027	247.50	0.000
21	0.038	0.006	252.17	0.000
22	0.018	-0.014	253.23	0.000
23	0.082	0.051	274.69	0.000
24	0.018	-0.009	275.69	0.000
25	0.042	0.008	281.29	0.000
26	0.035	0.008	285.29	0.000
27	0.049	0.017	292.86	0.000
28	0.062	0.039	305.04	0.000
29	0.052	0.021	313.56	0.000
30	0.031	0.003	316.53	0.000
31	0.025	-0.006	318.54	0.000
32	0.050	0.018	326.64	0.000
33	0.031	0.001	329.77	0.000
34	0.034	0.003	333.42	0.000
35	0.033	0.003	336.81	0.000
36	0.016	-0.009	337.62	0.000

Table 5: Correlogram of Daily Stock Returns of India

Lag	AC	PAC	Q-Stat	Prob
1	0.119	0.119	44.647	0.000
2	0.113	0.101	85.532	0.000
3	0.116	0.094	127.89	0.000
4	0.110	0.080	166.36	0.000
5	0.123	0.087	214.30	0.000
6	0.125	0.083	263.87	0.000
7	0.148	0.101	333.81	0.000
8	0.090	0.030	359.37	0.000
9	0.074	0.014	376.75	0.000
10	0.111	0.056	416.10	0.000
11	0.112	0.053	455.81	0.000
12	0.084	0.020	478.44	0.000
13	0.072	0.007	494.77	0.000
14	0.105	0.046	529.87	0.000
15	0.083	0.023	551.58	0.000
16	0.077	0.017	570.42	0.000
17	0.136	0.077	629.32	0.000
18	0.082	0.015	650.62	0.000
19	0.091	0.030	677.20	0.000
20	0.082	0.019	698.83	0.000
21	0.104	0.037	733.08	0.000
22	0.077	0.008	752.14	0.000
23	0.059	-0.008	763.20	0.000
24	0.080	0.011	783.61	0.000
25	0.055	-0.009	793.42	0.000
26	0.074	0.016	810.89	0.000
27	0.062	0.000	823.27	0.000
28	0.046	-0.017	830.01	0.000
29	0.042	-0.012	835.76	0.000
30	0.053	0.007	844.83	0.000
31	0.090	0.040	871.02	0.000
32	0.079	0.029	891.25	0.000
33	0.047	-0.006	898.28	0.000
34	0.074	0.023	915.74	0.000
35	0.089	0.042	941.12	0.000
36	0.056	-0.001	951.01	0.000

Table 6 :Correlogram of Daily Stock Returns of Mexico

Lag	AC	PAC	Q-Stat	Prob
1	-0.004	-0.004	0.0569	0.811
2	0.084	0.084	22.488	0.000
3	0.059	0.060	33.661	0.000
4	0.093	0.088	61.095	0.000
5	0.063	0.056	73.824	0.000
6	0.095	0.081	102.52	0.000
7	0.040	0.024	107.52	0.000
8	0.053	0.028	116.59	0.000
9	0.059	0.037	127.59	0.000
10	0.088	0.065	152.22	0.000
11	0.048	0.027	159.44	0.000
12	0.059	0.030	170.39	0.000
13	0.035	0.009	174.23	0.000
14	0.065	0.034	187.62	0.000
15	0.072	0.046	203.94	0.000
16	0.034	0.004	207.57	0.000
17	0.079	0.051	227.25	0.000
18	0.051	0.025	235.58	0.000
19	0.040	0.007	240.73	0.000
20	0.060	0.026	252.19	0.000
21	0.042	0.009	257.74	0.000
22	0.021	-0.011	259.16	0.000
23	0.083	0.051	281.06	0.000
24	0.019	-0.009	282.17	0.000
25	0.044	0.009	288.36	0.000
26	0.036	0.008	292.44	0.000
27	0.049	0.015	300.00	0.000
28	0.064	0.040	312.90	0.000
29	0.053	0.022	321.81	0.000
30	0.030	0.001	324.64	0.000
31	0.025	-0.007	326.70	0.000
32	0.051	0.017	334.92	0.000
33	0.030	-0.001	337.86	0.000
34	0.033	0.002	341.30	0.000
35	0.033	0.002	344.70	0.000
36	0.016	-0.009	345.50	0.000

Table 7: Correlogram of Daily Stock Returns of Russia

Lag	AC	PAC	Q-Stat	Prob
1	0.123	0.123	46.868	0.000
2	0.171	0.158	136.26	0.000
3	0.157	0.125	212.46	0.000
4	0.113	0.063	251.45	0.000
5	0.130	0.077	303.67	0.000
6	0.099	0.042	333.74	0.000
7	0.101	0.044	365.38	0.000
8	0.116	0.059	406.48	0.000
9	0.112	0.055	444.93	0.000
10	0.098	0.034	474.23	0.000
11	0.126	0.064	523.43	0.000
12	0.098	0.031	553.26	0.000
13	0.108	0.039	589.31	0.000
14	0.105	0.035	623.64	0.000
15	0.113	0.045	663.05	0.000
16	0.083	0.008	684.23	0.000
17	0.083	0.011	705.72	0.000
18	0.096	0.028	734.34	0.000
19	0.122	0.059	780.56	0.000
20	0.091	0.018	806.07	0.000
21	0.097	0.023	835.46	0.000
22	0.091	0.015	861.27	0.000
23	0.079	0.004	880.44	0.000
24	0.088	0.016	904.67	0.000
25	0.094	0.028	932.27	0.000
26	0.095	0.026	960.43	0.000
27	0.081	0.007	980.61	0.000
28	0.073	-0.001	997.02	0.000
29	0.102	0.035	1029.5	0.000
30	0.104	0.035	1062.9	0.000
31	0.062	-0.012	1074.9	0.000
32	0.086	0.012	1097.9	0.000
33	0.097	0.029	1127.1	0.000
34	0.077	0.005	1145.6	0.000
35	0.124	0.057	1193.2	0.000
36	0.091	0.021	1219.2	0.000

Table 8: Correlogram of Daily Stock Returns of Turkey

Lag	AC	PAC	Q-Stat	Prob
1	0.143	0.143	66.699	0.000
2	0.172	0.155	163.14	0.000
3	0.170	0.133	257.53	0.000
4	0.171	0.118	352.97	0.000
5	0.137	0.068	413.66	0.000
6	0.133	0.059	471.37	0.000
7	0.161	0.088	555.51	0.000
8	0.149	0.070	627.83	0.000
9	0.143	0.059	694.79	0.000
10	0.143	0.054	761.28	0.000
11	0.129	0.035	815.73	0.000
12	0.147	0.055	885.86	0.000
13	0.149	0.058	958.60	0.000
14	0.144	0.047	1026.1	0.000
15	0.094	-0.012	1054.7	0.000
16	0.144	0.046	1122.5	0.000
17	0.117	0.019	1167.6	0.000
18	0.105	0.007	1203.6	0.000
19	0.153	0.063	1279.9	0.000
20	0.125	0.026	1331.0	0.000
21	0.131	0.031	1387.1	0.000
22	0.141	0.043	1451.7	0.000
23	0.119	0.013	1498.0	0.000
24	0.122	0.019	1546.5	0.000
25	0.101	-0.002	1580.2	0.000
26	0.118	0.014	1625.5	0.000
27	0.121	0.025	1673.5	0.000
28	0.112	0.014	1714.8	0.000
29	0.117	0.018	1759.6	0.000
30	0.093	-0.011	1787.7	0.000
31	0.114	0.017	1830.0	0.000
32	0.121	0.026	1877.8	0.000
33	0.125	0.029	1929.3	0.000
34	0.105	0.009	1965.4	0.000
35	0.109	0.007	2004.5	0.000
36	0.125	0.028	2055.5	0.000

Table 9: Arch Test table

Series	H0: No arch effect		Ho: Null hypothesis is rejected		Arch effect present
India	F-statistic	1.391735	Probability	0.060774	
	Obs*R-squared	49.89395	Probability	0.061690	YES
Brazil					
	F-statistic	0.762226	Probability	0.845575	
	Obs*R-squared	27.52452	Probability	0.843709	YES
China					
	F-statistic	1.575734	Probability	0.015968	
	Obs*R-squared	56.38197	Probability	0.016483	NO
Mexico					
	F-statistic	0.776179	Probability	0.828283	
	Obs*R-squared	28.02348	Probability	0.826363	YES
Russia					
	F-statistic	1.040742	Probability	0.402646	
	Obs*R-squared	37.46095	Probability	0.401948	YES
Turkey					
	F-statistic	0.667853	Probability	0.935484	
	Obs*R-squared	24.14013	Probability	0.934309	YES

Estimated GARCH Test for the Daily Returns of emerging equity market: Table 10

S.NO.	Term	India	Brazil	China	Mexico	Russia	Turkey
1.	α_1	0.061426	-0.008299	-0.011776	-0.008156	0.060167	0.023458
2.	β_1	-0.160613	-0.965046	-0.243629	-0.965699	0.270912	0.895963
3.	$\alpha_1+\beta_1$	-0.099187	-0.9733450	-0.255405	-0.973855	0.331079	0.919421
4.	**Forecasted return value**	-0.331885	-0.111992	-0.376700	-0.114398	-0.070990	-0.474090
5.	**Forecasted variance**	0.999964	0.999982	0.999996	0.999983	0.999985	0.999883
6.	**Akaike info criterion**	2.917833	2.813982	2.958796	2.813605	2.897278	2.926092
7.	**Schwarz criterion**	2.925479	2.821663	2.966258	2.821257	2.905134	2.933589
8.	**Durbin-Watson static**	1.762341	2.011053	1.943094	2.008217	1.752708	1.711763

Estimated E-GARCH Test for the Daily Returns of emerging equity market: Table 11

Country	India			Brazil		China	
S.NO.	Term	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
1.	C	-16.71642	0.0000	-11.93683	0.0741	-3.420103	0.0000
2.	C(2)	-	-	-	-	-	-
3	C(3)	-0.004710	0.0001	-0.003930	0.0777	-0.011876	0.0228
4	C(4)	0.010160	0.0000	0.006690	0.1167	0.024416	0.0016
5.	C(5)	0.008235	0.0000	0.006521	0.1021	0.029218	0.0000
	C(6)	0.983554	0.0000	0.988408	0.0000	0.981185	0.0000
6.	Forecasted return value	16.72551		11.12153		0.401207	
7.	Forecasted variance	0.975578		0.956798		0.007650	
8.	Akaike info criterion	2.756647		2.725080		2.828416	
9.	Schwarz criterion	2.770032		2.738525		2.841478	
10.	Durbin-Watson static	1.935196		2.098009		2.089764	

Table12: Estimated E-GARCH Test for the Daily Returns of emerging equity market continued

Country	Mexico			Russia		Turkey	
S.NO.	**Term**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
1.	**C**	-15.27324	0.0135	-21.55260	0.0003	-3.316213	0.0000
2.	**C(2)**	-	-	-	-	-	-
3.	**C(3)**	-0.003291	0.0236	-0.001436	0.1858	-0.029915	0.0001
4.	**C(4)**	0.005323	0.0414	0.005188	0.0057	0.056725	0.0000
5.	**C(5)**	0.005100	0.0273	0.006573	0.0014	0.067507	0.0000
	C(6)	0.988030	0.0000	0.978679	0.0000	0.959816	0.0000
6.	**Forecasted return value**	19.54292		22.1935		0.331691	
7.	**Forecasted variance**	0.972284		0.984470		0.099476	
8.	**Akaike info criterion**	2.723795		2.754658		2.750740	
9.	**Schwarz criterion**	2.737191		2.768406		2.763862	
10.	**Durbin-Watson static**	2.096350		1.999072		1.935856	

Estimated PARCH Test for the Daily Returns of emerging equity market: Table 13

Country	India			Brazil		China	
S.NO.	**Term**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
1.	**C**	-0.226889	0.0000	-0.015339	0.3809	-0.259605	0.0000
2.	**C(2)**	0.137711	0.0213	0.046805	0.0944	1.337595	0.0014
3.	**C(3)**	-0.019604	0.0405	-0.007916	0.1936	-0.020384	0.4411
4.	**C(4)**	1.000000	0.0020	1.000000	0.2451	1.000000	0.6192
5.	**C(5)**	0.885196	0.0000	0.959577	0.0000	-0.229351	0.5596
6.	**Forecasted return value**	-0.22689		-0.01534		-0.25961	
7.	**Forecasted variance**	0.991108		0.989694		0.987564	
8.	**Akaike info criterion**	2.840213		2.755011		2.876881	
9.	**Schwarz criterion**	2.851686		2.766535		2.888077	
10.	**Durbin-Watson static**	1.747044		1.991144		1.919907	

Table 14: Estimated PARCH Test for the Daily Returns of emerging equity market continued

Country	Mexico			Russia		Turkey	
S.NO.	**Term**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
1.	**C**	-0.018877	0.2805	0.016270	0.3668	-0.367032	0.0000
2.	**C(2)**	0.046148	0.0937	0.190905	0.0419	0.140696	0.0408
3	**C(3)**	-0.007868	0.1921	0.060222	0.0109	-0.008191	0.3754
4	**C(4)**	1.000000	0.2411	-0.499221	0.0018	1.000000	0.4424
5.	**C(5)**	0.960162	0.0000	0.774534	0.0000	0.873334	0.0000
6.	**Forecasted return value**	-0.01888		0.01627		-0.36703	
7.	**Forecasted variance**	0.989922		0.993521		0.991799	
8.	**Akaike info criterion**	2.755410		2.827485		2.857936	
9.	**Schwarz criterion**	2.766892		2.839269		2.869184	
10.	**Durbin-Watson static**	1.987600		1.741379		1.695529	

Table 15: COMPARISION OF BEST FIT MODEL

	India	**Brazil**	**China**	**Mexico**	**Russia**	**Turkey**
Garch						
Akaike info criterion	2.917833	2.813982	2.958796	2.813605	2.897278	2.926092
Schwarz criterion	2.925479	2.821663	2.966258	2.821257	2.905134	2.933589
EGARCH						
Akaike info criterion	2.756647	2.725080	2.828416	2.723795	2.754658	2.750740
Schwarz criterion	2.770032	2.738525	2.841478	2.737191	2.768406	2.763862
PARCH						
Akaike info criterion	2.840213	2.755011	2.876881	2.755410	2.827485	2.857936
Schwarz criterion	2.851686	2.766535	2.888077	2.766892	2.839269	2.869184

Table 16: Calculation of VaR

Country	VaR value at 95 % significant level
India	-2022089.793
Brazil	-2039133.464
China	-1988134.686
Mexico	-2022089.793
Russia	-2043939.735
Turkey	-1996832.785