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Research Article

Econometric Models for Volatility Analysis in Interdependence ofVarious Stock Markets

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Abstract

Investing money in the stock market is assumed to be risky because stock markets are volatile. It is volatile because macroeconomics variables influence it and effect stock prices. A lot of researches were carried out in the past to measure volatility through various econometric models but still it is an ongoing process. This study was undertaken to look into the various econometrics models applied to analysis the volatility in interdependence of various stock markets. Various models like Descriptive Statistics, tests for stationarity i.e. ADF Test, PP test and GARCH family models for heteroscedasticity were undertaken in the study.

Keywords: Volatility, Stationarity, Heteroscedasticity, GARCH Models

Introduction

Business investment is concerned with the provision of funds for investment in business enterprise, an investor must offer whatever is invested in this way, and this means that the investor must sacrifice consumption and save to offer the funds. Savers and the users of their funds come jointly in the market for investment, where the normal rules of supply and demand apply unless there is government interfering with interest rates. The cost of money is the rate of interest rewarded for the use. If the demand for investment funds is greater than the funds offered for investment by savers, then the rate of interest will increase until people in the market are induced to sacrifice consumption and make their reserves available for investment. Stock markets are said to replicate the health of the country’s financial system. On the other hand, major economic indicators find out stock market movements to a large level. From a systematic analysis of the various financial indicators and its implications on the stock markets, it is experimental that stock market movements are mostly influenced by wide money supply, inflation, credit / deposit ratio and fiscal deficit distant from political insecurity. The innovative issues of securities are made available in the ‘primary market’. The securities that are already wonderful and owned by the investors are regularly bought and sold through the ‘secondary market’, generally known as ‘stock market’.

Stock prices are changed every day by the market. Buyers and sellers cause prices to change as they decide how valuable each stock is. Basically, share prices change because of supply and demand. If more people want to buy a stock than sell it - the price moves up. Conversely, if more people want to sell a stock, there would be more supply (sellers) than demand (buyers) - the price would start to fall. Volatility in the stock return is an integral part of stock market with the alternating bull and bear phases. In the bullish market, the share prices soar high and in the bearish market share prices fall down and these ups and downs determine the return and volatility of the stock market. Volatility is a symptom of a highly liquid stock

A stock market or equity market is a public (a loose network of economic transactions, not a physical facility or discrete) entity for the trading of company stocks and derivatives at an agreed price; these are securities listed on a stock exchange as well as those only traded privately. The stock market is one of the most important sources for companies to raise money. This allows businesses to be publicly traded, or raise additional financial capital for expansion by selling shares of ownership of the company in a public market. The liquidity that an exchange provides affords investors the ability to quickly and easily sell securities. This is an attractive feature of investing in stocks, compared to other less liquid investments such as real estate.

Evolution of Stock Market

The origin of the stock market relates back to the year 1494, when the Amsterdam Stock Exchange was set up. In India it dates back to the 18th century, an era when the East India Company was a dominant Institution in those days and business in its loan securities used to be transacted towards the close of the eighteenth century.By 1830's business on corporate stocks and shares in Bank and Cotton presses took place in Bombay. Though the trading list was broader in 1839, there were only half a dozen brokers recognized by banks and merchants during 1840 and 1850.

In 1860-61 the American Civil War broke out and cotton supply from United States of Europe was stopped; thus, the 'Share Mania' in India begun. The number of brokers increased to about 200 to 250. However, at the end of the American Civil War, in 1865, a disastrous slump began (for example, Bank of Bombay Share which had touched Rs 2850 could only be sold at Rs. 87). At the end of the American Civil War, the brokers who thrived out of Civil War in 1874, found a place in a street (now appropriately called as Dalal Street) where they would conveniently assemble and transact business. In 1887, they formally established in Bombay, the “Native Share and Stock Brokers' Association” (which is alternatively known as “The Stock Exchange”). In 1895, the Stock Exchange acquired a premise in the same street and it was inaugurated in 1899.
Thus, the Stock Exchange at Bombay was consolidated

“The Bombay Stock Exchange” (BSE) was founded in the year 1875. “The Ahmadabad Shares and Stock Association” was formed in the year 1894. The Calcutta Stock Exchange Association was formed by about 150 brokers on 15th June 1908. In the year 1920, one stock exchange was established in Northern India and one in Madras called “The Madras Stock Exchange”. “The Madras Stock Exchange Association Pvt. Ltd.” was established in the year 1941 and other various Regional Stock Exchange. The Over the Counter Exchange of India (OTCEI) broadly based on the lines of NASDAQ (National Association of Securities Dealers Automated Quotation) of the USA was promoted and approved on August 1989. The National Stock Exchange of India Ltd. was incorporated in November 1992. Presently only NSE and BSE are currently active and providing On-line Trading. Other stock exchanges have closed their operations.

Stock Market Volatility

Volatility measures the risk of a security. It is used in alternative pricing method to measure the fluctuations in the returns of the fundamental assets. Volatility indicates the pricing behavior of the security and helps estimation of the fluctuations that may occur in a short period of time. It is a rate at which the price of a security increases or decreases for a given set of returns. Volatility is measured by calculating the standard deviation of the annualized returns over a given period of time. It shows the range to which the price of a security may increase or decrease.If the prices of a security fluctuate rapidly in a short time span, it is termed to have high volatility. If the prices of a security fluctuate slowly in a longer time span, it is termed to have low volatility.

Volatility in International Stock Markets

In the present period of liberalization, privatization and globalization, the international investments and diversification of portfolio globally is an important matter, especially in the time period when stock markets are extremely volatile. Normally, people invest in the stock market with the reason of earning returns. An shareholder designs his portfolio in which he includes different stocks or group of stock on sectoral basis to attain his purpose of maximum returns with minimum risk. On account of different factors like economic condition, political stability, tax and inflationary conditions, there is probability that less correlation in stock returns across different countries is potential.

In recent years, the interest in country fund specially in emerging economies has increased. Emerging markets are an attractive position for investment because of various reasons like open market system, moderate guidelines towards Foreign Direct Investment and Foreign Institutional Investment. Further, whereas constructing internationally diversified range of securities, the correlation in the returns of stocks from two different countries required to be calculated.

In recent years, new terms have emerged to explain the largest developing countries such as BRIC that stands for Brazil, Russia, India, and China, along with BRICS (BRIC + South Africa), BRICET (BRIC + Eastern Europe and Turkey) , BRICK (BRIC+ South Korea), BRICM (BRIC + Mexico), Next Eleven (Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, Philippines, South Korea, Turkey, and Vietnam) and CIVETS (Colombia, Indonesia, Vietnam, Egypt, Turkey and South Africa). These countries do not contribute to any ordinary agenda, but some experts believe that they are enjoying an increasing function in the world economy and on political platforms.

Goldman Sachs argues that the economic potential of Brazil, Russia, India and China is such thatthey could become among the four most dominant economies by the year 2050. The thesis wasproposed by Jim O'Neill, global economist at Goldman Sachs. These countries encompass over25% of the world's land coverage and 40% of the world's population and hold a combined GDP(PPP) of 18.486 trillion dollars. On almost every scale, they would be the largest entity on theglobal stage. These four countries are among the biggest and fastest growing emerging markets.According to the research conducted by the Goldman Sachs in 2003, If the things go right givensound political decision making and good luck the BRIC economies together could becomelargest than those of the world’s six most developed nations in less than 30 years.

Volatility Index (VIX)

The Volatility Index (VIX) is a contrarian response indicator that helps to find out when there is too much optimism or fear in the market. When reaction reaches one extreme or the other, the market typically reverses course. The Volatility Index works well in conjunction with other "overall market indicators." By studying its communication, traders will have a better understanding of investor response, and thus potential reversals in the market.The VIX rises when put option buying increases; and falls when call buying activity is more robust. The most popular measure of market volatility in the US is the CBOE Market Volatility Index (the

"VIX") which is also known rather ominously as the "fear gauge." The VIX measures a weighted average of the implied volatility of a wide range of S&P 500 options with a 30 day maturity. Quite simply, the VIX is the implied volatility of the S&P 500 and is frequently thought of as the market's broad expectation of volatility over the next 30 day period. The VIX has been on a downward trajectory since 2010.

Volatility in Indian Stock Market (post liberalization)

The high volatility is due to much foreign equity inflows. This results into dependence of Indian equity market on global capital market variations. It means any happening outside India will have its impact here as well. As when US economy was improving, resulted into falling rupeeled negative sentiments to stock market crash. Domestic savings are lower which is increasing more foreign investments. According to RBI Handbook of Statistics (September, 2013), only 3.1% of incremental financial assets of household sector in fiscal year 2013 is invested in shares and debentures. Retail investor is participating less in equity market. Bank accounts consist of about 54% of the total household financial savings show that people want to invest less in risky assets. So, decline in domestic equity savings is biggest problem.

Review of Literature

Park & Fatemi (1993) measured the linkages between the emerging Pacific-Basin equity markets and three major developed markets. It examined the relative influence of the U.S., U.K., and Japanese markets on each of the seven Pacific-Basin equity markets and the response patterns of these markets to a shock originating in one of the three developed markets. The researchers found the relative importance of these developed equity markets in generating unexpected variations in the stock market returns of each of the seven Pacific-Basin countries. In this paper, VAR analysis found linkages between each of the seven Pacific-Basin equity markets and the three developed equity markets of the U.S., the U.K., and Japan.

Yilmaz (1999) presented an empirical analysis of volatility and contagion across 19 emerging and developed stock markets in the 1990s. The researchers covered U.S.A., U.K., Japan, Hong Kong, Singapore and 7 other Asian countries (Taiwan, Korea, Malaysia, Thailand, Indonesia, Philippines, and India), 4 Latin American countries (Argentina, Brazil, Chile and Mexico), as well as Turkey, South Africa and Russia. The reseachers applied Generalized Autoregressive Conditional Heteroscedasticity (GARCH) technique to obtain robust estimates of volatility contagion in ISE (Istanbul Stock Exchange).

Bala & Premaratne (2004) investigated volatility co-movement between the Singapore stock market(Straits Times Industrial) and the markets of US(Dow Jones Industrial Average), UK(FTSE 100) , Hong Kong (Hang Seng) and Japan (Nikkei 225) by using daily returns from 1992 to 2002. The empirical results of this study indicated that there is a high degree of volatility co-movement between Singapore stock market and that of Hong Kong, US, Japan and UK. This paper used the econometric methods of Uni-variate GARCH(1), Multi-variate and asymmetric Multi-variate GARCH models with GJR extension.

Shin (2005) evaluated the relationship between expected stock returns and conditional volatility. The daily data has been converted into weekly for this study cover 14 emerging international well-established emerging markets which have stock price index series available from the International Finance Corporation (IFC) Emerging Markets database. The sample period was used from January 1989 to May 2003, after the 1987 international stock market crash. The researcher examined the relationship between stock market returns and volatility; both parametric and semi parametric GARCH-M specifications are used. The basic finding of thisstudy was largely consistent with the literature using a parametric GARCH-M model, where the existence of a weak relationship between risk and return is documented. This study showed different findings on risk-return tradeoff patterns between developed and emerging markets could be attributable to the different threshold levels of volatility.

Chukwuogor (2006)examined 15 emerging and developed European financial markets to analyze the financial markets' trends such as the annual returns, daily returns and volatility of returns. To find mean returns and standard deviations of the returns for the selected indices, a set of parametric and non-parametric tests has applied. It is found in this study that seven of the European Financial markets experienced negative returns on Monday and seven others also experienced negative returns on Wednesday. There was normally high volatility of returns in the European markets.

Dhankar & Chakraborty (2007)investigated the presence of non-linear dependence and GARCH effects in three major emerging markets of South Asia, India, Sri Lanka and Pakistan. In this paper, it was realized that merely identifying non-linear dependence was not enough. This study investigated whether the non-linear dependence is caused by predictable conditional volatility. It has been found that the simple GARCH (1, 1) model has fitted all the market return series adequately and accounted for the non-linearity found in the series. The researchers testedthe independent and identical distribution behavior of stock return series of theses major countries. The application of the BDS test and ARMA test strongly rejected the null hypothesis of independent and identical distribution of the return series as well as the linearly filtered return series for all the markets under study.

Khedhiri & Muhammad (2008) investigated the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects, in order to explore a parsimonious model for the UAE stock market and predict its future performance. They used switching regime ARCH methodology to assess the impact of stock market openness to foreign investors on the market returns and they analyzed its observed irregular performance. The results of this study cast a better performance of the SWARCH models in representing and forecasting the market volatility described by means of low, medium and high volatility episodes.

Siddiqui (2008) examined the relationships between selected European stock markets and SENSEX. The present study is based on secondary data, which covers the most recent period using daily closing figure from 19/10/1999 to 25/04/2008. The research methodology employed included testing for stationarity, implementation of the Granger Causality test and Johansen Co integration test. Stock markets under study found integrated. The degree of correlation between the markets varies between low to high.

Mangala & Dhawan (2009) examined the existence of day-of-the-week effect across stock markets of six countries - three developed and three emerging economies. Popular stock market indices namely Dow Jones, FTSE and Nikkei represent developed stock markets while Bovespa, Heng Seng and Nifty represent emerging stock markets This paper examined the mean and volatility of daily returns of six stock indices from emerging and developed stock markets over fifteen years period commencing from January 1994 to December 2008.. In this paper parametric and non-parametric tests have been used to examine the equality of mean returns across various days of the week. Kruskall Wallis test was applied to comparison and it showed that week start is highly volatile in all markets.

Tripathi & Sethi (2010) examined the integration of the Indian stock market with the major global stock markets of Japan, the United Kingdom, the United States and China over the period ranging from 1 January 1998 to 31 October. The analysis of daily data showed that the Indian stock market is integrated with the US stock market, but not with that of Japan, the

UK andChina.

Singh & Singh (2010) focused the linkages of the two leading emerging markets i.e. Chinese and Indian market with developed markets by using daily data from January 2000 to December 2009. The stock market indices of China, India, United States, United Kingdom, Japan and Hong Kong were examined in this study. Correlation test, Granger causality and the co-integration test applying error correction model have been used for calculating linkages of these markets.

Sheu & Cheng (2011) aimed to compare the effect of volatility of China and U.S. stock market respectively on the Taiwan and Hong Kong. They employed vector autoregressive and multivariate generalized autoregressive conditional heteroskedastic model for two separated sub- periods 1996-2005 and 2006-2009 to examine the return and volatility spillover effects among U.S., Taiwan, Hong Kong and China stock markets.

Gupta & Aggarwal (2011) found the correlation of Indian Stock market with five other major Asian economies: Japan, Hong Kong, Indonesia, Malaysia and Korea. There exists a very weak correlation between the Indian markets and Hong Kong, Indonesia, Malaysia and Japan. There are comparatively higher correlation was found between the Indian and the Korean markets, which seemed to have weakened in the short run. Comparatively higher correlation was found between the Indian and the Korean markets, which seemed to have weakened in the short run. With the use of platykurtic distribution, the volatility of the Indian markets weekly returns were similar to it other Asian counterparts.

Mulyadi & Anwar (2012) employed GARCH (1, 1) and GARCH-X model to see return and volatility spillover between three stock markets USA, UK, and Greece stock exchange composite. The result of this study shows that during all period, there are return spillover between three stock markets which is all significant in 1%.

Paramati et al. (2012) examined the long-run relationship between Australia and three developed (Hong Kong, Japan and Singapore) and four emerging (China, India, Malaysia and Russia) markets of Asia. In this paper bivariate Johansen co-integration test provides results in supporting the long-run relationship between Australia-Hong Kong, Australia-India, and Australia-Singapore in the post-crisis period, the causal relationship from Australia to Asian markets disappears after the crisis. Results of VAR models demonstrated that there is no consistent lead-lag association between the sampled markets.

Srikanth & Aparna (2012) examined month-wise average prices of BSE-Sensex, NYSE, NASDAQ, S&P500, HangSeng, Nikkei225, SSE Composite index and FTSE100 have been selected to study the degree of stock market integration. The study covered a period of 10 years from January 2000 to December 2009. The results of these studies support the view that there is a substantial integration between domestic and international financial markets. BSE-Sensex has witnessed greater fluctuations which has been indicated by very high Ce-efficient of variation compared to other select indices.

Verma & Mahajan (2012) examined the impact of 2008 U.S. crisis on the stock return volatility of Indian stock market ARCH (Autoregressive Conditional Hetroscedasticity) models have been used to detect the presence of volatility in the light of global financial meltdown.This study used dummy variables in an augmented E-GARCH to capture the influence of crisis on return volatility of Indian stocks.

Gupta et al. (2013) aimed to understand the nature and different patterns of volatility in Indian equity market This study examined the volatility of returns in Indian stock market The daily observations comprising of closing data of SENSEX of Bombay Stock Exchange and S&P CNX Nifty of National Stock Exchange for the period of 10 years i.e. from January 2003 to December 2012 was used for analysis in this study. GARCH models were used to see the volatility of Indian equity market

Gupta (2013) focused for the investor to know to what extent domestic market is correlated and integrated with the foreign markets. The data is collected for the period from July 2002 to December 2012 in this paper. Various tools like Coorelation, Augmented Dickey – Fuller test, Jarque-Bera test, Jonansen Co – Integration test, Correlations, Granger Causility test were applied in this paper. This study attempted to find out the interdependence of Indian stock markets with other foreign markets. The paper found that all stock markets has been affecting and also affected by other stock markets. The degree of correlation between different markets varies.

Palamalai et al.(2013) examined the stock market integration among major stock markets of emerging Asia-Pacific economies, viz. India, Malaysia, Hong Kong, Singapore, South Korea, Taiwan, Japan, China, and Indonesia. Johansen and Juselius (1990) multivariate cointegration approach and VECM have been used to investigate the dynamic linkages among selected emerging Asia-Pacific stock markets. Granger causality/Block exogeneity Wald test based on the vector error correction model (VECM) approach, and variance decomposition analysis were used to investigate the dynamic linkages between markets. The results of Granger causality/Block exogeneity Wald test and variance decomposition analysis revealed the stock market interdependencies and dynamic interactions among the selected emerging Asia-Pacific economies.

Nisha& Vinayak (2013) explained the volatility in stock markets for the economic health of the economy. The data used in this study consisted of the daily closing points of BSE100 and S&P CNX500 for the period of ten years from January 2003 to December 2012.The two volatility models are used in this study, GARCH (1,1) and TGARCH (1,1). The results of GARCH model showed that there was more impact of past volatility on the present volatility in comparison to impact of past shocks or news on the conditional volatility. The results of T-GARCH models proved in this study that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, which indicated the existence of leverage effects in the returns of the BSE100 index of Bombay Stock Exchange and S&P CNX500 index of National Stock Exchange during the study period.

Gupta (2014) attempted to look at the efficiency of Indian stock market BSE index, Sensex to represent the Indian stock market The daily closing points were taken for the sample period often years from January 2003 to December 2012. Different statistical tools like Unit Root test, Runs test and Kolmogorov-Smimov test (K-S test) were used to analyze the data with the help of software Eviews5.

Econometric Models for Volatility Analysis in Interdependence of Various Stock Markets

Various Statistical & Econometric tools used for analyzing Volatility in Interdependence of various stock markets includes-

- Descriptive Statistics
- Unit Root Test
- Augmented Dickey Fuller Test
- Phillips–Perron Test
- Granger Causality Test
- Vector Auto Regression Model
- Variance Decomposition and Impulsive Responses
- GARCH Models for Heteroscedasticity

Descriptive Statistics: The descriptive statistics of the selected stock indices and their returns of for a period includes mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jaruqe bera test etc.

Unit Root Test:A unit root test is an essential condition to test the stationary nature of the selected time series. In the study, the Augmented Dickey-Fuller test is used to check the null hypothesis of the presence of a unit root in the selected series. The outcome of ADF test for a unit root for selected stock markets under study is reported in the study. In unit root test the optimal lag length was taken with the Schwartz Info Criterion (SCI) and maximum leg was put to 36. Phillips- Perron Test checks the null hypothesis of variable autocorrelation prevalent in the series. The method is Bartlett Kernel and Newey Best Bandwidth is used at the time of application of PP Test. Augmented Dickey Fuller and PP unit root test was performed including intercept at level for the period of ten years from April 2007 to March 2017. For testing stationarity, let us consider an AR (1) model:

$\gamma t = 1\gamma t{-}1 + \text{s}t$

The simple AR(1) model represented in above equation is called a *random walk model*. In

thisAR(1) model if □p₁□<1, then the series is I(0) i.e. stationary in level, but if $p_1 = 1$ then thereexist what is called unit root problem. In other words, series is non-stationary.

Augmented Dickey Fuller Test

Dickey-Totaler test involve estimating regression equation and carrying out the hypothesis test.The simplest approach to testing for a unit root is with an AR(1) model. AR(1) process:

$\gamma t = + p\gamma t{-}1 + \text{s}t$

where *c* and ρ are parameters and is assumed to be white noise. If -1<p<1, then y is a stationary

series while if ρ=1 , y is a non-stationary series. If the absolute value of ρ is greater than one, the series is explosive. Therefore, the hypothesis of a stationary series is involves whether the absolute value of ρ is strictly less than one.

Phillips–Perron Test

The Phillips–Perron test (named after Peter C. B. Phillips and Pierre Perron in 1998) is alsoa unit root test. This test suggests an alternative method (nonparametric) for controlling for serial correlation. This test is used in time series analysis to test the null hypothesisthat a time series is integrated of order 1. This method estimates the non-augmented DF test of the null hypothesis δ=0 in

$\Delta yt = \delta y_{t-1} + \mu t$

where Δ is the first difference operator. The ADF test addresses this issue by introducing lags of

Δy_t as regressors in the test equation.Similar to this test, the Phillips–Perron test addresses the matter that the process generating data for y_t might have a higher order of autocorrelation than the equation of the test – makingy_{t-1} endogenous. Whilst this test is robust with respect to unspecified autocorrelation and heteroscedasticity test equation. (Kaur, 2004) used the same for their research work.

Johansen's Cointegration Test

Johansen's co integration test is considered to be most influential among the various available tests. Johansen's Co integration test involves quite complex mathematics; therefore in the studythe results obtained from the E views software are reported and discussed. Johansen's Co integration test is used to study the long term equilibrium relationship between the different time series of the same integrated order. Johansen's Co integration test is based on reduced rank of VAR method. Johansen's Cointegration test procedure is intended to identify the number of long term equilibrium relationships. In Johansen's test, the eigen values are arranged in descending order and then therank of Co integration of matrix H is evaluated using the Lamda Max Test and Trace Test based on maximum- likelihood statistics.

$$\Delta x = \theta_2(y_t - \beta x_t)_{t-1} + \sum_{i=1} \gamma_{2i} \Delta Y_{t-i} + \sum_{j=1} \square_{2j} \Delta x_{t-j} + \epsilon_{2t}$$

This test permits more than one co-integrating relationship so is more usually applicable than the Engle–Granger test which is based on the Dickey–Totaler test for unit roots in the residuals from a single co-integrating relationship. Bose (2005); and Paramati et al. (2012); applied Johansen test in research.

Granger Causality Test

This technique considered for determining whether one time series is useful in forecasting another. If two variables, x and y are correlated, it is possible that: x is caused by y, y is causedby x, Both x and y are caused by some other variable C. Causality cannot be incidental from contemporaneous correlations. Granger Causality is based on the simple logic that effect cannot precede cause. We may have mainly three situations: One way causality; No causality between x and y; and Two-way or feedback causality.

Granger causality measures precedence and information content but does not by itself point out causality in the more common use of the term. Let *y* and *x* be stationary time series. To test thenull hypothesis that *x* does not Granger-cause *y*, one first finds the proper lagged values of *y* to include in a univariate autoregression of *y*:

$$Y_t = + \sum_{i=1}^{\mathbf{i}} \alpha_i y_{t-1} + \sum_{j=1}^{\mathbf{j}} \beta_j x_{t-j} + \epsilon_t$$

$$X_t = \square + \sum_{i=1} \square_i y X_{t-1} + \sum_{j=1} \theta_j Y_{t-j} + \epsilon_t$$

Bose (2005) & Paramati et al. (2012); applied Granger Causality Test earlier.

Vector Auto Regression Model

The vector auto regression (VAR) models are the natural extensions of the univariate ARMA models. VAR is an alternative of dynamic simultaneous equation models involving too many arbitrary decisions. In a standard VAR, all the variables are treated as endogenous variables andthe independents variables includes only lagged values of these endogenous variables. The contemporaneous terms of the selected variables are not included in the list of independent variables. The VAR model is based on the assumption that the contemporaneous innovations in the variables are uncorrelated. Before estimating the system of equations the order of VAR (represented as p) is to be decided. The information criteria such as Akaiki Information Criterion (AIC) or Schwarz Bayesian Criterion (SBC) or Hannin Quin (HQ)is used for this purpose. The lagged value is selected to minimize the information criterion.

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \cdots + \beta_{1k} y_{1t-k} + \alpha_{11} y_{2t-1} + \cdots + \alpha_{1k} y_{2t-k} + u_{1t}$$

where u_{it} is a white noise disturbance term with $E(u_{it}) = 0$, $(i = 1, 2)$,$E(u_{1t}u_{2t}) = 0$.As should already be evident, an important feature of the VAR model is its flexibility and the ease of generalization. For example, the model could be extended to encompass moving average errors, which would be a multivariate version of an ARMA model, known as a VARMA. Instead of having only two variables, $y_{1t}$and y_{2t}, the system could also be expanded to include g variables, y_{1t}, y_{2t}, y_{3t}, . . . , y_{gt}, each of which has an equation. Another useful facet of VAR models is the compactness with which the notation can be expressed.

Variance Decompositions and Impulse Responses

Block *F*-tests and an examination of causality in a VAR will suggest which of the variables inthe model have statistically significant impacts on the future values of each of the variables in the system. But *F*-test results will not, by construction, is able to explain the sign of the relationshipor how long these effects require to take place. That is, *F*-test results will not reveal whether changes in the value of a given variable have a positive or negative effect on other variables in the system, or how long it would take for the effect of that variable to work through the system. Such information will, however, be given by an examination of the VAR's impulse responsesand variance decompositions.

Variance decompositions offer a slightly different method for examining VAR system dynamics. They give the proportion of the movements in the dependent variables that are due to their 'own' shocks, versus shocks to the other variables. A shock to the *i* th variable will directly affect that variable of course, but it will also be transmitted to all of the other variables in the systemthrough the dynamic structure of the VAR. Variance decompositions determine how much of the *s*-step-ahead forecast error variance of a given variable is explained by innovations to each explanatory variable for $s = 1, 2, \ldots$ In practice, it is usually that own series shocks explain mostof the (forecast) error variance of the series in a VAR. To some extent, impulse responses and variance decompositions offer very similar information. Singh and Sharma (2012) used variance decompositions in research work done by them.

Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables. So, for each variable from each equation separately, a unit shock is applied to the error, and the effects upon the VAR system over time are noted. Thus, if there are g variables in a system, a total of $g2$ impulse responses could be generated. The way that this is achieved in practice is by expressing the VAR model as a VMA -- that is, the vector autoregressive model is written as a vector moving average. Provided that the system is stable, the shock should gradually die away. To illustrate how impulse responses operate, consider the following bivariate VAR (1).

$y_t = A_1 y_{t-1} + u$

GARCH Models for Heteroscedasticity

One of the most important issues before applying the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) methodology is to first examine the residuals for evidence of heteroscedasticity. To test for the presence of heteroscedasticity in residuals, the Lagrange Multiplier (LM) test for ARCH effects proposed by Engle (1982) is applied.

ARCH LM Test: The study aims to study the volatility of the selected Indian and global stock indices. For the purpose the residuals of the ARMA (1,1) forecasting model on the different stock indices returns are examined. As most of the stochastic financial time series have the feature of volatility clustering which indicates that high volatile periods are followed by high volatility and low volatile periods are followed by low volatility, the study also examine the volatility clustering in the behavior of residuals of the ARMA (1,1) model applied on the selected Index returns, the ARCH LM test is applied in the study for the purpose. The ARCHLM test regresses the lagged residual terms with the residual term of the selected sample.

GARCH (1,1) Model: GARCH (1,1) model is also applied in the study on the selected index returns. In GARCH (1,1) model, the dependent variable σ_t^2 represents the conditional volatility in the Index returns, the intercept (α_0) represents the hypothetical long term average conditional volatility in index returns, the first independent variable is ARCH term followed by second independent variable known as GARCH term.

GARCH (1,1) model as proposed by Bollerslev in 1986 is the most popular model for analyzing the conditional volatility of a financial time series. GARCH (1,1) model is represented as

$$\sigma_t^2 = {}_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where, the dependent variable σ_t^2 represents the conditional volatility, α_0 represents the intercept coefficient and represents the hypothetical long term average conditional volatility, the first independent variable u_{t-1}^2 is known as ARCH term and second independent variable σ^2

$t-1$ is known as GARCH term. GARCH (1,1) model is equivalent to ARCH model plus the inclusion of GARCH term in it. The GARCH term is representing the forecasted conditional volatility in the series at previous lag. In GARCH model the sum of slope coefficients of ARCH term (α_1)and GARCH terms (β_1) measures the volatility persistence. In practice, the sum of slope coefficients α and β is usually observed very close to 1, which indicates that the volatility of financial series is highly persistent. The high level of volatility persistence indicates that the volatility on any day is highly affected by the volatility at previous lag. The effect of any unexpected shock due to news or information comes unexpectedly caused volatility in the financial series. The volatility in the financial series dies out at a decaying rate of (1- α_1–β_1). If (α_1+ β_1)is found to be one then the effect of shock will never die out. This means the volatility on any day is similar to the volatility on previous day and it will also continue in indefinite future also. The volatility will come down only if (α_1+ β_1) < 1 i.e. the declining rate is non zero and positive. Therefore, this condition is also analyzed while estimating the GARCH model.

The Threshold GARCH (T-GARCH) Model: In the study TGARCH model is applied on the selected index returns in order to study the asymmetric effect of positive and negative shocksis that they impose response of volatility similar or symmetric to positive as well as negative shocks in the system. This is due to the reason that conditional variance as measured using GARCH model is affected by the magnitudes of lagged residuals and not their signs. In fact there are many evidence found in the literature that an unexpected negative shock to financial time series such as stock indices is likely to cause more volatility as compared to a positive shock of the same magnitude. The TARCH model (also known as GJR model) is a modified version of GARCH model where one additional dummy variable is added in the model which examines the presence of possible asymmetries in the conditional volatility. The dummy variable in the TARCH model represents the presence of negative shocks in the system. In the research study the TARCH model along with dummy representing the presence of negative shocks in the lagged error terms used in order to analyze the volatility in the selected Index returns. The conditional variance in TARCH model is given by

$$\sigma_t^2 = \alpha_o + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 I_{t-1}$$

Where, I_{t-1}= 1 if μ_{t-1} < 0= 0
otherwise
The results of TARCH model applied on the Index returns indicates that probability value of the dummy coefficient as represented by *RESID(-1)^2*(RESID(-1)<0)*is found to be less than five

percent level of significance. This indicates the presence of significant asymmetric effect in the conditional volatility of selected Index returns.
The Exponential GARCH (E-GARCH) Model: Another modified model in GARCH family is exponential GARCH model. The EGARCH (exponential GARCH) model is a popular model among the different available asymmetric GARCH models. E-GARCH model was originally proposed by Nelson (1991) and it is based on log-transformation of conditional variance. In EGARCH model the conditional variance is always remains positive. In EGARCH model the ARCH term is divided into two different independent variables indicating the *sign effect* of shocks on Index volatility and the *size (magnitude) effect* of shocks on the volatility in the financial time series. In this study the following specification of the EGARCH model is used in order to study the conditional volatility in the selected Index returns

$$\ln(\sigma^2) = \omega + \beta \ln(\sigma^2 \quad) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma}} \quad \mu_{t-1} + \alpha \left[- \sqrt{\frac{2}{\pi}} \right] t \quad t$$

-1 $2t-1$ $2\pi t-1$

The EGARCH (exponential GARCH) model is a popular model among the different available asymmetric GARCH models. In EGARCH model the conditional variance is always remains positive. The EGARCH model is used to study the sign and size effects of the unexpected shocks which comes in the system. The second term in the EGARCH model indicates the impact of GARCH term (volatility persistence) on the future conditional volatility in selected Index returns. The third term in the EGARCH model indicates the sign effect of the ARCH (previous shock) on the conditional volatility in the selected Index returns. The fourth term in the EGARCH model indicates the size effect of the ARCH term on the conditional volatility in the selected Index returns. The results of EGARCH model applied on the selected Index returns indicates that p value of the GARCH term in the model is found to be less than five percent level of significance. In this study the following specification of the EGARCH model is used in order to study the conditional volatility in the selected Index returns.
GARCH in Mean:GARCH- in-Mean or GARCH-M model which was originally proposed by
Engle, Lilien and Robins (1987), assumes that the conditional mean is a linear function of conditional variance. Here the conditional variance may follow any of the GARCH specification. The GARCH M model can also be written as
$$Index return_t = \; + \beta_1 y_{t-1} + \beta_2 s_{t-1} + \beta_3 \sigma^2_t$$
This GARCH in mean model assumes the assumption of non-negativity and stationary
conditions as in case of GRACH (1, 1) model. The GARCH in mean model is applied in the study in order to examine that how the price discovery process in the selected index response to any change in conditional volatility. If conditional volatility is related to the returns in the index then in such case the impact of the conditional volatility on the conditional return must
be positive and significant. GARCH-in-mean model assumes the assumption of non-

negativity and stationary conditions as in case of GRACH (1, 1) model. Reviews and theories suggested that return and risk are related and higher is the risk premium higher will be the expected return. If the volatility associated with the financial asset returns signifies risk, it may be expected according to the 'risk-return tradeoff theory' that during the high volatile periods the expected returns should be higher.

GARCH (1,1) with Exogenous Variables: The square of the residuals of the ARMA(1,1) equation applied on the selected International Stock Indices are estimated the squared residuals are assumed to be the proxy of volatility in the underlying International Stock Markets. The squared residuals is treated as a exogenous variable in the GARCH (1,1) model applied for the sensex returns. In case if the International Markets is opened after opening of the Indian Stock Market the previous day volatility is considered. The GARCH (1,1) model applied on the sensex with exogenous volatility in International Stock Markets is representing as

$$\sigma_t^2 = \alpha_o + \alpha_1 \mu_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 I_{t-1}$$

In the above equation the β_3 indicates the spillover effect in the direction of volatility in International stock volatility.

Dynamic Conditional Correlation (DCC) Model with GARCH (1,1): The DCC model framework starts with fitting the most suitable univariate GARCH specifications for each selected series. The selected univariate GARCH specifications is expected to best explain the Index return behaviour. The univariate GARCH specifications for the study includes the ARMA (1,1) with GARCH order (1,1) using the model GARCH assuming the multivariate normal (Gaussian error) distribution. Most of the financial returns time series also display strong persistence level in volatility. This indicates the existence of volatility clustering in most of the financial time series. The presence of volatility clustering in the financial series is one of the common phenomenon with the presence of heteroscedasticity in the error terms. The next step is after defining the univariate GARCH specifications is to use the standardized residuals obtained from the estimated univariate GARCH models. This is in order to estimate the time-varyingDCC series by maximizing the log-likelihood functions.

Conclusion

The various mathematical, statistical & econometrics models considered in the study depict the wide picture for analyzing the volatility of stock market. Descriptive statisticsanalysis was considered which further included mean, median, maximum, minimum, standard deviation, skweness, kurtosis, Jaruge bera test etc. used to forecast the volatility. Another important segment was found of testing stationarity of the time-series data for which Unit Root Test, ADF Test and PP Test were applied. Granger Causality Test, Vector Auto Regression Model, Variance Decomposition and Impulser Responses were identified various important tools for measuring volatility. Various GARCH family models were found very popular and significant to analysis the volatility of stock prices for checking interdependence of various stock markets. All these models are extensively applied by the researchers in analyzing stock markets and still the search of further models is going on.

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