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Predicting the Volatility of Stock Markets and Measuring its Interaction with Macroeconomic Variables: Indian Evidence, Case Study of NIFTY and SENSEX

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Abstract

This paper investigates the effects of economic factors on India's stock markets. It utilized Johansen cointegration test and Innovation Accounting techniques to study the short-run dynamics as well as long-run relationship between stock prices and four macroeconomic variables from the Indian economy. It also attempts to forecast the volatility of stock markets with the help from Autoregressive Conditional Heteroskedastic models (ARCH). We found co-movements between stock market index and macroeconomic variables in a long-run equilibrium path. The variations in the stock prices are mainly attributed to its own variations and to smaller extent by other macroeconomic variables. EGARCH method emerged as the best forecasting tool available, among others. However, it is advisable not to forecast beyond one period in cases of such volatile series, because of the randomness involved as visible from the forecast errors obtained from different methods.

***Keywords**:* Volatility; Stock prices; Macroeconomic Variables; Forecasting

1. Introduction

The relationship between macro-economic factors and stock market developments has been the subject of interest among researchers over the last two decades.

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It has often been argued that some fundamental macroeconomic factors such as exchange rate, interest rate, and inflation are the key determinants of stock prices. Chen, Rolland and Ross [1] showed that economic state variables do tend to affect future dividends as well as discount rate and thus stock prices. Fama [2] also showed a strong positive correlation between common stock returns and real variables such as capital expenditure, industrial production, GNP, money supply and interest rate.

Until recently, the most widely used framework in this regard was the arbitrage pricing theory(APT) model which, in finance is a general theory of asset pricing which has become influential in the pricing of stocks. APT holds that the expected return of a financial asset can be modeled as a linear function of various macro-economic factors or theoretical market indices, where sensitivity to changes in each factor is represented by a factor-specific beta coefficient. The model-derived rate of return will then be used to price the asset correctly - the asset price should equal the expected end of period price discounted at the rate implied by model. If the price diverges, arbitrage should bring it back into line. However, with the development of cointegration analysis, has allowed for another approach to examine the relationship between economic variables and stock markets. An advantage of co-integration analysis has been the realization of the dynamic comovements among the variables and adjustment process towards the long term equilibrium could be examined. Mukherjee and Naka [3] employed Johansen co-integration test in the vector error correction model (VECM) and found that Japanese stock market was cointegrated with six macroeconomic variables. Mayasmai and Koh[4] used the same analysis for Singapore stock market and found it to be cointegrated with five macroeconomic variables.

This paper extends the same analysis on the Indian stock markets which is represented by Bombay stock exchange (BSE) where the index chosen is SENSEX. The BSE Index, SENSEX, is India's first stock market index that enjoys an iconic stature, and is tracked worldwide. It is an index of 30 stocks representing 12 major sectors. The SENSEX is constructed on a 'free-float' methodology, and is sensitive to market sentiments and market realities. The objective is to investigate the dynamic relationship between stock prices and four macroeconomic variables. The important contribution of this paper towards the exiting literature would be the inclusion of more pronounced set of variables which can truly reflect the broader picture of the factors affecting the stock markets.

Second objective of this paper is concerned with predicting the volatility of stock markets. The volatility quantifies the uncertainty about future asset price fluctuations. To model and forecast stock market volatility has been the subject of much recent empirical and theoretical investigation by academics and practitioners alike. First, volatility has received a great deal of concern from policy makers and financial market participants because it can be used as a measurement of risk. Second, greater volatility in the stock, bond and foreign exchange markets has raised important public policy issues about the stability of financial markets and the impact of volatility on the economy. Therefore another goal of this paper is to investigate the extent to which, it is possible to predict the volatility of NIFTY's weekly index(The NSE's key index is the S&P CNX NIFTY, known as the Nifty, an index of fifty major stocks weighted by market capitalization) which has been a major indicator for National Stock Exchange. The rest of the paper is organized as follow: Second section covers the relationship between macroeconomic variables and stock markets. Third will review the literatures, while fourth describes data sources and definitions and fifth section will capture the methodology. Finally, sixth section will present empirical results and conclusions.

2. Relationship between Macroeconomic variables and stock price movements:

This study has looked upon the following variables:

- Interest rate (INT)
- Exchange rate (EXRATE)
- Money supply (M3)
- Net inflows of Foreign Institutional Investors (FIIs)

The intuition behind the relationship between interest rates and stock prices is straightforward. An increase in the rate of interest raises the opportunity cost of holding cash and is likely to lead to a substitution effect between stocks and other interest bearing securities. Additionally, changes in interest rates are expected to affect the discount rate in the same direction via their effect on the nominal risk-free rate

The exchange rate being measured in terms of dollars is expected to have a positive relationship with stock prices. Solnik [5] indicated that both exchange rate levels and changes affect the performance of a stock market. For an export-dominated country, currency depreciation will have a favorable impact on the domestic stock market, as the product exported from the country will become cheaper in the foreign countries. As a result, if the demand for goods exported is elastic, the volume of exports would increase, which in turn would cause higher cash flows and thus a surge in the stock prices of domestic companies. The opposite should hold in case of appreciation. It is also hypothesized that trade balance is positively related with stock prices, as it is a possible indicator of country's competitiveness and its performance on economic front.

The effect of money supply on stock prices is also a matter of empirical proof. Since the rate of inflation is positively related to money growth rate [2], an increase in the money supply may lead to an increase in the discount rate and lower stock prices. However, this negative effect may be countered by the economic stimulus provided by money growth, which would likely increase cash flows and stock prices [3].

Lastly FIIs, over the years, have been allowed to operate in Indian stock markets. It now includes institutions such as pension funds, mutual funds, investment trusts, asset management companies etc. Therefore it's appropriate to hypothesize a positive relation between FIIs inflows and stock markets.

3. Literature reviews

Hagen H.W. Bluhm, JunYu[6] compared two basic approaches to forecast volatility in the German stock market. The first approach used various univariate time series techniques while the second approach made use of volatility implied in option prices. It was showed that the model rankings were sensitive to the error measurements as well as the forecast horizons. The result indicated that it was difficult to state which method was the clear winner. Mats Palmquist, Björn Viman [7] investigated the extent to which it is possible to predict the volatility for the OMX-index and further to compare, evaluate and rank the methods used, to see which one predicts most accurately. In this paper, simpler methods like historical average and random walk and more complex methods like EWMA (Exponential weighted moving average) and GARCH (1, 1) were used. Overall, the forecast results with EWMA estimators were very close to the forecast result with the more complicated GARCH (1, 1) model. The random walk performed second worst and the historical average the worst. Chris Brooks [8] explored a number of statistical models for predicting the daily stock return volatility of an aggregate of all stocks traded on the NYSE. An application of linear and non-linear Granger causality tests highlighted evidence of bidirectional causality, although the relationship was stronger from volatility to volume than the other way around.

Madhusudan Karmakar [9] estimated conditional volatility models in an effort to capture the salient features of stock market volatility in India and evaluate the models in terms of out-of sample forecast accuracy. It also investigated whether there was any leverage effect in Indian companies. Nikolay Gospodinov, Athanasia Gavala, Deming Jiang [10] investigated the time series properties of S&P 100 volatility and the forecasting performance of different volatility models. It considered several nonparametric and parametric volatility measures, such as implied, realized and model-based volatility, and showed that these volatility processes exhibit an extremely slow mean-reverting behavior and possible long memory. Amita Batra [11] analyzed time variation in volatility in the Indian stock market during 1979-2003. It examined if there had been an increase in volatility persistence in the Indian stock market on account of the process of financial liberalization in India. The analysis revealed that the period around the BOP crisis and the initiation of economic reforms in India was the most volatile period in the stock market. Structural shifts in volatility were more likely to be a consequence of major policy changes and any further incremental policy changes may had only a benign influence on stock return volatility.

H.R. Badrinath and Prakash G. Apte [12] examined the stock market, the foreign exchange market and the call money market in India for evidence of volatility spillovers using multivariate EGARCH models which facilitated the study of asymmetric responses. The results indicated the existence of asymmetric volatility spillovers across these markets. The results also indicated that either the information assimilation across markets was slow or that the spillovers were on account of contagion. Gautam Goswami and Sung-Chang Jung [13] investigated the effects of economic factors on Korean stock market. It used Vector Error Correction Model (VECM), and looked at the short-run dynamics as well as long-run relationship between stock price and nine macroeconomic variables from Korean economy. It was found that the Korean stock market was co-integrated with nine macroeconomic variables. The Korean stock prices were positively related to industrial production, inflation and short-term interest rate, and negatively related to long-term interest rates and oil prices. Anokye M. Adam, George Tweneboah[14] examined the role of macroeconomic variables on stock prices movement in Ghana. It used the Databank stock index to represent Ghana stock market and (a) inward foreign direct investments, (b) the treasury bill rate (as a measure of interest rates), (c) the consumer price index (as a measure of inflation), and (d) the exchange rate as macroeconomic variables. It established cointegration between macroeconomic variables identified and Stock prices in Ghana, which indicated long run relationship. Results of Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) indicated that interest rate and Foreign Direct Investment (FDI) were the key determinants of the share price movements in Ghana.

Ramin Cooper Maysami, Tiong Sim Koh [4] examined the long-term equilibrium relationships between the Singapore stock index and selected macroeconomic variables, as well as among stock indices of Singapore, Japan, and the United States. With help from appropriate vector error-correction models, it detected that changes in two measures of real economic activities, industrial production and trade, were not integrated of the same order as changes in Singapore's stock market levels. However, changes in Singapore's stock market levels did form a co-integrating relationship with changes in price levels, money supply, short- and long-term interest rates, and exchange rates. While changes in interest and exchange rates contributed significantly to the co-integrating relationship, those in price levels and money supply did not. Christopher Gan, Minsoo Lee, Hua Hwa Au Yong, Jun Zhang [15] employed co-integration tests and examined the relationships between the New Zealand Stock Index and a set of seven macroeconomic variables from January 1990 to January 2003.Specifically, it employed the Johansen Maximum Likelihood and Granger-causality tests to determine whether the New Zealand Stock Index was a leading indicator for macroeconomic variables. They found that NZSE40 was consistently determined by the interest rate, money supply and real GDP and no evidence was found that the New Zealand Stock Index was a leading indicator for changes in macroeconomic variables. Nai-Fu Chen, Richard Roll and Stephen A. Ross [1] examined whether innovations in macroeconomic variables are risks that are rewarded in stock market. The variables included were spread between long and short term interest rates, index of industrial production, spread between high and low grade bonds and expected and unexpected inflations. It was found that these sources of risk were significantly priced. Further, neither the market portfolio nor the aggregate consumption was priced separately. Andreas Humpe and Peter Macmillan [16] analysed within the framework of a standard discounted value model, whether a number of macroeconomic variables influenced stock prices in the US and Japan. A cointegration analysis was applied in order to model the long term relationship between industrial production, the consumer price index, money supply, long term interest rates and stock prices in the US and Japan. For the US, it was found that the data was consistent with a single cointegrating vector, where stock prices were positively related to industrial production and negatively related to both the consumer price index and a long term interest rate. However, for the Japanese data, two cointegrating vectors were found. For one vector, the stock prices were influenced positively by industrial production and negatively by the money supply. For the second cointegrating vector, industrial production was found to be negatively influenced by the consumer price index and a long term interest rate.

Nil Günsel and Sadõk Çukur [17] investigated the performance of the Arbitrage Pricing Theory (APT) in London Stock Exchange for the period of 1980-1993 as monthly. The study developed seven pre-specified macroeconomic variables. The term structure of interest rate, the risk premium, the exchange rate, the money supply and unanticipated inflation were similar to those derived in Chen, Roll and Ross [1]. Ramin Cooper Maysami, Lee Chuin Howe and Mohamad Atkin Hamzah[18] looked at the long-term equilibrium relationships between selected macroeconomic variables and the Singapore stock market index (STI), as well as with various Singapore Exchange Sector indices—the finance index, the property index, and the hotel index was examined. The study concluded that the Singapore's stock market and the property index form cointegrating relationship with changes in the short and long-term interest rates, industrial production, price levels, exchange rate and money supply.

4. Data

For the first objective, a total of four macroeconomic variables and BSE SENSEX data are used. All variables are in natural logarithm and are monthly frequencies from January 2000 to December 2008. However, for the second objective, the concern has been to predict the volatility of stocks as measured by NIFTY's weekly index over the time period 7th July 2008 to 29th December 2008, on a weekly basis, where the estimation period ranges from 12th august 2002 to 30 June 2008. The definitions of each variable are described in table 1 below.

Table 1		
Variable	Source	Definition
BSE Sensex **(lnbse)**	Yahoofinance.com	Official published index of the market weighted value of closing prices for 30 shares listed on the Bombay stock exchange
NIFTY Weekly index	Nseindia.com	Official published index of the market weighted value of closing prices for 30 shares listed on the National stock exchange
Interest rate **(lnint)**	Monthly review of Indian economy published by C.M.I.E.	Month end yield on 91-days Treasury bill rate
Exchange rate **(lnexrate)**	Monthly review of Indian economy published by C.M.I.E.	Month end exchange rate of Indian rupee against dollar
Money supply **(lnm3)**	Monthly review of Indian economy published by C.M.I.E.	Month end M3 money supply
Foreign Institutional Investors **(Lnfii)**	R.B.I. Official website	Net inflows of FIIs
* Parenthesis represents log of the variable		

5. Methodology

A) For first objective- This paper employs the Johansen multivariate cointegration test to determine whether selected macroeconomic variables are cointegrated (hence possibly causally related) with stock prices. Furthermore, the impulse response and Error Variance Decomposition analyses are used to examine the dynamic relations between stock indices and various macroeconomic variables. The Augmented Dickey-Fuller (ADF) test and Phillips-perron test is used to determine the order of integration for all time series variables. The lag lengths for the time series analysis are determined by the minimum Akaike Information Criteria and Schwarz Information Criteria. Brief descriptions of the procedures are as follows.

Unit Root Test

In order to check for the stationarity of the macroeconomic variables, Augmented Dickey-Fuller unit root test is used for all the variables in this study. To test the unit root hypothesis, the following form of the Augmented Dickey- Fuller test is used on each of the variables.

$$\Delta X_t = \alpha + Bt + \rho X_{t-1} + \Sigma \lambda i \, \Delta X_{t-I} + \varepsilon_t \qquad (1)$$

where Xt = the logarithm of the variable in period t

T = Time Trend

ε_t = Disturbance term with mean 0 and variance σ^2

In the unit root test, the null hypothesis to be tested is that the coefficient of x with one lag is equal to zero (Ho: p = 0). If unit root test rejects the null hypothesis then the series has no unit root, it means that the series is stationary and thus can be used for Vector Auto Regression (VAR). But, if the unit root test cannot reject the null hypothesis, it means that the series are not stationary and one to apply difference operator to make the series stationary before VAR is applied. In the presence of unit roots, a multivariate regression analysis may give rise to spurious results i.e., may have high R^2, but the least square estimates are not consistent and statistical inferences may not hold. Moreover, Phillips-Perron test is also used to avoid the restrictive assumptions in Dickey-Fuller test that errors are statistically independent and have a constant variance. Phillips-Perron test has milder assumption on error terms and its test statistic is a modification of Dicky-Fuller t-statistics.

If however the variables are non-stationary but a linear combination of the variables are stationary, then the VAR on differenced data gives rise to two problems. Firstly, there are important information that are lost due to differencing. Secondly, VAR method's deficiency to include long-term relations among variables gives rise to misspecification bias. A cointegration analysis is more appropriate than VAR because it can investigate the long-term as well as short-term dynamic comovements among macroeconomic variables.

Johansen Multivariate Cointegration Test

. The relationships among the variables are based on the following model:

$$\Delta X_T = \Gamma_1 \Delta X_{T-1} + \Gamma_2 \Delta X_{T-2} + \ldots + \Gamma_{K-1} \Delta X_{T-K-1} + \Pi X_{T-K} + \eta + \varepsilon_T \qquad (2)$$

$\Gamma i = -I + \Pi_1 + \Pi_2 + \ldots\ldots + \Pi_i$ for i= 1,2, k-1

where $\Pi = -I + \Pi_1 + \Pi_2 + \ldots\ldots + \Pi_K$ I is a identity matrix

The matrix Γi comprises the short-term adjustment parameters, and matrix Π contains the long-term equilibrium relationship information between the X variables. The Π could be decomposed into the product of two n×r matrix α and β so that $\Pi = \alpha\beta'$ where the β matrix contains r cointegration vectors and α represents the speed of adjustment parameters.

Johansen [19] developed two likelihood ratio tests for testing the number of cointegration vectors (r): the trace test and the maximum Eigenvalue test. The trace statistics tests the null hypothesis of r = 0 (i.e. no cointegration) against the alternative that r > 0 (i.e. there is one or more cointegration vetcor). The maximum Eigenvalue statistics test the null hypothesis that the number of cointegrating vectors is r against the specific alternative of r + 1 cointegrating vectors.

Innovation Accounting

Innovation accounting such as the impulse response function and the forecast error variance decomposition (FEVD) is used to analyze the interrelationships among the variables chosen in the system. The impulse response functions are responses of all variables in the model to a one unit structural shock to one variable in the model. The impulse responses are plotted on the Y-axis with the periods from the initial shock on the X-axis. Formally, each φ_{jk} (i) is interpreted as the time specific partial derivatives of the vector moving average (∞) function as shown by Enders [20].

$$Ø_{jk}(i)=ӘX_{JI}/ӘE_k \qquad (3)$$

Equation (3) measures the change in the j^{th} variable in period t resulting from a unit shock to the k^{th} variable in the present period. The FEVD measures the proportion of movement in a sequence attributed to its own shock to distinguish it from movements attributable to shocks to another variable. In the FEVD analysis, the proportion of Y variance due to Z shock can be expressed as:

$$\sigma^2_z[a_{12}(0)^2 + a_{12}(1)^2 + \ldots\ldots + a_{12}(m-1)^2]/\sigma_y(m)^2 \qquad (4)$$

One can see that as m period increases the $\sigma_y\,(m)^2$ also increases. Further, this variance can be separated into two series: y_t and z_t series. Consequently, the error variance for y can be composed of e_{yt} and e_{zt}. If e_{yt} approaches unity, it implies that y_t series is independent of z_t series. It can be said that y_t is exogenous relative to z_t. On the other hand, if e_{yt} approaches zero (indicates that e_{zt} approaches unity) the y_t is said to be endogenous with respect to the z_t .

B) For second objective- some important aspects need to be discussed:

Returns

In this paper, weekly index return data of NIFTY's is used. The returns are defined as the natural logarithm of the quota of today's and yesterday's index. The continuous compounded return is defined as:

$$Rt = \ln(I_t / I_{t-1}) \qquad (5)$$

Where It stands for the index value at time t, with deduction for possible dividends and I_{t-1} stands for the index value at time t-1. The daily returns are computed for the time period 12th August 2002 to 30th June 2008.

Volatility

Volatility is the basic concept in this paper and needs to be explained. The volatility is a measure of the uncertainty about future asset price movements. The volatility is often defined as the variance or the standard deviation of a time series. Unlike financial asset returns, volatilities are not directly observable on the market. Consequently, when an attempt is made to benchmark the accuracy of volatility forecasting models, researchers are necessarily required to make an auxiliary assumption about how the ex post or realized volatilities are calculated. To assess the performance of various methods, forecasted volatilities are then compared with actual volatilities. Unfortunately, as mentioned the actual volatility is not directly observed and hence it has to be estimated. A common approach in the literature is to use following formula, which is within the week variances of daily returns in each week during the forecasting period.

$$\sigma_t^2=1/n\sum^n_{t=1} [R_t-E(R_t)]^2 \qquad (6)$$

Accuracy of Forecasts

There are varieties of statistics to evaluate and compare forecast errors in the volatility forecasting literature. The most popular measures used in the literature are mean error (ME), root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) defined as follows:

$$ME = 1/n \sum^n_{t=1} (\sigma^2_t - \sigma^2_t) \qquad (7)$$

$$MAE = 1/n \sum^n_{t=1} \left| \sigma^2_t - \sigma^2_t \right| \qquad (8)$$

$$RMSE = \sqrt{} [1/n \sum^n_{t=1} (\sigma^2_t - \sigma^2_t)] \qquad (9)$$

$$MAPE = 1/n \sum^n_{t=1} \left| (\sigma^2_t - \sigma^2_t)/ \sigma^2_t \right| \qquad (10)$$

Models to be used are:

1. Symmetric GARCH model [GARCH (1, 1)]
2. Asymmetric GARCH models
   - Exponential GARCH
   - Threshold ARCH (GJR-GARCH)
   - Power ARCH

All the models are estimated over the seven year period from 12th august 2002 to 30th June 2008. The parameter estimates are then used to obtain the forecast for the week just ahead. The start and end dates of the parameter estimation period (in-sample period) are then rolled forward one week and the model parameters are re-estimated. These new estimates are then used to obtain the forecast for another week just ahead. This procedure is repeated, rolling forward the estimation window one week at a time, until the forecast for the final week (29th December, 2008) is obtained.

6. Empirical results:

In table 2, the descriptive statistics of the logarithmic data for all variables are presented. The point to note is that all variables are not normally distributed with the exception of interest rate as confirmed by jarque-bera test. (At 5% level of significance)

Table 2					
	LNBSE	LNEXRATE	LNFII	LNINT	LNM3
Mean	8.777211	3.807301	2.436272	1.853171	10.75622
Median	8.628842	3.815732	5.459586	1.885553	10.72812
Maximum	9.917736	3.891820	8.861775	2.348514	11.51734
Minimum	7.941509	3.673004	-9.103979	1.444563	10.12801
Std. Dev.	0.592212	0.055562	5.927982	0.231249	0.431338
Skewness	0.378926	-0.731726	-0.776089	0.042876	0.268029
Kurtosis	1.739451	2.996994	1.844375	2.051213	1.852507
Jarque-Bera	9.644818	9.548426	16.69523	4.046160	7.151608
Probability	0.008047	0.008445	0.000237	0.132247	0.027993
Sum	939.1616	407.3812	260.6811	198.2893	1150.195
Sum Sq. Dev.	37.17578	0.327238	3724.943	5.668456	19.72158
Observations	107	107	107	107	107

6.1 Unit Root Test:

To check for the stationarity of variables, Augumented Dicky Fuller (ADF) test for both level data and first differenced data is utilized. Table 3 and Table 4 shows the results for ADF test at 12 lags and 4 lags respectively. The level data results presented in both tables clearly indicates the presence of unit root for all the variables with the exception of Foreign Institutional Investors (LNFII).However, when these variables are tested for first difference (as shown in both tables); they reject the hypotheses of unit root and are generally stationary. This suggests that all the variables are integrated of order one, I (1) with the exception of LNFII. Till this point, the concern is regarding LNFII, which has remained a non stationary process at both lags even after differencing. The plausible reason for this could be the non robustness of lag length. The plausibility turns into reality when LNFII is tested for stationarity at six lags (not shown).The LNFII variable turned into integrated process of order one. To add weights to the above results, Phillips - Perron test is also carried out for unit roots as shown in table 5. Since Phillips - Perron test is a generalization of the Dickey-Fuller procedure that allows for fairly mild assumptions concerning the distribution of errors; the conclusion is based predominantly from this test statistics.

Table 3:

ADF test for both level and first differenced data with 12 lags

	Level data			**First differenced data**		
	Without constant and trend	With constant	With constant and trend	Without constant and trend	With constant	With constant and trend
Lnbse	0.562	-0.701	-2.027	-10.608**	-10.590**	-10.549**
Lnexrate	0.494	-1.879	-2.111	-6.438**	-6.436**	-6.423**
Lnm3	4.001	-0.210	-2.371	-5.558**	-7.179**	-7.144**
Lnint	-0.533	-1.868	-1.733	-13.357**	-13.302**	-13.373**
Lnfii	-6.717**	-7.457**	-7.719**	-12.293**	-12.246**	-12.195**
(*), (**) and (***) indicate significance level at 10%, 5% and 1% respectively						

Table 4:

ADF test for both level and first differenced data with 4 lags

	Level data			**First differenced data**		
	Without constant and trend	With constant	With constant and trend	Without constant and trend	With constant	With constant and trend
Lnbse	0.538	-0.967	-1.669	-3.514**	-3.525**	-3.380**
Lnexrate	0.484	-2.300	-2.541	-2.128**	-2.125	-1.988
Lnm3	2.475	-0.393	-2.766	-2.087**	-3.238**	-3.106
Lnint	-0.443	-1.479	-1.247	-5.585**	-5.561	-6.022**
Lnfii	-3.126**	-3.735**	-4.037**	-7.640**	-7.614**	-7.619**
(*), (**) and (***) indicate significance level at 10%, 5% and 1% respectively						

Table 5:

PP test for both level and first differenced data

(Bandwidth 2: newey west using bartlett kernel)						
	Level data			**First differenced data**		
	Without constant and trend	With constant	With constant and trend	Without constant and trend	With constant	With constant and trend
Lnbse	.553	-0.722	-2.062	-10.607**	-10.588**	-10.548**
Lnexrate	.499	-1.808	-1.979	-6.404**	-6.379**	-6.365**
Lnm3	5.208	-0.182	-2.211	-5.587**	-7.169**	-7.134**
Lnint	-0.552	-1.968	-1.823	-14.436**	-14.410**	-16.376**
Lnfii	-6.791**	-7.457**	-7.677**	-41.113**	-55.579**	-64.548**
(*), (**) and (***) indicate significance level at 10%, 5% and 1% respectively						

6.2 Johanson Cointegration Test

Since the prerequisite for a cointegration test is that the variables should be integrated of the same order, which is indeed the case in this study where all the four variables are integrated of order one, therefore the next step is to estimate the model and determine the rank, r to find the number of cointegrating relations in the model. The model lag length selection is determined by both Schwarz (SIC) and Akaike (AIC) Information Criterion in the general VAR model, where the test for lag structure indicated the use of one lag as the most appropriate. The aim is to choose the number of parameters, which minimizes the value of the information criteria. The SIC has the tendency

to underestimate the lag order, therefore AIC is selected as the appropriate indicator. With the appropriate lag length of one, an intercept and no trend properly specified for the cointegrating equation, the result of which are presented in tables 6 and 7. The trace statistic suggests one cointegrating vectors and the maximum eigenvalue statistic also suggests one cointegrating vector at the 5 % significance level. This indicates co-movement between stock market index and macroeconomic variables in a long-run equilibrium path. The normalized cointegrating coefficient for LNBSE is shown in table 8.

Table 6

Lag interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.459473	103.4348	69.81889	0.0000
At most 1	0.177985	38.83770	47.85613	0.2668
At most 2	0.102591	18.25810	29.79707	0.5470
At most 3	0.059264	6.892565	15.49471	0.5902
At most 4	0.004540	0.477797	3.841466	0.4894

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

The results are in line with theory and have got the right signs except for LNINT. As the Indian economy has grown over the time, it has allowed different types of FIIs to operate in Indian stock markets. It now includes institutions such as pension funds, mutual funds, investment trusts, asset management companies, nominee companies, incorporated/institutional portfolio managers, university funds, endowments, foundations and charitable trusts/societies with a track record. Proprietary funds have also been permitted to make investments through the FII route subject to certain conditions. With so much of investment routes headed towards India, it is natural for FIIs to have a positive relation with stock prices.

The India's stock market relationship with short-term interest rates is positive. The above results are consistent with Mukherjee and Naka's [3] findings for Japan as well as Bulmash and Trivoli's [21] findings for the U.S. Mukherjee and Naka [3] explained this by noting that the long-term interest rate may serve as a better proxy for the nominal risk-free component of the discount rate in stock valuation models. Alternatively, Bulmash and Trivoli [21] suggested that the long-term interest rate is a surrogate for expected inflation that is incorporated into the discount rate. Since the focus of this paper is short term interest rate, the desired result is not achieved.

Table 7

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.459473	64.59714	33.87687	0.0000
At most 1	0.177985	20.57960	27.58434	0.3024
At most 2	0.102591	11.36554	21.13162	0.6108
At most 3	0.059264	6.414769	14.26460	0.5606
At most 4	0.004540	0.477797	3.841466	0.4894

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Since the coefficient on LNEXRATE is insignificant, this yields (Table 8) the following cointegrating relationship:

LNBSE = 0.243 LNFII + 1.359 LNINT + 1.970 LNM3

Table 8

Normalized cointegrating coefficients (standard error in parentheses)

LNBSE	LNFII	LNEXRATE	LNINT	LNM3
1.000000	-0.243394**	-1.102869	-1.359855**	-1.970412**
	(0.02615)	(2.84487)	(0.49013)	(0.37043)

** denotes 5% level of significance

Money supply changes and stock returns in India are positively related, and this is also consistent with the findings for the U.S. [21] and Japan [3]. There are a few possible explanations for this. One is that an increase in money supply has a direct positive liquidity effect on the stock market. Another possibility, suggested by Mukherjee and Naka[3] is that injections of money supply have an expansionary effect that boosts corporate earnings. The third explanation follows from Fama's[2] comments on inflation: increases in real activity that drive stock returns also stimulate the demand for money via the simple quantity theory model, thus creating the positive relation between money supply and stock prices.

6.3 Innovation accounting

The cointegration analysis only captures the long-run relationship among the variables; it does not provide information on the responses of variables in the system to shocks or innovations in other variables. To find out, how the Stock markets in India responds to shocks or innovation in the macroeconomic variables, Innovation Accounting is used such as Impulse Response Function and Variance Decomposition based on Vector Error Correction Model (VECM results not shown). Figure 1 shows Impulse Response Function for various variables while the Variance decomposition is presented in table 9.

Table 9

Variance Decomposition

Period	S.E.	LNBSE	LNFII	LNINT	LNM3
1	0.088414	100.0000	0.000000	0.000000	0.000000
2	0.126391	96.02726	0.002250	2.440007	1.530478
3	0.157116	95.69641	0.141260	2.752316	1.410013
4	0.183304	95.89667	0.159644	2.622658	1.321030
5	0.207127	95.89386	0.186346	2.702288	1.217503
6	0.229119	95.82407	0.187752	2.808408	1.179769
7	0.249302	95.80103	0.195477	2.847809	1.155688
8	0.267986	95.78144	0.200413	2.884228	1.133921
9	0.285479	95.76034	0.205501	2.916201	1.117956
10	0.301989	95.74516	0.210930	2.938831	1.105080
Cholesky ordering: LNBSE, LNFII, LNINT, LNM3					

The above table gives clear insights that variations in LNBSE are mainly attributed to its own variations and to small extents by LNINT, LNM3 and LNFII. The point to note is that, in the first quarter, none of the above variables affects LNBSE. However, with the passage of time, small effects could be felt, which could really be termed as minuscule effects on LNBSE. Another point to be highlighted is that the effects of LNINT and LNFII on LNBSE increases with the time lag which suggests that markets takes time to adjust to their variations.

As for the Impulse Response Function, figure 1 suggests that LNFII doesn't have an immediate effect on LNBSE, negative responses in the second quarter, but positive long run association with one standard innovation in LNFII. The responses of LNBSE to LNINT and LNM3 are in line with the findings of this paper, which suggests a positive long run association from the first quarter itself, as visible from the graphs.

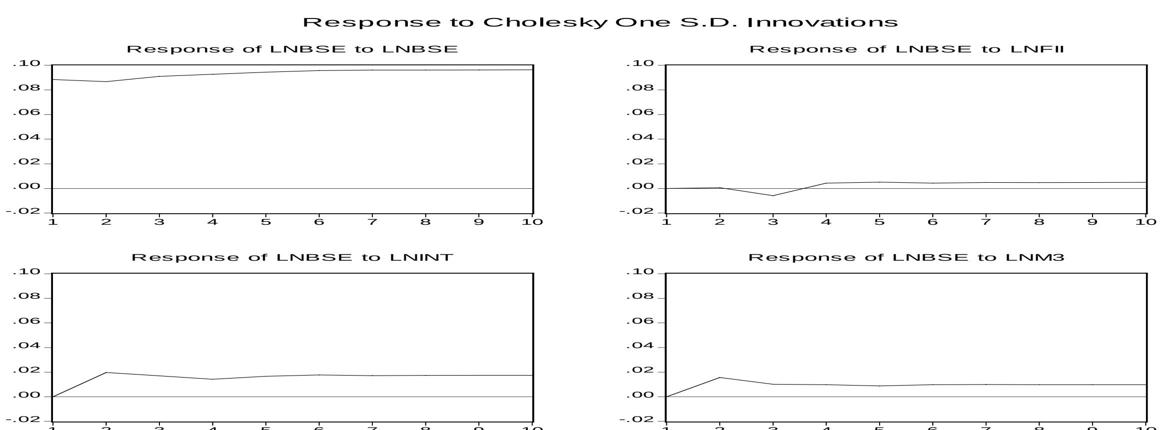

Figure 1: Impulse Response Function of LDSI to Shocks in Macroeconomic variables

6.4 Properties of Market Returns:

For our second objective, some summary statistics of the returns of NIFTY's weekly index defined as Rt are shown in table 10.

Table 10	
Statistics	Rt
Mean	1.000458
Standard deviation	.004612
Skewness	-0.753191
Kurtosis	5.902303
Maximum	1.018372
Minimum	.978364
N	333
Jarque-berra test	148.3591**
ADF test at level(with constant and trend)	-6.668**
PP test at level(with constant and trend)	-16.864**
** Denotes 5% significance level	

The average of the returns *Rt* is positive which suggests that the series have increased over the period. The statistics also show that the returns are negatively skewed which implies that the return distributions of the shares traded in our markets has a higher probability of earning negative returns. The value of the kurtosis is greater than 3, which is the case of the series not normally distributed. The daily stock returns are, thus, not normally distributed — a conclusion which is confirmed by Jarque-Bera test. Since the variable used here is the rate of returns which negates the non stationarity component and are thus stationary, this is indeed the result with both ADF and PP test.

6.5 RESULTS

A) GARCH estimation:

The GARCH family of models entails a joint estimation of the conditional mean and conditional variance equations. The model is due to Bollersev, is formulated as

$$R_t = \mu + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2_t) \qquad (11)$$

$$\sigma^2_{f.t} = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1} \qquad (12)$$

Since both variables on the RHS of the variance equation are known at time t, then a one- step-ahead conditional forecast can be made by simply iterating through the model without the need for successive substitutions or complex iterations of the conditional expectations operator.

In the GARCH (1, 1) model, the effect of a return shock on current volatility declines geometrically over time. The sizes of the parameters α_1 and β_1 determine the short-run dynamics of the resulting volatility time series. Large GARCH error coefficient α_1 means that volatility reacts quite intensely to market movements and so if α_1 is relatively high and β_1 is relatively low, then volatilities tend to be more 'spiky.' Large GARCH lag coefficients β_1 indicates that shocks to conditional variance takes long time to die out, so volatility is 'persistent', which is the case in this study as shown in table 11, where the coefficient of β_1 is large and is significant. If $\alpha_1 + \beta_1$ are close to unity, then a 'shock' at time t will persist for many future periods. A high value of $\alpha_1 + \beta_1$, therefore, implies a 'long memory', which is again a property of the return series used in this study as the value of $\alpha_1 + \beta_1$ in the GARCH estimation is very close to unity.

Table 11

GARCH (1, 1) - Dependent Variable: Rt

	Coefficient	Std. Error	z-Statistic	Prob.
C	1.000882	0.000230	4342.729	0.0000
	Variance Equation			
C	1.86E-06**	9.02E-07	2.062519	0.0392
ARCH(1)	0.242279**	0.088494	2.737786	0.0062
GARCH(1)	0.677076**	0.103500	6.541783	0.0000
** denotes 5% significance level				

B) TARCH and EGARCH estimation

A major criticism of symmetric GARCH model, as it stands is that positive and negative innovations have an identical effect upon the conditional variance since their sign becomes lost upon taking the square. There is a body of evidence that suggests that this restriction is not empirically valid; in other words, it has been noted that often negative shocks to the conditional mean equation have a larger effect upon volatility than positive shocks (leverage effect). Two models which remove the assumption of symmetric responses of volatility to shocks of different sign are the EGARCH model due to Nelson and the GJR model due to Glosten, Jaganathan and Runkle. Under these formulations, the conditional variance equations become

$$\sigma^2_{f.t} = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1} + \gamma S^-_t \varepsilon^2_{t-1} \qquad (13)$$

$$\log(\sigma^2_{f.t}) = \omega + \alpha_1 \varepsilon^2_{t-1} + \beta \log(\sigma^2_{t-1}) + \gamma \varepsilon_{t-1} / \sqrt{\sigma^2_{t-1}} + \alpha[\,|\varepsilon_{t-1}| / \sqrt{\sigma^2_{t-1}} - \sqrt{2/\Pi}\,] \qquad (14)$$

for the GJR-GARCH and EGARCH models respectively. In former equation, the asymmetry arises from the inclusion of a dummy variable, S^-_t, which takes the value one when $\varepsilon_{t-1} <= 0$and zero otherwise. In this model, good news ($\varepsilon_t < 0$) and bad news($\varepsilon_t > 0$) have differential effects on the conditional variance: good news has an impact of α and bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, then leverage effects exists. If γ is not equal to zero, the news impact is asymmetric. This very case is presented in Table 12 where the coefficient $\gamma>0$ (third coefficient in the variance equation) and is significant. Therefore, the return series Rt has leverage effect and also has the asymmetric component.

In the latter equation, the asymmetry arises from the direct inclusion of the term in ε_{t-1}, normalized by the standard deviation of the data. The latter model also has the advantage that no non-negativity constraints are required of the coefficients as they are for the other forms of GARCH model, since even negative parameter values would not cause the variance itself (σ^2_{ft}) to be negative. Here, the presence of leverage effect is tested by the hypotheses that $\gamma<0$.The news impact is asymmetric if γ is not equal to zero. This is indeed true as shown in Table 13 (Third coefficient in the variance equation is negative and significant).

Table 12

TARCH- Dependent Variable: Rt

	Coefficient	Std. Error	z-Statistic	Prob.
C	1.000802	0.000235	4250.040	0.0000
	Variance Equation			
C	2.09E-06**	9.48E-07	2.200121	0.0278
ARCH(1)	0.137578	0.086554	1.589502	0.1119
(RESID<0)*ARCH(1)	0.203224**	0.102078	1.990872	0.0465
GARCH(1)	0.658632**	0.100867	6.529683	0.0000

Table 13

EGARCH- Dependent Variable: Rt

	Coefficient	Std. Error	z-Statistic	Prob.
C	1.000805	0.000229	4377.026	0.0000
	Variance Equation			
C	-2.034263**	0.739185	-2.752036	0.0059
|RES|/SQR[GARCH](1)	0.350227**	0.106447	3.290139	0.0010
RES/SQR[GARCH](1)	-0.154905**	0.052226	-2.966072	0.0030
EGARCH(1)	0.841048**	0.063316	13.28333	0.0000
** denotes 5% significance level				

C) PARCH estimation

Taylor and Schwert introduced standard deviation GARCH model, where the standard deviation is modeled rather than the variance. This model, along with several other models, is generalized in Ding et al with the power ARCH specification. In this model, the power parameter δ of the standard deviation can be estimated rather than imposed, and additional γ parameters are added to capture asymmetry of up to order r:

$\sigma_t^{\delta} = w + \Sigma \beta_j \sigma^{\delta}_{t-j} + \Sigma \alpha_i (\varepsilon_{t-i} - \gamma_i \varepsilon_{t-i})^{\delta}$ (15)

Where $\delta > 0$, $\gamma_i <= 1$ for i=1…..r, $\gamma i = 0$ for all i>r and r<=p (16)

The symmetric model sets $\gamma_i = 0$ for all i. Note that if $\delta = 2$ and $\gamma_i = 0$ for all i, the PARCH model is simply a standard GARCH specification. PARCH estimation is again a confirmation of asymmetry present in return series Rt as the coefficient C4 is positive and significant as shown in table 14.

Table 14 PARCH- Dependent Variable: Rt				
	Coefficient	Std. Error	z-Statistic	Prob.
C	1.000797	0.000231	4334.584	0.0000
	Variance Equation			
C(2)	0.000557**	0.000238	2.341575	0.0192
C(3)	0.174642**	0.055318	3.157043	0.0016
C(4)	0.438449**	0.181982	2.409291	0.0160
C(5)	0.727513**	0.080859	8.997327	0.0000
** denotes 5% significance level				

6.6 The Volatility Forecast Evaluation

A) Evaluation of forecast errors- The results are presented in tables 16, 17, 18 and 19. Following conclusions could be drawn.

- Absolute measures of forecast error don't follow the usual pattern, which states that errors should increase with longer time horizons. This suggests that the series are so volatile that it is not so much predictable.
- Relative measures of forecast error, however has increased over the time period for all the methods, except for EGARCH.
- Only GARCH is the process where both measures of forecast error have increased over the time period.

Table 15 **Forecast errors for GARCH**			
	One week ahead	Three weeks ahead	Six weeks ahead
MAE	4.69E-05	4.67E-05	4.87E-05
MSE	5.30E-09	5.29E-09	5.59E-09
RMSE	7.28E-05	7.28E-05	7.47E-05
MPE	-5.17025	-5.80E+00	-7.85E+00
RMSPE	7.609951	8.710543	11.85955

Table 16 Forecast errors for TARCH			
	One week ahead	Three weeks ahead	Six weeks ahead
MAE	5.07E-05	4.16E-05	4.29E-05
MSE	7.01E-09	7.57E-09	4.46E-09
RMSE	8.37E-05	7.49E-05	6.68E-05
MPE	-5.41168	-5.501095	-7.190143
RMSPE	7.946366	8.268005	11.53041

Table 17 Forecast errors for EGARCH			
	One week ahead	Three weeks ahead	Six weeks ahead
MAE	3.56E-05	2.19E-05	1.78E-05
MSE	2.84E-09	8.30E-10	4.35E-10
RMSE	5.33E-05	2.88E-05	2.09E-05
MPE	-4.56163	-3.672351	-4.199557
RMSPE	7.051415	6.033145	8.147095

Table 18 Forecast errors for PARCH			
	One week ahead	Three weeks ahead	Six weeks ahead
MAE	4.34E-05	3.97E-05	1.15E-04
MSE	4.01E-09	4.31E-05	1.77E-07
RMSE	6.33E-05	6.57E-03	0.000421
MPE	-5.1709	-11.17838	-24.8274
RMSPE	7.521302	35.786	91.2675

B) Evaluation of methods across different time horizons: The results are presented in tables 19, 20 and 21.The results are supplemented by figures 2, 3 and 4. Following conclusions could be drawn.

- One dominant result which came out is the emergence of EGARCH as the best forecasting tool available , as it has got minimum errors at every time horizons.

Table 19

For One Week Ahead Forecast

	MAE	MSE	RMSE	MPE	RMSPE
GARCH	4.69E-05	5.30E-09	7.28E-05	-5.170254	7.609951
TARCH	5.07E-05	7.01E-09	8.37E-05	-5.411685	7.946366
EGARCH	3.56E-05	2.84E-09	5.33E-05	-4.561634	7.051415
PARCH	4.34E-05	4.01E-09	6.33E-05	-5.1709	7.521302

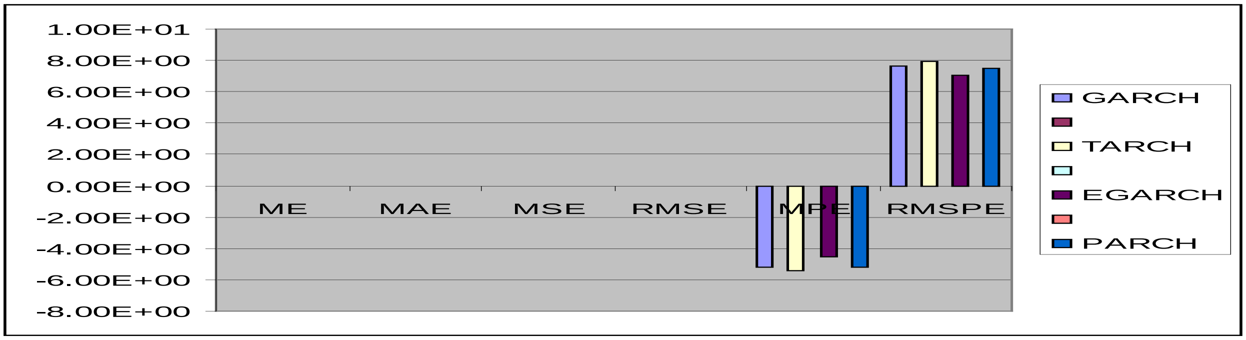

Figure 2: For One Week Ahead Forecast

Table 20

For three Weeks Ahead Forecast

	MAE	MSE	RMSE	MPE	RMSPE
GARCH	4.67E-05	5.29E-09	7.28E-05	-5.80E+00	8.710543
TARCH	4.16E-05	7.57E-09	7.49E-05	-5.501095	8.268005
EGARCH	2.19E-05	8.30E-10	2.88E-05	-3.672351	6.033145
PARCH	3.97E-05	4.31E-05	6.57E-05	-11.17838	35.786

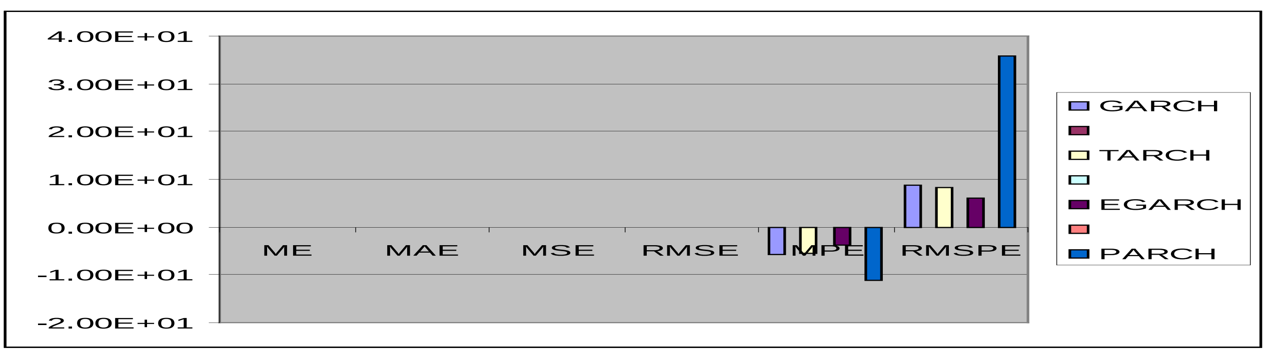

Figure 3: For three Weeks Ahead Forecast

Table 21 For six Week Ahead Forecast					
	MAE	MSE	RMSE	MPE	RMSPE
GARCH	4.87E-05	5.59E-09	7.47E-05	-7.85E+00	11.85955
TARCH	4.29E-05	4.46E-09	6.68E-05	-7.190143	11.53041
EGARCH	1.78E-05	4.35E-10	2.09E-05	-4.199557	8.147095
PARCH	1.15E-04	1.77E-07	0.000421	-24.8274	91.2675

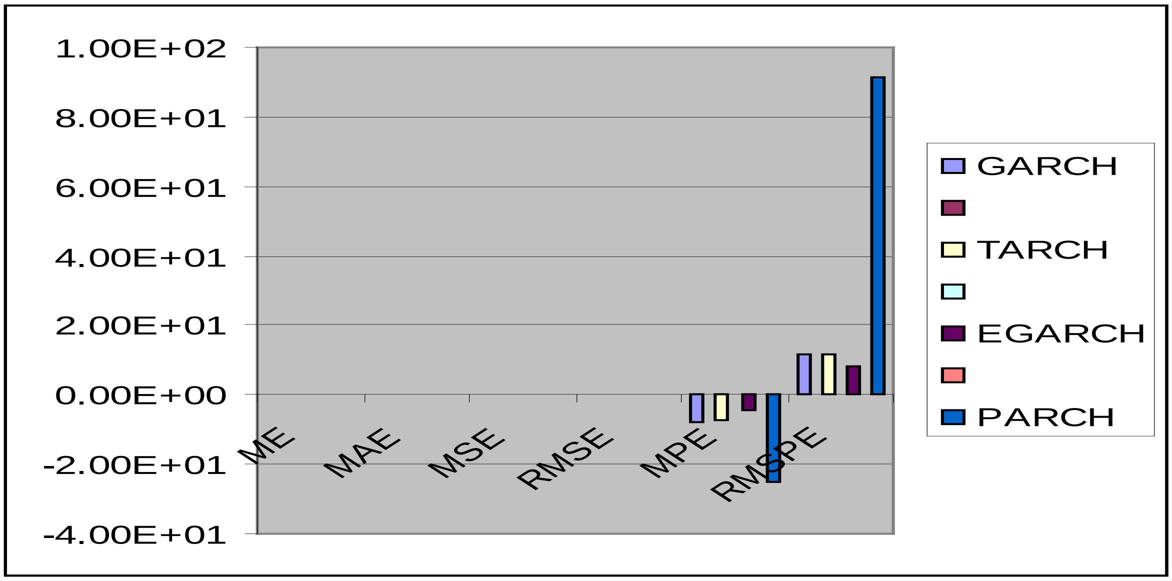

Figure 4: For six Weeks Ahead Forecast

7. Conclusions

This paper examined role of four macroeconomic factors on the stock prices variations with the help of cointegration analysis and innovation accounting techniques. The results were robust as one cointegrating vector was found. However, innovation accounting techniques divulged further details where it was found that the variations in stock prices were mainly attributed to its own variations. The other important fact which came out of this paper was the emergence of EGARCH method as the best forecasting tool available, among others. However, as there is so much of randomness involved which is very much visible from the forecast errors obtained for different methods, it is advisable not to forecast beyond one period in cases of such volatile series.

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