ECONOMETRIC MODELING OF MACROECONOMIC DETERMINANTS OF STOCK MARKET VOLATILITY IN INDIA WITH SPECIAL REFERENCE TO NSEIL

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ABSTRACT

Modeling and forecasting volatility of a financial time series has become a very prominent area for research last few years. These models provide precise estimate of conditional variance process and make a good forecast of future volatility that may help the stakeholders in obtaining efficient portfolio and accurate derivative prices of financial instruments. This paper aims at developing an econometric model for predicting stock market variability affected due to variations in the macroeconomic indicators. This paper considered twelve years' monthly data of Returns of Monthly Averages of S&P CNX Nifty (NRTS) as dependent variable and fifteen independent macroeconomic variables selected from different segments of economy. In the process, variables as described in the econometric function for stock market returns at NSE are first tested for unit root and stationary and then causal links among dependent and independent variables are explored by using Granger causality in bi-variate and multivariate VAR framework. The Multivariate GARCH models developed for predicting NRTS affected due to variations in various sets of macroeconomic variables indicate that though these models are capable of measuring the impact of changes in one/ set of series on the other series of same amplitude, but, are suitable in short period only.

Keywords: Stock market volatility, Macroeconomic determinants, Econometric modeling, VAR frameworks, DCC MGARCH model

INTRODUCTION

Volatility is a symptom and an integral part of a highly liquid stock market alternating bull and bear phases. Investors interpret a rise in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets. The issues of volatility and risk have become more important in recent times for financial practitioners, market participants, regulators, policy makers and researchers. The volatility of stock market indicators goes beyond anyone's reasonable explanations. Industry performances, economic and political changes are among the major factors that can affect the stock market behavior. Stock market volatility, in general, is affected by both micro and macro variables. Micro variables include corporate results announcements, business life cycles, business risk, financial Leverage etc., and macro variables, the indicators of country's economy, primarily include gross domestic product, inflation rate, interest rate, exchange rate, petroleum and gold prices, forex reserves, stock trading volume, foreign institutional investment etc. Economists view that though stock performance of a particular company is influenced by micro variables, the macro variables drop impact on the whole stock market behavior.

The relationship between macroeconomic variables and stock market returns by now, is well documented in literature. A significant research has been done to investigate the relationship between stock market returns and a range of macroeconomic variables across a number of stock markets in different time horizons. Bhattacharya and Mukherjee (2001, 2006) investigated causal relationship between stock indices (BSE Sensex) and selected macroeconomic variables, viz., money supply, index of industrial production, national income, inflation rate, real effective exchange rate, foreign exchange reserves and trade balance. They found no evidence of causal linkages between stock returns and the macroeconomic variables under consideration. Kumar (2009) in a study conducted on return at NSE observed a causal linkage between FII and stock returns. He however mentioned that there exists no long-run equilibrium relationship between stock returns. Corradi, Distaso and Mele (2009) and Ali et al. (2010) also rejected the hypotheses of causal relation between selected macroeconomic indicators and stock returns at KSE, Pakistan. Kumar and Puja (2012) discovered that macroeconomic variables and the stock market indices are cointegrated and, hence, there exists long-run equilibrium relationship between them.

Sharma and Mahendru (2010) developed regression model to analyze long term relationship between selected macroeconomic variables and stock prices at BSE, India. They observed highly significant impact of exchange rates and gold prices and very limited impact of forex reserves and inflation on stock prices. Maysami, Howe and Hamzah (2004) in a study indicated that Singapore stock market form co-integrating relationship with changes in the short and long-term interest rates, industrial production, price levels, exchange rates, and money supply. Adam and Tweneboah (2008) also, in similar way observed long run cointegrating relationship between selected macroeconomic variable and Stock return in Ghana. Flad (2006) and Humpe and Macmillan (2007) also observed that macroeconomic factors help to forecast volatility of stock returns. Diebold and Yilmaz (2008) in a study conducted cross section analysis of stock market returns in forty four countries observed clear link between macroeconomic fundamentals and stock market volatilities. Asaolu and Ogunmuyiwa (2011) also investigated impact of macroeconomic variables on Average stock prices and observed weak relationship between average share prices and macroeconomic variables in Nigeria. To encapsulate, a number of studies found evidences of causal relationship between macroeconomic variables and stock market performance, while some rejected the hypotheses of relationship between these variables. Thus, the findings of studies are not substantial in drawing exact relationship between diverse macroeconomic variables and stock prices. This entails identification of a set of macroeconomic variables that can be used for modeling stock market volatility.

To discover and analyze causal relations and dynamic interactions between macroeconomic variables and stock market performance and to forecast stock market indices, many researchers in the past used regression methods and ARIMA models. But, they failed to produce accurate forecast because of non-linearity in data series and inherent limitations of modeling techniques. This paper is an attempt to develop an econometric model for predicting stock market variability affected due to variations in the macroeconomic indicators. It considered twelve years' monthly data spanning from 1999-00 to 2010-11 on daily return of S&P CNX Nifty as dependent variable and fifteen independent macroeconomic variables grouped into five major categories, viz. real economy indicators, forex market indicators, money market indicators, stock market indicators and commodity market indicators (table 1). The paper is divided into five sections. Section one is concerned with theoretical foundations and review of literature, section two is about econometric methodologies and model specifications. It discusses issues related with confirmation of the stationarity of time series data through ADF unit root test, lag order selection, checking of the interdependence of macroeconomic determinants and the stock market volatility via Granger Causality test after declaring the variables in bi-variate and multivariate Vector Auto Regression (VAR) frameworks, GARCH modeling and estimation through DCC MGARCH model. Section three portrays analysis and findings, section four is concerned with estimation of stock market behavior via DCC MGARCH model, and section five concludes the paper. The analysis of data is done by using STATA (SE 12.0).

Table 1: The Data

Dependent Variable			Data Source
	NRTS	Log. Returns of Monthly Averages of S&P CNX NIFTY (Base: November 3, 1995 = 1000)	dbie.rbi.org.in
Independent Variables	(A) Real Economy Indicators		
	GDP	GDP at Factor Cost: Current Prices- Rs. Crore (Base: 2004-05)	dbie.rbi.org.in
	IIP	Monthly Index of Industrial Production (Base: 1993-94=100)	dbie.rbi.org.in
	WPI	Wholesale Price Index: Monthly Avg. (Base: 2004-05=100)	dbie.rbi.org.in
	(B) Forex Market Indicators		
	BOP	India's Overall Balance of Payments: Quarterly (Rs. Crore)	dbie.rbi.org.in
	FXRE	Monthly Foreign Exchange Reserves (Rs. Crore)	dbie.rbi.org.in
	FXRA	Monthly Average of Exch. Rate of INR (Rs. per unit of USD)	dbie.rbi.org.in
	(C) Money Market Indicators		
	RPR	Repo Rate	dbie.rbi.org.in
	TBR	Monthly Avg. of Implicit Yield at Cut-off Price: 91 Day T Bills	dbie.rbi.org.in
	PLR	Prime Lending Rate (SBAR: State Bank Advance Rate)	in.reuters.com
	(D) Stock Market Indicators		
	FII	Monthly Net Investment by FIIs in the India (Rs. Crore)	dbie.rbi.org.in
	TRV	Monthly Traded Volume in Corp. Debt at NSE (Rs. Crore)	dbie.rbi.org.in
	MCP	Monthly Market Capitalization-NSE (Rs. Crore)	dbie.rbi.org.in
	(E) Commodity Market Indicators		
	CRO	Monthly Cushing, OK WTI Spot Price FOB (USD per Barrel)	eia.gov
	GLD	Monthly Avg. of Gold Prices: Mumbai (Rs. per 10 Gm.)	dbie.rbi.org.in
	SLV	Monthly Avg. of Silver Prices: Mumbai (Rs. per Kg.)	dbie.rbi.org.in

Econometric Modeling Methodology

The econometricians have mentioned three phases of econometric models. These are specification, estimation and prediction. Model specification hypothesizes that the dependent variable Y is linearly related to the explanatory variable X (Gujarati, 2004). Based on variables considered in present study (table 1), the econometric function for stock market returns at NSE can be specified as:

$$NRTS_t=\beta_0+\beta_1 GDP_t+\beta_2 IIP_t+\beta_3 WPI_t+\beta_4 BOP_t+\beta_5 FXRE_t+\beta_6 FXRA_t+\beta_7 RPR_t+\beta_8 TBR_t+\beta_9 PLR_t$$

$$+\beta_{10} FII_t+\beta_{11} TRV_t+\beta_{12} MCP_t+\beta_{13} CRO_t+\beta_{14} GLD_t+\beta_{15} SLV_t+\varepsilon_t$$

Econometric methodology states that before using time series data for further investigation it must be tested for unit root and stationary. To confirm the stationarity of data series by identifying the appropriate level of differencing and declaring the order of integration, ADF unit root test is employed. The basic equation of ADF unit root test is:

$$\Delta X_t = \beta_1 + \beta_2 t + \beta_3 X_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta X_{t-i} + \varepsilon_t$$

Here, ε_t is pure white noise error term, p is maximum length of the lagged dependent variable, and α_i is the parameter of lagged first. The test results (table 2) indicate that NRTS and FII are stationary at I(0), SLV is stationary at I(2) and all other variables are stationary at I(1).

For fitting a VAR of the correct order four lag order selection criterions are common. Among these Final Prediction Error (FPE) is not an information criterion. However, it is included as an information criterion to minimize the prediction error. The Akaike Information Criterion (AIC) measures the discrepancy between the given model and the true model, which, in principle should be minimum.

Table 2: ADF Unit Root Test Results

S. No.	Variables	Lag Order	Order of Integration	T-Statistics	P-Value
1.	NRTS	3	I(0)	-5.537	0.000*
2.	GDP	1	I(0)	1.753	0.998
	DGDP	3	I(1)	-5.513	0.000*
3.	IIP	4	I(0)	0.879	0.992
	DIIP	3	I(1)	-5.533	0.000*
4.	WPI	4	I(0)	1.889	0.998
	DWPI	4	I(1)	-5.332	0.000*
5.	BOP	4	I(0)	-3.026	0.032
	DBOP	3	I(1)	-7.283	0.000*
6.	FXRE	4	I(0)	-0.024	0.956
	DFXRE	3	I(1)	-4.871	0.000*
7.	FXRA	2	I(0)	-2.183	0.212
	DFXRA	1	I(1)	-7.669	0.000*
8.	RPR	3	I(0)	-2.123	0.235
	DRPR	2	I(1)	-7.873	0.000*
9.	TBR	1	I(0)	-1.980	0.295
	DTBR	1	I(1)	-7.774	0.000*
10.	PLR	3	I(0)	-1.440	0.562
	DPLR	2	I(1)	-6.354	0.000*
11.	FII	1	I(0)	-5.859	0.000*
12.	TRV	2	I(0)	-1.237	0.657
	DTRV	1	I(1)	-12.120	0.000*
13.	MCP	1	I(0)	0.090	0.965
	DMCP	0	I(1)	-11.445	0.000*
14.	CRO	3	I(0)	-1.677	0.443
	DCRO	2	I(1)	-5.172	0.000*
15.	GLD	1	I(0)	2.560	0.999
	DGLD	0	I(1)	-11.433	0.000*

16.	SLV DSLV DDSLV	4 4 3	I(0) I(1) I(2)	2.669 -2.596 -8.484	0.999 0.093 0.000*

Notes:
(i) Variable labels without any prefix are stationary at their own level, I(0); labels prefixed with D are stationary after differencing once, I(1); and the variables prefixed with DD are stationary after differencing twice, I(2).
(ii) * denotes rejection of null hypothesis at 99% confidence level.
(iii) The respective critical value is -3.497.
(vi) Akaike Information Criterion is used for lag order selection.

The Hannan-Quinn Information Criterion (HQIC) and Schwarz's Bayesian Information Criterion (SBIC) are also interpreted similar to the AIC. The model form of log likelihood (LL) for VAR is:

$$LL = \left(\frac{T}{2}\right)\left\{\ln\left(\left|\hat{\Sigma}^{-1}\right|\right) - K\ln(2\pi) - K\right\}$$

Here, T is number of observations, K is number of equations, and $\hat{\Sigma}$ is the maximum likelihood estimate denoted as $E[u_t u_t']$. In this, u_t is the $K \times 1$ vector of disturbances. The results of VAR lag order selection based on all the four criterions (table 3) show maximum value of log likelihood for four lags, thus it selects the model with four lags. The minimum value based information viz., FPE and AIC also confirm the lag order of four for the VAR estimation. But SBIC and HQIC chose a model with two lags. This paper considered lag order of four for further estimation as it is also supported by the likelihood ratio test.

Table 3: VAR Lag Order Selection Criteria

Lag	LL	LR	DF	Sig.	FPE	AIC	SBIC	HQIC
0	-14270.3				0.000	204.091	204.227	204.427
1	-12215.7	4109.2	256	0.000	0.000	178.396	180.719*	184.112*
2	-11881.1	669.19	256	0.000	0.000	177.274	181.782	188.368
3	-11493.8	774.61	256	0.000	0.000	175.398	182.092	191.871
4	-11168.1	651.44*	256	0.000	0.000*	174.402*	183.282	196.254

Notes: * indicates lag order selected by the criterion.

The causal relationship between stock market volatility and selected macroeconomic determinants, and also the relationship among selected macroeconomic determinants is traced using Granger causality test proposed by Granger (1969) in the Vector Auto Regression (VAR) framework.

Granger Causality test assumes that variables under consideration are stationary. If the time series has unit root or unit roots in it, then it should be differenced once or twice or more for following the stationary process. The mathematical form of Granger Causality test in a bi-variate autoregressive framework is as follows.

$$X(t) = \sum_{j=1}^{p} A_{11,j}X(t-j) + \sum_{j=1}^{p} A_{12,j}Y(t-j) + \varepsilon_1(t)$$

$$Y(t) = \sum_{j=1}^{p} A_{21,j}X(t-j) + \sum_{j=1}^{p} A_{22,j}Y(t-j) + \varepsilon_2(t)$$

Here, X and Y are the variables, p is the maximum length of the lagged observations, A is the matrix that contains coefficients of the model, and ε_1 and ε_2 are the prediction errors.

Vector Auto-regression (VAR) models, used for forecasting and also for analyzing causal relationship among economic time series variables, are multi-equation systems in which all the variables are treated as endogenous variable. The use of VARs for causal inferences is known as structural modeling. Mathematically, in a VAR model, each of the endogenous variables is explained by its lagged or past values and the lagged values of other endogenous variables in the model. A bi-variate VAR model for X and Y variables can be formulated as:

$$X_t = A_0 + A_1X_{t-1} + A_2X_{t-2} \dots A_pX_{t-p} + A_1Y_{t-1} + A_2Y_{t-2} \dots A_pY_{t-p} + u_t$$

$$Y_t = A_0 + A_1X_{t-1} + A_2X_{t-2} \dots A_pX_{t-p} + A_1Y_{t-1} + A_2Y_{t-2} \dots A_pY_{t-p} + u_t$$

Here, A_o is a vector of constant terms, A_p is the matrices of constants to be estimated, u_t is a vector of residuals and assumed to be white noise and p is the lag length. With the same notations, a multivariate VAR model for the variables X, Y and Z can be framed as:

$$X_t = A_0 + A_1X_{t-1} + A_2X_{t-2} \dots A_pX_{t-p} + A_1Y_{t-1} + A_2Y_{t-2} \dots A_pY_{t-p} + A_1Z_{t-1} + A_2Z_{t-2} \dots A_pZ_{t-p} + u_t$$

$$Y_t = A_0 + A_1X_{t-1} + A_2X_{t-2} \dots A_pX_{t-p} + A_1Y_{t-1} + A_2Y_{t-2} \dots A_pY_{t-p} + A_1Z_{t-1} + A_2Z_{t-2} \dots A_pZ_{t-p} + u_t$$

$$Z_t = A_0 + A_1X_{t-1} + A_2X_{t-2} \dots A_pX_{t-p} + A_1Y_{t-1} + A_2Y_{t-2} \dots A_pY_{t-p} + A_1Z_{t-1} + A_2Z_{t-2} \dots A_pZ_{t-p} + u_t$$

In a VAR model no contemporaneous variables as explanatory are included on the right-hand side, thus all the equations have same form since they share the same right-hand side. In a VAR equation all the included variables are treated as endogenous and depend on all the others.

The VAR models can be used for forecasting, but not for structural analysis and policy evaluation. Thus, an analytical research requires further test such as Granger Causality and models such as Multi-variate GARCH for identifying the proper sensitivity among the variables.

To delve deeper into the association of macroeconomic environment of the country and stock market performance, the study used Generalized ARCH (GARCH) models. These models are considered efficient for modeling the volatility of financial assets (Francq and Zakoian, 2010). The newly developed Multivariate GARCH (MGARCH) models allow the conditional covariance matrix of the dependent variables to follow a flexible dynamic structure. They also allow the conditional mean to follow a VAR structure. MGARCH implements four commonly used parameterizations viz., the Diagonal Vech (DVECH) model, the Constant Conditional Correlation (CCC) model, the Dynamic Conditional Correlation (DCC) model, and the Varying Conditional Correlation (VCC) model. The general form of MGARCH model is written as:

$$y_t = Cx_t + \epsilon_t \text{ , and } \epsilon_t = H_t^{1/2} v_t$$

Here, y_t is an m × 1 vector of dependent variables, C is an m × k matrix of parameters, x_t is a k × 1 vector of independent variables which may contain lags of y_t. $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t, and v_t is an m × 1 vector of zero-mean, unit variance, and independent and identically distributed innovations. Various MGARCH models proposed in the literature differ in how they trade off flexibility and parsimony in their specifications for H_t (matrix generalization of uni-variate GARCH models). Increased flexibility allows a model to capture more complex H_t processes and increased parsimony makes parameter estimation feasible for more data sets. An important measure of the flexibility parsimony trade-off is how fast the number of model parameters increases with the number of time series m.

The DVECH MGARCH models (Bollerslev, Engle and Wooldridge, 1988), despite large number of parameters and diagonal structure implies that each conditional variance and each conditional covariance depends on its own past but not on the past of the other conditional variances and co-variances. Conditional Correlation MGARCH (CCMGARCH) models use nonlinear combinations of uni-variate GARCH models to represent the conditional co-variances. In each of the conditional correlation models, the conditional co-variance matrix is positive definite by construction and has a simple structure which facilitates parameter estimation. In CCMGARCH models, H_t is decomposed into a matrix of conditional correlations R_t and a diagonal matrix of conditional variancesD_t. The basic CC MGARCH model is written as:

$$H_t = D_t^{1/2} R_t D_t^{1/2}$$

In the above equation, each conditional variance follows a uni-variate GARCH process and the parameterizations of R_t vary across models. There are three CC models implemented in MGARCH which differ in a way that how they parameterize R_t. These are as follows.

- Constant Conditional Correlation MGARCH Model: The model was proposed by Bollerslev in 1990. In this model the correlation matrix is time invariant. The model restricts R_t to a constant matrix, reduces the number of parameters, and simplifies the estimation. But, it may be too strict in many empirical applications.
- Dynamic Conditional Correlation MGARCH Model: In DCCMGARCH model (Engle, 2002) the conditional quasi correlations R_t follow a GARCH (1,1) process. To preserve parsimony, the model restricts all the conditional quasi correlations to follow the same dynamics. The DCC model is more flexible than the CCC model without introducing an inestimable number of parameters for a reasonable number of series.
- Varying Conditional Correlation MGARCH Model: In VCCMGARCH model (Tse and Tsui, 2002) the conditional correlations at each period are weighted sum of a time-invariant component, a measure of recent correlations among the residuals, and last period's conditional correlations. The model, for parsimony restricts all the conditional correlations to follow the same dynamics.

To develop a model for predicting the volatility of NRTS caused due to selected macroeconomic determinants, the study used DCC MGARCH model because it is as flexible as VCC MGARCH model, more flexible than CCC, and more parsimonious than the DVECH MGARCH model. In DCC MGARCH models, conditional variances are modeled as uni-variate GARCH models and the conditional co-variances are modeled as nonlinear functions of the conditional variances. The conditional quasi correlation parameters that weight the nonlinear combinations of the conditional variances follow the GARCH-like process (Engle, 2002). MGARCH models are dynamic multivariate regression models in which the conditional variances and co-variances of the errors follow an autoregressive-moving-average structure. MGARCH models differ in the parsimony and flexibility of their specifications for a time-varying conditional covariance matrix of the disturbances, denoted by H_t. In a DCC MGARCH model:

$$h_{ij,t} = p_{ij,t}\sqrt{h_{ii,t}h_{jj,t}}$$

Here, the diagonal elements $h_{ii,t}$ and $h_{jj,t}$ follow uni-variate GARCH processes and $p_{ij,t}$, t follows the dynamic process. As in $p_{ij,t}$, t varies with time, the model is popularized as the Dynamic Conditional

Correlation MGARCH model. The basic DCC MGARCH model proposed by Engle (2002) can be written as:

$$y_t = Cx_t + \epsilon_t, \epsilon_t = H_t^{1/2} v_t, H_t = D_t^{1/2} R_t,$$
$$R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \mathrm{diag}(Q_t)^{-1/2}, \text{ and}$$
$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \tilde{\epsilon}_{t-1} \tilde{\epsilon}'_{t-1} + \lambda_2 Q_{t-1}$$

In the above equations, y_t is an m × 1 vector of dependent variables; C is a m × k matrix of parameters; X_t is a k × 1 vector of independent variables, which may contain lags of y_t; $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t; v_t is an m × 1 vector of normal, independent and identically distributed innovations; D_t is a diagonal matrix of conditional variances; and R_t is a matrix of conditional quasi correlations. $\tilde{\epsilon}_t$ is an m × 1 vector of standardized residuals, $D_t^{-1/2} \epsilon_t$; λ_1 and λ_2 are parameters that govern the dynamics of conditional quasi correlations (these are non-negative and satisfy $0 \leq \lambda_1 + \lambda_2 < 1$); and Q_t is the stationary time series. The DCC MGARCH model reduces to the CCC MGARCH model, if $\lambda_1 = \lambda_2 = 0$.

RESULTS AND DISCUSSION

To explore the existence of causality/ exogeneity between Returns of Monthly Averages of S&P CNX NIFTY (NRTS) and the selected macroeconomic variables selected from different segments of economy (the real economy indicators, forex market indicators, money market indicators, stock market indicators and commodity market indicators) the Granger causality test in a bivariate VAR framework is applied. The test results explored in bi-variate VAR framework at 5 percent level of significance (table 4 and 5) indicate that DMCP and NRTS, and NRTS and DRPR have unidirectional causality and a bidirectional causal relationship is observed between DBOP and NRTS. All the other variables under study have no causal relation with NRTS.

Table 4: Granger Causality Test for NRTS and Selected Indicators in Bivariate Framework

S. No.	Null Hypothesis	F-Stat.	P-Value	H_O Rejected/Not Rejected	Causality Inference
1	NRTS doesn't Granger cause to DGDP	1.019	0.399	H_O Not Rejected	Exogeneity
2	DGDP doesn't Granger cause to NRTS	0.912	0.458	H_O Not Rejected	
3	NRTS doesn't Granger cause to DIIP	0.968	0.427	H_O Not Rejected	Exogeneity
4	DIIP doesn't Granger cause to NRTS	0.046	0.995	H_O Not Rejected	
5	NRTS doesn't Granger cause to DWPI	1.637	0.168	H_O Not Rejected	Exogeneity
6	DWPI doesn't Granger cause to NRTS	1.521	0.199	H_O Not Rejected	
7	NRTS doesn't Granger cause to DBOP	2.932	0.023*	H_O Rejected	Bidirectional Causality Feedback
8	DBOP doesn't Granger cause to NRTS	2.372	0.050*	H_O Rejected	
9	NRTS doesn't Granger cause to DFXRE	1.823	0.128	H_O Not Rejected	Exogeneity
10	DFXRE doesn't Granger cause to NRTS	1.316	0.267	H_O Not Rejected	
11	NRTS doesn't Granger cause to DFXRA	1.207	0.310	H_O Not Rejected	Exogeneity
12	DFXRA doesn't Granger cause to NRTS	1.110	0.354	H_O Not Rejected	
13	NRTS doesn't Granger cause to DRPR	3.702	0.006*	H_O Rejected	Unidirectional Causality NRTS→DRPR
14	DRPR doesn't Granger cause to NRTS	1.846	0.123	H_O Not Rejected	
15	NRTS doesn't Granger cause to DTBR	1.444	0.223	H_O Not Rejected	Exogeneity
16	DTBR doesn't Granger cause to NRTS	2.045	0.091	H_O Not Rejected	
17	NRTS doesn't Granger cause to DPLR	0.498	0.736	H_O Not Rejected	Exogeneity
18	DPLR doesn't Granger cause to NRTS	1.128	0.345	H_O Not Rejected	
19	NRTS doesn't Granger cause to FII	0.649	0.628	H_O Not Rejected	Exogeneity
20	FII doesn't Granger cause to NRTS	2.096	0.084	H_O Not Rejected	
21	NRTS doesn't Granger cause to DTRV	0.292	0.882	H_O Not Rejected	Exogeneity
22	DTRV doesn't Granger cause to NRTS	0.674	0.610	H_O Not Rejected	
23	NRTS doesn't Granger cause to DMCP	0.729	0.573	H_O Not Rejected	Unidirectional Causality DMCP→NRTS
24	DMCP doesn't Granger cause to NRTS	9.236	0.000*	H_O Rejected	
25	NRTS doesn't Granger cause to DCRO	1.387	0.241	H_O Not Rejected	Exogeneity
26	DCRO doesn't Granger cause to NRTS	1.596	0.179	H_O Not Rejected	
27	NRTS doesn't Granger cause to DGLD	0.459	0.765	H_O Not Rejected	Exogeneity
28	DGLD doesn't Granger cause to NRTS	0.851	0.494	H_O Not Rejected	
29	NRTS doesn't Granger cause to DDSLV	0.230	0.921	H_O Not Rejected	Exogeneity
30	DDSLV doesn't Granger cause to NRTS	0.100	0.982	H_O Not Rejected	

Notes: (i) [*] denotes rejection of null hypothesis at 95% confidence level.
(ii) No. of Observations: 140 for all the hypotheses.

Table 5: Bi-variate VAR Framework for NRTS and Explanatory Variables

Equation No.		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DGDP_{t-1}$	$DGDP_{t-2}$	$DGDP_{t-3}$	$DGDP_{t-4}$	Constant
1	$NRTS_t$	0.423 (0.000)	-0.239 (0.007)	0.219 (0.013)	-0.102 (0.216)	0.000 (0.531)	0.000 (0.361)	-0.000 (0.618)	-0.000 (0.109)	0.007 (0.187)
2	$DGDP_t$	81735.59 (0.159)	4737.621 (0.940)	76178.45 (0.217)	-56787.43 (0.331)	-0.053 (0.524)	-0.069 (0.397)	0.185 (0.030)	-0.047 (0.576)	10216.09 (0.012)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DIIP_{t-1}$	$DIIP_{t-2}$	$DIIP_{t-3}$	$DIIP_{t-4}$	Constant
3	$NRTS_t$	0.425 (0.000)	-0.255 (0.004)	0.236 (0.007)	-0.110 (0.192)	0.000 (0.720)	0.000 (0.987)	-0.000 (0.996)	0.000 (0.957)	0.006 (0.224)
4	$DIIP_t$	19.153 (0.232)	-9.795 (0.570)	29.568 (0.083)	-5.701 (0.726)	-0.684 (0.000)	-0.161 (0.126)	0.197 (0.063)	0.051 (0.573)	2.260 (0.037)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DWPI_{t-1}$	$DWPI_{t-2}$	$DWPI_{t-3}$	$DWPI_{t-4}$	Constant
5	$NRTS_t$	0.423 (0.000)	-0.239 (0.007)	0.232 (0.008)	-0.123 (0.140)	-0.004 (0.544)	0.000 (0.911)	0.009 (0.235)	-0.017 (0.026)	0.012 (0.078)
6	$DWPI_t$	1.050 (0.240)	1.154 (0.228)	0.609 (0.521)	0.551 (0.542)	0.320 (0.000)	0.060 (0.470)	0.303 (0.000)	-0.267 (0.001)	0.259 (0.001)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DBOP_{t-1}$	$DBOP_{t-2}$	$DBOP_{t-3}$	$DBOP_{t-4}$	Constant
7	$NRTS_t$	0.377 (0.000)	-0.275 (0.002)	0.203 (0.019)	-0.142 (0.081)	0.000 (0.303)	0.000 (0.237)	0.000 (0.005)	0.000 (0.301)	0.008 (0.097)
8	$DBOP_t$	87385.92 (0.001)	-11175.7 (0.676)	10800.92 (0.683)	-17486.41 (0.482)	-0.056 (0.502)	-0.018 (0.815)	-0.344 (0.000)	-0.079 (0.356)	-620.345 (0.695)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DFXRE_{t-1}$	$DFXRE_{t-2}$	$DFXRE_{t-3}$	$DFXRE_{t-4}$	Constant
9	$NRTS_t$	0.449 (0.000)	-0.220 (0.015)	0.201 (0.025)	-0.084 (0.311)	-0.000 (0.050)	0.000 (0.514)	0.000 (0.316)	-0.000 (0.675)	0.008 (0.189)
10	$DFXRE_t$	52491.59 (0.075)	-5870.142 (0.854)	32335.05 (0.306)	34024.19 (0.249)	0.146 (0.083)	-0.053 (0.529)	0.165 (0.057)	-0.023 (0.786)	5321.314 (0.014)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DFXRA_{t-1}$	$DFXRA_{t-2}$	$DFXRA_{t-3}$	$DFXRA_{t-4}$	Constant
11	$NRTS_t$	0.389 (0.000)	-0.283 (0.004)	0.297 (0.002)	-0.169 (0.071)	-0.009 (0.298)	-0.006 (0.457)	0.014 (0.117)	-0.010 (0.240)	0.008 (0.140)
12	$DFXRA_t$	-0.533 (0.580)	0.347 (0.733)	-2.138 (0.034)	0.095 (0.922)	0.312 (0.001)	-0.082 (0.399)	-0.137 (0.157)	0.130 (0.166)	0.036 (0.515)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DRPR_{t-1}$	$DRPR_{t-2}$	$DRPR_{t-3}$	$DRPR_{t-4}$	Constant
13	$NRTS_t$	0.455 (0.000)	-0.274 (0.002)	0.241 (0.008)	-0.059 (0.485)	0.001 (0.899)	-0.016 (0.084)	0.006 (0.476)	-0.018 (0.038)	0.005 (0.337)
14	$DRPR_t$	-0.213 (0.778)	2.975 (0.000)	-0.567 (0.496)	0.330 (0.672)	-0.219 (0.010)	-0.317 (0.000)	0.044 (0.596)	0.057 (0.482)	-0.087 (0.077)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DTBR_{t-1}$	$DTBR_{t-2}$	$DTBR_{t-3}$	$DTBR_{t-4}$	Constant
15	$NRTS_t$	0.423 (0.000)	-0.260 (0.003)	0.232 (0.009)	-0.098 (0.237)	0.020 (0.070)	-0.009 (0.423)	-0.005 (0.613)	-0.024 (0.032)	0.006 (0.184)
16	$DTBR_t$	0.365 (0.553)	1.285 (0.053)	-0.234 (0.726)	0.102 (0.869)	0.107 (0.205)	-0.000 (0.994)	0.052 (0.541)	0.001 (0.988)	-0.029 (0.446)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DPLR_{t-1}$	$DPLR_{t-2}$	$DPLR_{t-3}$	$DPLR_{t-4}$	Constant
17	$NRTS_t$	0.413 (0.000)	-0.233 (0.009)	0.243 (0.005)	-0.106 (0.195)	0.009 (0.707)	-0.050 (0.043)	-0.020 (0.391)	0.013 (0.555)	0.007 (0.181)
18	$DPLR_t$	0.189 (0.503)	-0.336 (0.261)	-0.010 (0.972)	0.154 (0.575)	0.017 (0.829)	0.355 (0.000)	-0.074 (0.346)	-0.153 (0.053)	0.004 (0.807)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	FII_{t-1}	FII_{t-2}	FII_{t-3}	FII_{t-4}	Constant
19	$NRTS_t$	0.334 (0.000)	-0.227 (0.017)	0.215 (0.019)	-0.094 (0.275)	0.000 (0.006)	-0.000 (0.348)	0.000 (0.673)	-0.000 (0.286)	0.004 (0.440)
20	FII_t	641.839 (0.944)	-4855.599 (0.610)	14981.32 (0.103)	-1404.536 (0.872)	0.312 (0.001)	0.101 (0.292)	0.092 (0.338)	-0.058 (0.534)	1582.194 (0.009)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DTRV_{t-1}$	$DTRV_{t-2}$	$DTRV_{t-3}$	$DTRV_{t-4}$	Constant
21	$NRTS_t$	0.441 (0.000)	-0.268 (0.003)	0.246 (0.005)	-0.108 (0.193)	-0.000 (0.684)	0.000 (0.694)	-0.000 (0.523)	-0.000 (0.588)	0.007 (0.182)
22	$DTRV_t$	61.266 (0.953)	-726.456 (0.515)	1082.802 (0.328)	-20.251 (0.984)	-0.785 (0.000)	-0.193 (0.077)	-0.155 (0.156)	-0.147 (0.088)	50.525 (0.446)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DMCP_{t-1}$	$DMCP_{t-2}$	$DMCP_{t-3}$	$DMCP_{t-4}$	Constant
23	$NRTS_t$	0.194 (0.062)	-0.061 (0.555)	0.177 (0.078)	-0.220 (0.008)	0.000 (0.000)	-0.000 (0.171)	-0.000 (0.204)	0.000 (0.031)	0.005 (0.235)
24	$DMCP_t$	559048.8 (0.303)	-382442.8 (0.477)	471265.7 (0.368)	-515257 (0.237)	-0.021 (0.842)	0.029 (0.810)	-0.007 (0.953)	0.176 (0.151)	34453.94 (0.164)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DCRO_{t-1}$	$DCRO_{t-2}$	$DCRO_{t-3}$	$DCRO_{t-4}$	Constant
25	$NRTS_t$	0.411 (0.000)	-0.264 (0.003)	0.207 (0.020)	-0.056 (0.508)	0.000 (0.767)	0.001 (0.345)	0.000 (0.466)	-0.002 (0.015)	0.007 (0.170)
26	$DCRO_t$	9.502 (0.159)	-4.725 (0.509)	-1.767 (0.803)	11.223 (0.099)	0.308 (0.001)	0.278 (0.003)	-0.059 (0.520)	-0.196 (0.025)	0.247 (0.554)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DGLD_{t-1}$	$DGLD_{t-2}$	$DGLD_{t-3}$	$DGLD_{t-4}$	Constant
27	$NRTS_t$	0.429 (0.000)	-0.242 (0.006)	0.237 (0.007)	-0.117 (0.153)	-0.000 (0.276)	0.000 (0.154)	0.000 (0.554)	0.000 (0.890)	0.005 (0.373)
28	$DGLD_t$	277.625 (0.595)	379.966 (0.497)	145.730 (0.7920)	-395.942 (0.444)	0.024 (0.773)	-0.058 (0.492)	0.039 (0.644)	0.040 (0.638)	110.321 (0.004)
		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DDSLV_{t-1}$	$DDSLV_{t-2}$	$DDSLV_{t-3}$	$DDSLV_{t-4}$	Constant
29	$NRTS_t$	0.423 (0.000)	-0.249 (0.006)	0.227 (0.011)	-0.095 (0.255)	0.000 (0.825)	0.000 (0.959)	0.000 (0.683)	-0.000 (0.772)	0.006 (0.192)
30	$DDSLV_t$	468.552 (0.775	662.141 (0.704)	-736.36 (0.670)	957.419 (0.555	-0.444 (0.000)	-0.609 (0.000)	-0.310 (0.002)	-0.029 (0.753)	156.594 (0.401)

Notes:
(i) Related P-values are shown in parentheses "( )".
(ii) Significant at 95% confidence level.
(iii) Variable labels without any prefix are stationary at their own level, I (0); labels prefixed with D are stationary after differencing once, I (1); and the variables prefixed with DD are stationary after differencing twice, I (2).

As the results of VAR and causality test in bi-variate framework are not suitable for drawing valid conclusions, and attempt was made to apply Granger causality test in a multivariate VAR framework. The results contained in table 6 and 7 reveal that apart from the results of causality relation in bi-variate VAR framework (viz., NRTS is a Granger cause to DBOP and DRPR, and DBOP and DMCP is a Granger cause to NRTS), there are some more causal relations in multivariate VAR framework. These are:

- NRTS is affected by DBOP and DMCP. Bi-directional causal relationship is observed between NRTS and DBOP.
- DIIP is affected by DGDP and DWPI, and DWPI is affected by DGDP and DIIP. Thus, DGDP is a granger cause to DIIP and DWPI. Further, DIIP and DWPI are found to have bi-directional causality (relationship of Feedback).
- DBOP is influenced by NRTS, DFXRE, and DFXRA; while DFXRE is affected by DBOP and DFXRA. Bilateral causality is observed between DBOP and DFXRE, and DFXRE and DFXRA.
- Among money market indicators, DRPR is affected by NRTS, DTBR and DPLR; while DTBR explain variations in DPLR.
- FII is a factor which affects changes in DMCP, but it is affected by DTRV. DMCP is found to be a granger cause to NRTS.
- DDSLV is a granger cause to DCRO and DGLD. DGLD and DDSLV have bidirectional causality, (i.e., relationship of Feedback).

Table 6: Granger Causality Test for NRTS and Selected Indicators in Multivariate Framework

S. No.	Null Hypothesis	F-Stat.	P-Value	H_O Rejected/ Not Rejected	Causality Inference
NRTS and Real Economy Indicators					
1	NRTS doesn't Granger Cause to DGDP	1.019	0.399	H_O Not Rejected	Exogeneity
2	DGDP doesn't Granger Cause to NRTS	0.912	0.458	H_O Not Rejected	
3	NRTS doesn't Granger Cause to DIIP	0.968	0.427	H_O Not Rejected	Exogeneity
4	DIIP doesn't Granger Cause to NRTS	0.046	0.995	H_O Not Rejected	
5	NRTS doesn't Granger Cause to DWPI	1.637	0.168	H_O Not Rejected	Exogeneity
6	DWPI doesn't Granger Cause to NRTS	1.521	0.199	H_O Not Rejected	
7	DGDP doesn't Granger Cause to DIIP	25.490	0.000*	H_O Rejected	Unidirectional Causality DGDP→DIIP
8	DIIP doesn't Granger Cause to DGDP	0.690	0.599	H_O Not Rejected	
9	DGDP doesn't Granger Cause to DWPI	2.905	0.024*	H_O Rejected	Unidirectional Causality DGDP→DWPI
10	DWPI doesn't Granger Cause to DGDP	2.270	0.065	H_O Not Rejected	
11	DIIP doesn't Granger Cause to DWPI	4.618	0.001*	H_O Rejected	Bidirectional Causality Feedback
12	DWPI doesn't Granger Cause to DIIP	3.515	0.009*	H_O Rejected	
NRTS and Forex Market Indicators					
1	NRTS doesn't Granger Cause to DBOP	2.932	0.023*	H_O Rejected	Bidirectional Causality Feedback
2	DBOP doesn't Granger Cause to NRTS	2.372	0.050*	H_O Rejected	
3	NRTS doesn't Granger Cause to DFXRE	1.823	0.128	H_O Not Rejected	Exogeneity
4	DFXRE doesn't Granger Cause to NRTS	1.316	0.267	H_O Not Rejected	
5	NRTS doesn't Granger Cause to DFXRA	1.207	0.310	H_O Not Rejected	Exogeneity
6	DFXRA doesn't Granger Cause to NRTS	1.110	0.354	H_O Not Rejected	
7	DBOP doesn't Granger Cause to DFXRE	3.457	0.010*	H_O Rejected	Bidirectional Causality Feedback
8	DFXRE doesn't Granger Cause to DBOP	5.825	0.000*	H_O Rejected	
9	DBOP doesn't Granger Cause to DFXRA	1.978	0.101	H_O Not Rejected	Unidirectional Causality DFXRA→DBOP
10	DFXRA doesn't Granger Cause to DBOP	3.931	0.004*	H_O Rejected	
11	DFXRE doesn't Granger Cause to DFXRA	8.225	0.000*	H_O Rejected	Bidirectional Causality Feedback
12	DFXRA doesn't Granger Cause to DFXRE	5.026	0.000*	H_O Rejected	
NRTS and Money Market Indicators					
1	NRTS doesn't Granger Cause to DRPR	3.702	0.006*	H_O Rejected	Unidirectional Causality NRTS→DRPR
2	DRPR doesn't Granger Cause to NRTS	1.846	0.123	H_O Not Rejected	
3	NRTS doesn't Granger Cause to DTBR	1.444	0.223	H_O Not Rejected	Exogeneity
4	DTBR doesn't Granger Cause to NRTS	2.045	0.091	H_O Not Rejected	
5	NRTS doesn't Granger Cause to DPLR	0.498	0.736	H_O Not Rejected	Exogeneity
6	DPLR does not Granger Cause to NRTS	1.128	0.345	H_O Not Rejected	
7	DRPR does not Granger Cause to DTBR	0.843	0.499	H_O Not Rejected	Unidirectional Causality DTBR→DRPR
8	DTBR does not Granger Cause to DRPR	3.874	0.005*	H_O Rejected	
9	DRPR does not Granger Cause to DPLR	1.453	0.220	H_O Not Rejected	Unidirectional Causality DPLR→DRPR
10	DPLR does not Granger Cause to DRPR	4.713	0.001*	H_O Rejected	
11	DTBR does not Granger Cause to DPLR	4.434	0.002*	H_O Rejected	Unidirectional Causality DTBR→DPLR
12	DPLR does not Granger Cause to DTBR	1.583	0.182	H_O Not Rejected	
NRTS and Stock Market Indicators					
1	NRTS doesn't Granger Cause to FII	0.649	0.628	H_O Not Rejected	Exogeneity
2	FII doesn't Granger Cause to NRTS	2.096	0.084	H_O Not Rejected	
3	NRTS doesn't Granger Cause to DTRV	0.292	0.882	H_O Not Rejected	Exogeneity

4	DTRV doesn't Granger Cause to NRTS	0.674	0.610	H_O Not Rejected	
5	NRTS doesn't Granger Cause to DMCP	0.729	0.573	H_O Not Rejected	Unidirectional Causality DMCP→NRTS
6	DMCP doesn't Granger Cause to NRTS	9.236	0.000*	H_O Rejected	
7	FII doesn't Granger Cause to DTRV	1.617	0.173	H_O Not Rejected	Unidirectional Causality DTRV→FII
8	DTRV doesn't Granger Cause to FII	2.677	0.034*	H_O Rejected	
9	FII doesn't Granger Cause to DMCP	3.132	0.016*	H_O Rejected	Unidirectional Causality FII→DMCP
10	DMCP doesn't Granger Cause to FII	2.156	0.077	H_O Not Rejected	
11	DTRV doesn't Granger Cause to DMCP	0.397	0.810	H_O Not Rejected	Exogeneity
12	DMCP doesn't Granger Cause to DTRV	0.422	0.792	H_O Not Rejected	
NRTS and Commodity Market Indicators					
1	NRTS does not Granger Cause to DCRO	1.387	0.241	H_O Not Rejected	Exogeneity
2	DCRO does not Granger Cause to NRTS	1.596	0.179	H_O Not Rejected	
3	NRTS does not Granger Cause to DGLD	0.459	0.765	H_O Not Rejected	Exogeneity
4	DGLD does not Granger Cause to NRTS	0.851	0.494	H_O Not Rejected	
5	NRTS doesn't Granger Cause to DDSLV	0.230	0.921	H_O Not Rejected	Exogeneity
6	DDSLV doesn't Granger Cause to NRTS	0.100	0.982	H_O Not Rejected	
7	DCRO doesn't Granger Cause to DGLD	0.914	0.457	H_O Not Rejected	Exogeneity
8	DGLD doesn't Granger Cause to DCRO	1.830	0.126	H_O Not Rejected	
9	DCRO doesn't Granger Cause to DDSLV	2.193	0.073	H_O Not Rejected	Unidirectional Causality DDSLV→DCRO
10	DDSLV doesn't Granger Cause to DCRO	4.254	0.002*	H_O Rejected	
11	DGLD doesn't Granger Cause to DDSLV	3.835	0.005*	H_O Rejected	Bidirectional Causality Feedback
12	DDSLV doesn't Granger Cause to DGLD	2.890	0.024*	H_O Rejected	
Notes: (i) [*] denotes rejection of null hypothesis at 95% confidence level. (ii) No. of Observations: 140 for all the hypotheses.					

Table 7: VAR Framework for NRTS and Selected Macroeconomic Indicators in Multivariate Framework

NRTS and Real Economic Indicators										
Equation No.		**$NRTS_{t-1}$**	**$NRTS_{t-2}$**	**$NRTS_{t-3}$**	**$NRTS_{t-4}$**	**$DGDP_{t-1}$**	**$DGDP_{t-2}$**	**$DGDP_{t-3}$**	**$DGDP_{t-4}$**	
1	$NRTS_t$	0.419 (0.000)	-0.234 (0.007)	0.205 (0.017)	-0.139 (0.095)	0.000 (0.398)	0.000 (0.445)	-0.000 (0.285)	-0.000 (0.032)	
2	$DGDP_t$	75339.71 (0.181)	24487.16 (0.689)	106551.5 (0.077)	-43904.61 (0.453)	-0.101 (0.232)	-0.079 (0.346)	0.215 (0.046)	0.013 (0.901)	
3	$DIIP_t$	9.549 (0.419)	7.356 (0.566)	18.964 (0.133)	-3.967 (0.746)	0.000 (0.254)	0.000 (0.000)	0.000 (0.001)	-0.000 (0.137)	
4	$DWPI_t$	1.018 (0.215)	0.781 (0.380)	0.819 (0.350)	0.025 (0.976)	-0.000 (0.487)	-0.000 (0.061)	0.000 (0.583)	-0.000 (0.038)	
		$DIIP_{t-1}$	$DIIP_{t-2}$	$DIIP_{t-3}$	$DIIP_{t-4}$	$DWPI_{t-1}$	$DWPI_{t-2}$	$DWPI_{t-3}$	$DWPI_{t-4}$	Constant
5	$NRTS_t$	0.000 (0.377)	0.001 (0.128)	0.000 (0.474)	-0.000 (0.621)	-0.002 (0.725)	-0.000 (1.000)	0.013 (0.107)	-0.024 (0.005)	0.013 (0.069)
6	$DGDP_t$	-138.392 (0.744)	-215.753 (0.692)	-332.191 (0.476)	-376.010 (0.300)	-5287.772 (0.346)	558.7191 (0.927)	8530.99 (0.159)	11023.87 (0.067)	3571.18 (0.504)
7	$DIIP_t$	-0.832 (0.000)	-0.271 (0.017)	0.033 (0.731)	0.058 (0.441)	-3.770 (0.001)	1.621 (0.202)	-0.262 (0.836)	1.700 (0.178)	0.892 (0.426)
8	$DWPI_t$	0.009 (0.108)	0.006 (0.412)	0.018 (0.006)	0.014 (0.006)	0.426 (0.000)	-0.016 (0.849)	0.276 (0.002)	-0.139 (0.111)	0.197 (0.011)
NRTS and Forex Market Indicators										
Equation No.		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DBOP_{t-1}$	$DBOP_{t-2}$	$DBOP_{t-3}$	$DBOP_{t-4}$	
9	$NRTS_t$	0.393 (0.000)	-0.309 (0.001)	0.243 (0.011)	-0.183 (0.046)	0.000 (0.027)	0.000 (0.048)	0.000 (0.002)	0.000 (0.077)	
10	$DBOP_t$	61864.49 (0.016)	-38637.22 (0.157)	57805.76 (0.032)	-10846.44 (0.676)	-0.169 (0.058)	-0.128 (0.104)	-0.322 (0.000)	-0.047 (0.546)	
11	$DFXRE_t$	23811.45 (0.448)	-28206.16 (0.399)	-21480.93 (0.516)	49260.92 (0.122)	0.135 (0.215)	0.196 (0.042)	0.105 (0.261)	-0.052 (0.589)	
12	$DFXRA_t$	-1.157 (0.173)	1.766 (0.051)	-2.128 (0.017)	0.154 (0.858)	-0.000 (0.001)	0.000 (0.990)	-0.000 (0.072)	-0.000 (0.022)	
		$DFXRE_{t-1}$	$DFXRE_{t-2}$	$DFXRE_{t-3}$	$DFXRE_{t-4}$	$DFXRA_{t-1}$	$DFXRA_{t-2}$	$DFXRA_{t-3}$	$DFXRA_{t-4}$	Constant
13	$NRTS_t$	-0.000 (0.002)	0.000 (0.445)	0.000 (0.389)	0.000 (0.372)	0.002 (0.822)	-0.011 (0.257)	0.015 (0.106)	-0.009 (0.283)	0.009 (0.104)
14	$DBOP_t$	-0.041 (0.575)	0.028 (0.695)	-0.357 (0.000)	-0.105 (0.236)	-7213.156 (0.012)	-3729.374 (0.205)	6155.898 (0.026)	-332.834 (0.899)	3448.305 (0.043)
15	$DFXRE_t$	0.065 (0.476)	-0.040 (0.649)	0.301 (0.002)	0.062 (0.568)	-2381.83 (0.499)	-4785.984 (0.185)	-8373.471 (0.013)	5511.247 (0.087)	5254.46 (0.012)
16	$DFXRA_t$	0.000 (0.000)	-0.000 (0.000)	0.000 (0.993)	-0.000 (0.993)	0.251 (0.008)	0.081 (0.405)	-0.254 (0.005)	0.178 (0.040)	0.020 (0.719)

NRTS and Money Market Indicators										
Equation No.		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DRPR_{t-1}$	$DRPR_{t-2}$	$DRPR_{t-3}$	$DRPR_{t-4}$	
17	$NRTS_t$	0.461 (0.000)	-0.263 (0.003)	0.236 (0.011)	-0.083 (0.330)	-0.004 (0.690)	-0.011 (0.297)	0.009 (0.373)	-0.013 (0.182)	
18	$DRPR_t$	-0.579 (0.423)	2.826 (0.000)	-0.527 (0.512)	0.193 (0.794)	-0.307 (0.001)	-0.463 (0.000)	-0.063 (0.501)	0.096 (0.277)	
19	$DTBR_t$	-0.175 (0.778)	1.439 (0.031)	-0.713 (0.305)	0.227 (0.722)	0.151 (0.055)	0.077 (0.358)	0.112 (0.169)	0.122 (0.109)	
20	$DPLR_t$	0.102 (0.706)	-0.171 (0.555)	-0.337 (0.264)	0.020 (0.942)	0.011 (0.735)	-0.028 (0.427)	0.023 (0.511)	0.046 (0.161)	
		$DTBR_{t-1}$	$DTBR_{t-2}$	$DTBR_{t-3}$	$DTBR_{t-4}$	$DPLR_{t-1}$	$DPLR_{t-2}$	$DPLR_{t-3}$	$DPLR_{t-4}$	Constant
21	$NRTS_t$	0.026 (0.038)	-0.002 (0.832)	-0.004 (0.735)	-0.016 (0.209)	0.005 (0.852)	-0.034 (0.226)	-0.010 (0.675)	0.032 (0.188)	0.005 (0.262)
22	$DRPR_t$	0.177 (0.101)	0.258 (0.021)	0.064 (0.578)	-0.189 (0.085)	0.087 (0.720)	0.266 (0.281)	0.220 (0.296)	-0.567 (0.007)	-0.092 (0.044)
23	$DTBR_t$	0.000 (0.992)	-0.030 (0.750)	0.006 (0.946)	0.017 (0.857)	0.092 (0.662)	-0.048 (0.822)	-0.323 (0.076)	-0.319 (0.080)	-0.007 (0.858)
24	$DPLR_t$	0.120 (0.003)	0.123 (0.003)	0.028 (0.516)	-0.038 (0.354)	-0.165 (0.072)	0.261 (0.005)	-0.056 (0.480)	-0.134 (0.090)	0.015 (0.356)
NRTS and Stock Market Indicators										
Equation No.		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	FII_{t-1}	FII_{t-2}	FII_{t-3}	FII_{t-4}	
25	$NRTS_t$	0.213 (0.045)	-0.083 (0.432)	0.150 (0.147)	-0.200 (0.018)	-0.000 (0.754)	0.000 (0.807)	0.000 (0.616)	-0.000 (0.100)	
26	FII_t	4433.322 (0.692)	-7759.493 (0.487)	1622.859 (0.882)	-4140.863 (0.643)	0.397 (0.000)	0.000 (0.997)	0.174 (0.144)	-0.222 (0.051)	
27	$DTRV_t$	-534.432 (0.711)	-1664.621 (0.247)	1623.736 (0.247)	-57.936 (0.960)	0.015 (0.278)	-0.013 (0.374)	-0.042 (0.006)	0.019 (0.178)	
28	$DMCP_t$	625333.3 (0.243)	-560759 (0.293)	282686.3 (0.588)	-478368.1 (0.262)	4.462 (0.398)	8.394 (0.134)	1.847 (0.746)	-16.264 (0.003)	
		$DTRV_{t-1}$	$DTRV_{t-2}$	$DTRV_{t-3}$	$DTRV_{t-4}$	$DMCP_{t-1}$	$DMCP_{t-2}$	$DMCP_{t-3}$	$DMCP_{t-4}$	Constant
29	$NRTS_t$	-0.000 (0.628)	-0.000 (0.453)	-0.000 (0.369)	-0.000 (0.632)	0.000 (0.000)	-0.000 (0.274)	-0.000 (0.323)	0.000 (0.008)	0.008 (0.124)
30	FII_t	0.376 (0.581)	-0.510 (0.546)	-1.851 (0.023)	-1.950 (0.003)	-0.003 (0.228)	0.002 (0.401)	0.001 (0.572)	0.005 (0.050)	1816.552 (0.002)
31	$DTRV_t$	-0.773 (0.000)	-0.142 (0.191)	-0.161 (0.122)	-0.153 (0.066)	-0.000 (0.517)	0.000 (0.135)	0.000 (0.134)	-0.000 (0.518)	94.009 (0.218)
32	$DMCP_t$	15.554 (0.633)	-4.186 (0.917)	11.263 (0.772)	11.477 (0.711)	-0.113 (0.370)	-0.055 (0.698)	0.003 (0.981)	0.399 (0.006)	39194.96 (0.166)
NRTS and Commodity Market Indicators										
Equation No.		$NRTS_{t-1}$	$NRTS_{t-2}$	$NRTS_{t-3}$	$NRTS_{t-4}$	$DCRO_{t-1}$	$DCRO_{t-2}$	$DCRO_{t-3}$	$DCRO_{t-4}$	
33	$NRTS_t$	0.389 (0.000)	-0.218 (0.016)	0.203 (0.024)	-0.059 (0.488)	-0.000 (0.936)	0.001 (0.217)	0.000 (0.660)	-0.002 (0.035)	
34	$DCRO_t$	5.997 (0.360)	-3.605 (0.598)	-4.714 (0.486)	14.406 (0.026)	0.234 (0.007)	0.384 (0.000)	-0.142 (0.123)	-0.164 (0.060)	
35	$DGLD_t$	-75.313 (0.888)	745.753 (0.181)	277.359 (0.615)	-155.472 (0.768)	-3.816 (0.590)	-6.955 (0.350)	-10.459 (0.165)	9.701 (0.173)	
36	$DDSLV_t$	-508.378 (0.750)	1867.443 (0.263)	-16.116 (0.992)	771.755 (0.624)	-36.230 (0.088)	8.750 (0.695)	-43.974 (0.051)	-11.527 (0.588)	
		$DGLD_{t-1}$	$DGLD_{t-2}$	$DGLD_{t-3}$	$DGLD_{t-4}$	$DDSLV_{t-1}$	$DDSLV_{t-2}$	$DDSLV_{t-3}$	$DDSLV_{t-4}$	Constant
37	$NRTS_t$	-0.000 (0.038)	0.000 (0.065)	0.000 (0.897)	0.000 (0.737)	0.000 (0.075)	-0.000 (0.852)	0.000 (0.786)	-0.000 (0.951)	0.006 (0.293)
38	$DCRO_t$	-0.002 (0.146)	0.000 (0.547)	-0.001 (0.225)	0.003 (0.015)	0.001 (0.040)	-0.000 (0.914)	0.001 (0.001)	0.001 (0.013)	0.127 (0.779)
39	$DGLD_t$	-0.254 (0.029)	0.026 (0.819)	-0.035 (0.763)	0.188 (0.100)	0.131 (0.002)	0.066 (0.132)	0.131 (0.004)	0.050 (0.137)	118.289 (0.001)
40	$DDSLV_t$	-1.375 (0.000)	0.394 (0.255)	-0.666 (0.057)	0.434 (0.205)	-0.107 (0.407)	-0.563 (0.000)	-0.011 (0.935)	0.067 (0.500)	207.412 (0.061)

Notes: (i) Related P-values are showing in parentheses "( )". (ii) Significant at 95% confidence level.

In order to develop an appropriate causality model for predicting the behavior of NRTS caused due to selected macroeconomic variables an attempt was made to examine causal relation among all the explanatory and explained variables. The causality matrix (tables 8) indicated following relations.

- NRTS is Granger cause to DBOP and DRPR
- DGDP is Granger cause to DIIP, DWPI, FII and DMCP
- DIIP is Granger cause to DWPI, DFXRA, DTBR, DPLR, FII, DTRV, DCRO and DGLD

- DWPI is Granger cause to DIIP, DBOP, DTBR, DPLR, DCRO and DDSLV
- DBOP is Granger cause to NRTS, DIIP, DFXRE, DMCP, DCRO and DGLD
- DFXRE is Granger cause to DIIP, WPI, DBOP, DFXRA and DPLR
- DFXRA is Granger cause to DWPI, DBOP, DFXRE, DTRV and DMCP
- DRPR is not a Granger cause to any variable.
- DTBR is Granger cause to DGDP, DRPR, DPLR, FII and DTRV
- DPLR is Granger cause to DGDP, DRPR and DCRO
- FII is Granger cause to DGDP, DIIP, DWPI, DFXRA, DTBR, DMCP and DCRO
- DTRV is Granger cause to DIIP, DFXRA, FII and DDSLV
- DMCP is Granger cause to NRTS, DIIP, DWPI, DBOP, DFXRE, DFXRA, DCRO and DGLD
- DCRO is Granger cause to DWPI, DRPR, DTBR, DPLR and DMCP
- DGLD is Granger cause to DIIP, DWPI, DFXRE, DTRV and DDSLV
- DDSLV is Granger cause to DFXRE, DCRO and DGLD

The results of Granger causality are neither exhaustive not coincide with the theoretical foundations and literature available on economic relation among these variables, hence do not seem capable of further analysis for examining impact of macroeconomic determinants on stock market volatility. Although, some statements are in line with the fundamentals of economic theory, but others are illusionary. To cite, DCRO affects DRPR, DTBR and DPLR. Economic theory suggests no causal relationship between an internationally traded commodity and the interest rates structure that exists in the domestic money market.

Table 8: Causality Matrix for all Explanatory and Explained Variables

	NRTS	DGDP	DIIP	DWPI	DBOP	DFXRE	DFXRA	DRPR	DTBR	DPLR	FII	DTRV	DMCP	DCRO	DGLD	DDSLV
NRTS →		1.019 (0.39)	0.968 (0.42)	1.637 (0.16)	2.932 (0.02)*	1.8231 (0.12)	1.207 (0.31)	3.702 (0.00)*	1.444 (0.22)	0.498 (0.73)	0.649 (0.62)	0.292 (0.88)	0.729 (0.57)	1.387 (0.24)	0.459 (0.76)	0.230 (0.92)
DGDP →	0.912 (0.45)		25.490 (0.00)*	2.905 (0.02)*	0.827 (0.50)	0.930 (0.44)	1.583 (0.18)	0.118 (0.97)	0.275 (0.89)	0.355 (0.83)	2.958 (0.02)*	2.035 (0.09)	4.423 (0.00)*	0.328 (0.85)	1.662 (0.16)	1.334 (0.26)
DIIP →	0.046 (0.99)	0.690 (0.59)		4.618 (0.00)*	0.240 (0.91)	0.325 (0.86)	2.851 (0.02)*	0.258 (0.90)	3.646 (0.00)*	2.770 (0.02)*	2.425 (0.05)*	3.892 (0.00)*	1.433 (0.22)	2.753 (0.03)*	2.388 (0.05)*	1.770 (0.13)
DWPI →	1.521 (0.19)	2.270 (0.06)	3.515 (0.00)*		5.885 (0.00)*	1.876 (0.11)	1.200 (0.31)	2.217 (0.07)	4.013 (0.00)*	3.503 (0.00)*	0.477 (0.75)	0.797 (0.52)	1.223 (0.30)	4.761 (0.00)*	1.491 (0.20)	2.689 (0.03)*
DBOP →	2.373 (0.05)*	0.005 (0.99)	2.970 (0.02)*	0.946 (0.43)		3.457 (0.01)*	1.978 (0.10)	0.216 (0.92)	1.253 (0.29)	0.578 (0.67)	0.698 (0.59)	0.956 (0.43)	2.443 (0.04)*	2.564 (0.04)*	3.382 (0.01)*	2.235 (0.06)
DFXRE →	1.316 (0.26)	0.592 (0.66)	2.331 (0.05)*	4.465 (0.00)*	5.825 (0.00)*		8.225 (0.00)*	1.527 (0.19)	1.815 (0.12)	4.110 (0.00)*	0.428 (0.78)	0.234 (0.91)	1.050 (0.38)	1.987 (0.10)	1.357 (0.25)	1.097 (0.36)
DFXRA →	1.110 (0.35)	0.394 (0.81)	1.091 (0.36)	2.614 (0.03)*	3.931 (0.00)*	5.026 (0.00)*		1.737 (0.14)	1.308 (0.27)	1.373 (0.24)	0.929 (0.44)	2.873 (0.02)*	3.118 (0.01)*	1.723 (0.14)	1.045 (0.38)	1.616 (0.17)
DRPR →	1.846 (0.12)	1.489 (0.20)	0.188 (0.94)	2.179 (0.07)	0.891 (0.47)	1.089 (0.36)	0.187 (0.94)		0.843 (0.49)	1.453 (0.22)	0.110 (0.97)	1.070 (0.37)	0.719 (0.57)	0.866 (0.48)	0.264 (0.90)	0.269 (0.89)
DTBR →	2.045 (0.09)	3.226 (0.01)*	0.818 (0.51)	1.603 (0.17)	0.959 (0.43)	0.687 (0.60)	0.731 (0.57)	3.874 (0.00)*		4.434 (0.00)*	4.188 (0.00)*	3.307 (0.01)*	2.258 (0.06)	1.068 (0.37)	0.826 (0.51)	0.493 (0.74)
DPLR →	1.128 (0.34)	3.346 (0.01)*	0.894 (0.46)	2.320 (0.06)	0.961 (0.43)	1.958 (0.10)	0.270 (0.89)	4.713 (0.00)*	1.583 (0.18)		0.330 (0.85)	0.836 (0.50)	0.722 (0.57)	3.140 (0.01)*	1.287 (0.27)	1.342 (0.25)
FII →	2.096 (0.08)	4.983 (0.00)*	4.483 (0.00)*	4.145 (0.00)*	0.772 (0.54)	1.441 (0.22)	3.843 (0.00)*	1.845 (0.12)	2.339 (0.05)*	1.129 (0.34)		1.617 (0.17)	3.132 (0.01)*	6.792 (0.00)*	1.739 (0.14)	1.886 (0.11)
DTRV →	0.674 (0.61)	1.462 (0.21)	3.546 (0.00)*	0.354 (0.84)	0.852 (0.49)	1.009 (0.40)	3.167 (0.01)*	0.212 (0.93)	0.141 (0.96)	1.808 (0.13)	2.677 (0.03)*		0.397 (0.81)	0.543 (0.70)	1.070 (0.37)	4.002 (0.00)*
DMCP →	9.236 (0.00)*	1.518 (0.20)	2.546 (0.04)*	2.824 (0.02)*	3.692 (0.00)*	3.831 (0.00)*	5.163 (0.00)*	1.495 (0.20)	1.743 (0.14)	1.801 (0.13)	2.156 (0.07)	0.422 (0.79)		2.439 (0.05)*	2.651 (0.03)*	1.224 (0.30)
DCRO →	1.596 (0.17)	1.635 (0.16)	0.634 (0.63)	8.658 (0.00)*	2.023 (0.09)	0.759 (0.55)	0.928 (0.44)	5.268 (0.00)*	5.441 (0.00)*	2.490 (0.04)*	0.664 (0.61)	1.652 (0.16)	2.982 (0.02)*		0.914 (0.45)	2.193 (0.07)
DGLD →	0.851 (0.49)	0.863 (0.48)	2.381 (0.05)*	4.515 (0.00)*	0.356 (0.83)	2.409 (0.05)*	0.909 (0.46)	0.462 (0.76)	1.906 (0.11)	2.024 (0.09)	0.529 (0.71)	3.116 (0.01)*	0.257 (0.90)	1.830 (0.12)		3.835 (0.00)*
DDSLV →	0.100 (0.98)	0.144 (0.96)	1.628 (0.17)	1.701 (0.15)	0.891 (0.47)	2.793 (0.02)*	1.221 (0.30)	0.223 (0.92)	0.979 (0.42)	1.292 (0.27)	1.145 (0.33)	1.345 (0.25)	0.689 (0.60)	4.254 (0.00)*	2.890 (0.02)*	

Notes: (i) [*] denotes rejection of null hypothesis at 95% confidence level. (ii) No. of Observations: 140.
(iii) [→] shows the direction of causality hypothesized.

To look into the association of macroeconomic environment of the country and stock market performance, as discussed earlier, the study used DCC MGARCH model. The basic requirements of DCC MGARCH model are: (i) Q_t should always be a stationary time series, and (ii) Wald Chi^2 test must reject the null hypothesis that all the coefficients on the independent variables in the mean equations are zero. The time series data under consideration is already declared stationary (table 2). The results of Wald Chi^2 test presented in table 9 show that null hypothesis for all the variables under consideration are rejected at the 1 percent level of significance. Thus, the coefficients on all the independent variables one-by-one in the mean equations are non-zero.

Table 9: Results of Wald Chi^2 Test for DCC-MGARCH Models

S. No.	DCC-MGARCH Model	Wald Chi^2-statistics	P-value
1.	NRTS and DGDP	96.470	0.000*
2.	NRTS and DIIP	97.570	0.000*
3.	NRTS and DWPI	26.420	0.000*
4.	NRTS and DBOP	21.260	0.000*
5.	NRTS and DFXRE	274.330	0.000*
6.	NRTS and DFXRA	275.370	0.000*
7.	NRTS and DRPR	186.300	0.000*
8.	NRTS and DTBR	370.640	0.000*
9.	NRTS and DPLR	20541.700	0.000*
10.	NRTS and FII	384.050	0.000*
11.	NRTS and DTRV	164.320	0.000*
12.	NRTS and DMCP	589.530	0.000*
13.	NRTS and DCRO	347.730	0.000*
14.	NRTS and DGLD	187.310	0.000*
15.	NRTS and DDSLV	226.230	0.000*
Notes: [*] denotes rejection of null hypothesis at 99% confidence level.			

The results of DCC MGARCH models for NRTS and selected macroeconomic indicators group-wise (i.e., Real Economic Indicators, Forex Market Indicators, Money Market Indicators, Stock Market Indicators, and Commodity Market Indicators) presented in table 10 indicate that:

- Each of the univariate ARCH, univariate GARCH and DCC parameters of all the macroeconomic indicators under consideration, except WPI (significant at 4 percent) and TBR (significant at 2 percent) is statistically significant at 1 percent level of significance.
- The Dynamic Conditional Correlation Coefficient is positive for almost all the variables. It indicates that macroeconomic variables under study and stock market indicators (NRTS) rise or fall in the same direction. Negative DCC coefficients for DGDP, DWPI, DFXRA and DPLR are the signposts of their negative relation with NRTS.
- The estimates for adjustment parameters λ_1 and λ_2 are also statistically significant and satisfy the condition of $0 \leq \lambda_1 + \lambda_2 < 1$ for all the DCC MGARCH models for NRTS and macroeconomic indicators. All this indicate that the assumption of time-invariant conditional correlations maintained in the DCC MGARCH models is restrictive.

Table 10: Results of DCC MGARCH (1,1) Models

NRTS and Real Economy Indicators				
	Coefficient	**SE**	**Z-statistics**	**P-value**
NRTS and DGDP				
ARCH_NRTS				
ARCH (1,1)	0.041	0.133	0.320	0.000*
GARCH (1,1)	-0.097	0.842	-0.120	0.000*
ARCH_DGDP				
ARCH (1,1)	-0.064	0.051	-0.110	0.000*
GARCH (1,1)	-0.089	0.053	-0.140	0.000*
Dynamic Conditional Correlation				
Rho	-0.079	0.109	-0.730	0.000
λ_1	0.048	0.465	0.100	0.000
λ_2	0.103	1.120	0.090	0.000
NRTS and DIIP				
ARCH_NRTS				
ARCH (1,1)	0.065	0.059	1.100	0.001*
GARCH (1,1)	0.795	0.116	6.830	0.000*
ARCH_DIIP				
ARCH (1,1)	0.124	0.041	3.030	0.002*
GARCH (1,1)	0.899	0.043	20.550	0.000*
Dynamic Conditional Correlation				
rho	0.089	0.241	0.370	0.001
λ_1	0.025	0.066	0.380	0.001
λ_2	0.926	0.098	9.380	0.000
NRTS and DWPI				
ARCH_NRTS				
ARCH (1,1)	0.128	0.132	0.970	0.000*
GARCH (1,1)	0.151	0.853	1.310	0.000*
ARCH_DWPI				
ARCH (1,1)	0.076	0.037	2.070	0.038
GARCH (1,1)	0.911	0.052	17.400	0.000*
Dynamic Conditional Correlation				
rho	-0.140	0.095	-1.480	0.000
λ_1	0.134	0.118	1.140	0.000
λ_2	0.003	0.180	0.020	0.001
NRTS and Forex Market Indicators				
	Coefficient	S.E.	Z-statistics	P-value
NRTS and DBOP				
ARCH_NRTS				
ARCH (1,1)	0.092	0.077	1.200	0.003*
GARCH (1,1)	0.757	0.166	4.540	0.000*
ARCH_DBOP				
ARCH (1,1)	-0.056	0.001	-45.110	0.000*
GARCH (1,1)	0.235	0.012	3.530	0.000*
Dynamic Conditional Correlation				
rho	0.055	0.112	0.500	0.000
λ_1	0.392	0.201	1.950	0.030
λ_2	0.060	0.114	0.530	0.002
NRTS and DFXRE				
ARCH_NRTS				
ARCH (1,1)	0.399	0.210	2.540	0.000*
GARCH (1,1)	-0.189	0.001	-1.880	0.000*
ARCH_DFXRE				
ARCH (1,1)	0.322	0.106	3.040	0.002*
GARCH (1,1)	0.691	0.084	8.200	0.000*
Dynamic Conditional Correlation				
rho	0.115	0.107	1.070	0.020
λ_1	0.411	0.099	4.120	0.000
λ_2	0.003	0.062	0.050	0.009
NRTS and DFXRA				
ARCH_NRTS				
ARCH (1,1)	0.482	0.151	3.190	0.001*
GARCH (1,1)	-0.196	0.015	-1.980	0.000*
ARCH_DFXRA				
ARCH (1,1)	0.526	0.175	2.990	0.003*
GARCH (1,1)	0.462	0.093	4.930	0.000*
Dynamic Conditional Correlation				
rho	-0.419	0.092	-4.540	0.000
λ_1	0.280	0.125	2.230	0.025
λ_2	0.092	0.215	0.430	0.006
NRTS and Money Market Indicators				
	Coefficient	S.E.	Z-statistics	P-value
NRTS and DRPR				
ARCH_NRTS				
ARCH (1,1)	0.334	0.044	7.530	0.000*
GARCH (1,1)	-0.296	0.042	-6.950	0.000*
ARCH_DRPR				
ARCH (1,1)	1.470	0.480	3.320	0.000*
GARCH (1,1)	-0.007	0.001	-0.050	0.000*
Dynamic Conditional Correlation				
rho	0.270	0.109	2.470	0.013

λ_1	0.549	0.123	4.440	0.000
λ_2	0.001	0.013	0.070	0.001
NRTS and DTBR				
ARCH_NRTS				
ARCH (1,1)	0.383	0.160	3.820	0.004*
GARCH (1,1)	-0.278	0.077	-3.570	0.000*
ARCH_DTBR				
ARCH (1,1)	0.448	0.109	4.090	0.000*
GARCH (1,1)	-0.018	0.189	-0.100	0.023
Dynamic Conditional Correlation				
rho	0.097	0.120	0.810	0.042
λ_1	0.473	0.097	4.870	0.000
λ_2	0.013	0.156	0.080	0.003
NRTS and DPLR				
ARCH_NRTS				
ARCH (1,1)	0.244	0.058	5.730	0.000*
GARCH (1,1)	-0.877	0.042	-5.950	0.000*
ARCH_DPLR				
ARCH (1,1)	3.890	0.620	8.120	0.000*
GARCH (1,1)	-0.000	0.004	-0.030	0.000*
Dynamic Conditional Correlation				
rho	-0.031	0.139	-0.230	0.008
λ_1	0.473	0.396	1.190	0.023
λ_2	0.009	0.059	0.160	0.008
NRTS and Stock Market Indicators				
	Coefficient	S.E.	Z-statistics	P-value
NRTS and FII				
ARCH_NRTS				
ARCH (1,1)	0.423	0.054	5.230	0.000*
GARCH (1,1)	-0.221	0.048	-4.950	0.000*
ARCH_FII				
ARCH (1,1)	0.625	0.132	4.720	0.000*
GARCH (1,1)	0.572	0.070	8.080	0.000*
Dynamic Conditional Correlation				
rho	0.611	0.091	6.650	0.000
λ_1	0.493	0.147	3.350	0.001
λ_2	0.158	0.323	0.490	0.024
NRTS and DTRV				
ARCH_NRTS				
ARCH (1,1)	0.342	0.099	3.190	0.000*
GARCH (1,1)	0.048	0.032	0.030	0.000*
ARCH_DTRV				
ARCH (1,1)	0.513	0.071	6.480	0.000*
GARCH (1,1)	0.433	0.029	8.220	0.000*
Dynamic Conditional Correlation				
rho	0.141	0.032	2.962	0.000
λ_1	0.051	0.073	0.670	0.000
λ_2	0.574	0.223	1.800	0.000
NRTS and DMCP				
ARCH_NRTS				
ARCH (1,1)	0.352	0.109	3.230	0.001*
GARCH (1,1)	0.059	0.042	0.050	0.000*
ARCH_DMCP				
ARCH (1,1)	0.613	0.082	7.480	0.000*
GARCH (1,1)	0.443	0.043	10.200	0.000*
Dynamic Conditional Correlation				
rho	0.831	0.024	33.630	0.000
λ_1	0.054	0.083	0.650	0.051
λ_2	0.594	0.313	1.900	0.058
NRTS and Commodity Market Indicators				
	Coefficient	S.E.	Z-statistics	P-value
NRTS and DCRO				
ARCH_NRTS				
ARCH (1,1)	0.346	0.092	2.910	0.000*
GARCH (1,1)	-0.249	0.058	-4.270	0.000*
ARCH_DCRO				
ARCH (1,1)	0.488	0.135	3.610	0.000*
GARCH (1,1)	0.244	0.220	1.110	0.008*
Dynamic Conditional Correlation				
rho	0.250	0.108	2.300	0.021
λ_1	0.290	0.106	2.730	0.006
λ_2	0.234	0.211	1.110	0.007
NRTS and DGLD				
ARCH_NRTS				
ARCH (1,1)	0.438	0.101	3.820	0.000*
GARCH (1,1)	-0.290	0.032	-4.910	0.000*
ARCH_DGLD				
ARCH (1,1)	0.400	0.102	3.900	0.000*
GARCH (1,1)	0.619	0.081	7.580	0.000*
Dynamic Conditional Correlation				
rho	0.112	0.110	1.020	0.030
λ_1	0.349	0.116	3.000	0.003
λ_2	0.066	0.406	0.160	0.008
NRTS and DDSLV				
ARCH_NRTS				
ARCH (1,1)	0.400	0.103	3.860	0.000*
GARCH (1,1)	-0.215	0.042	-5.130	0.000*
ARCH_DDSLV				
ARCH (1,1)	0.404	0.143	2.820	0.005*
GARCH (1,1)	0.543	0.086	6.300	0.000*
Dynamic Conditional Correlation				
rho	0.116	0.098	1.190	0.023
λ_1	0.125	0.107	1.160	0.025
λ_2	0.429	0.608	0.710	0.042
Notes: [*] denotes rejection of null hypothesis at 99% confidence level.				

Predictions

Results for estimations (within the sample - from April 1999 to March 2011) and the predictions (out of the sample - from April 2011 to March 2015) of variations in NRTS due to selected macroeconomic indicators (group wise) based on DCC MGARCH models are presented through figure 1 to 5. These figures show estimations and predictions of NRTS based on past behaviour of itself, and the variations in selected independent variables (group wise).

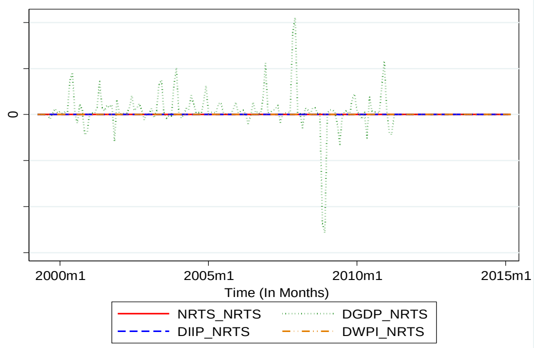

Figure 1: Predictions for NRTS due to Real Economy Indicators

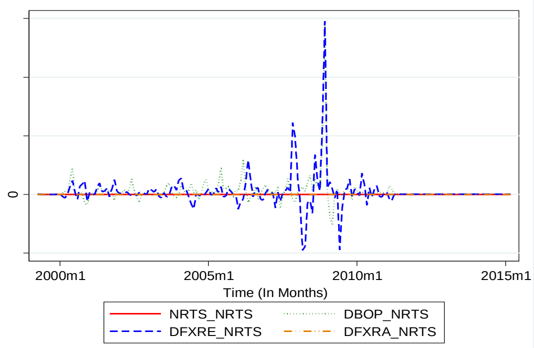

Figure 2: Predictions for NRTS due to Forex Market Indicators

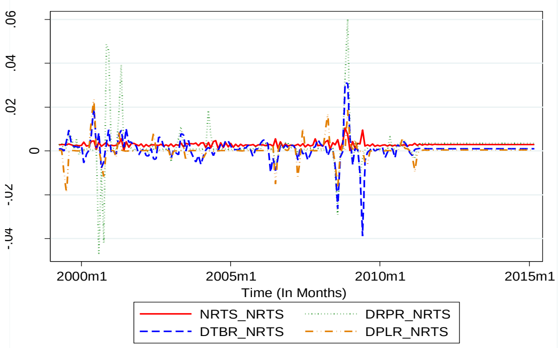

Figure 3: Predictions for NRTS due to Money Market Indicators

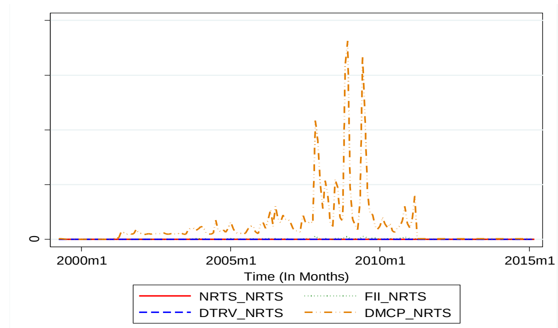

Figure 4: Predictions for NRTS due to Stock Market Indicators

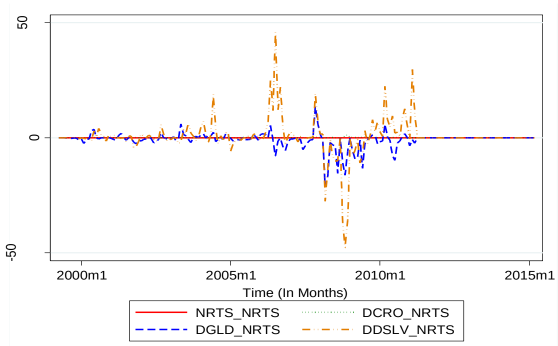

Figure 5: Predictions for NRTS due to Commodity Market Indicators

Figure 1 shows that predicted values of NRTS are much closer to the values of DWPI and DIIP. The behaviour of NRTS is significantly different from DGDP. Thus, it can be concluded that the DWPI and DIIP are much better predictors of NRTS than the DGDP. Figure 2 shows that among Forex market indicators, DFXRA is only better predictor of NRTS. It is much closer to NRTS as compared to DFXRE and DBOP. Figure 3 indicates that none of the money market indicators is favorable for predicting stock returns at NSE. Among stock market indicators (figure 4) FII and DTRV are much closer to NRTS, hence better predictors of NRTS. Predictions and estimations for NRTS due to commodity market indicators presented through figure 5 indicate that the behaviour of DGLD and DDSLV is different from the real behavior of NRTS. However, DCRO proves favorable for predicting the behavior of NRTS, as movements in DCRO are much closer to the movements in NRTS.

CONCLUSION

This paper is an attempt to trace the impact of macroeconomic determinants on the stock market volatility by using econometrics techniques. In the process, variables as described in the stock market function are first tested for unit root and stationary and then causal links among macroeconomic determinants and stock market are explored by applying Granger causality in both the bi-variate and multivariate VAR framework. The Multivariate GARCH models developed for predicting NRTS affected due to variations in various sets of macroeconomic variables indicate that though these models are capable of measuring the impact of changes in one/ set of series on the other series of same amplitude. It is important to mention here that the econometrics techniques used to predict the behaviour of stock market due to selected macroeconomic indicators are suitable in short period only, because predicted values of all the variables became constant after six months.

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