Analyzing Relationship between India VIX and Stock Market Volatility

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Abstract

The paper empirically analyzes the relationship between India VIX and volatility in the Indian stock market. India VIX is a volatility index based on the index option prices of Nifty. The study examines the daily VIX and CNX Nifty Index volatility data for the 5-year period between 2009 and 2014. The study results reveal that Indian VIX has negative relationship with Nifty Index and market return. Based on block significance test, variance decompositions and impulse responses of vector auto-regression (VAR) model, the study finds that shocks in Indian VIX have significant explanatory power for Nifty index volatility. There is existence of dynamic interrelationship and lead-lag interactions between India VIX and stock market volatility. Furthermore, the findings reveal that India VIX is a good forecasting indicator for Nifty Index's volatility over a one-month period. Additionally it is found that VAR model has superior forecasting ability for future stock market volatility.

Keywords: Implied volatility, Stock market volatility, Volatility forecasting, Volatility index

1. Introduction

Stock prices volatility has received a great attention from both academies and practitioners over the last two decades because it can be used as a measure of risk in financial markets. Over recent years, there has been a growth in interest in the study of stock market volatility. There are various measures of stock market volatility. The volatility can also be measured through volatility indices. The first volatility index (VIX) was introduced by Chicago Board of Options Exchange (CBOE) in 1993 to measure market expectations of the near-term volatility implied by stock index option prices. After that, the volatility index has also been introduced in several developed and emerging markets. VIX is calculated on the basis of implied volatility derived from option prices. It essentially offers a market-determined, forward-looking estimate of one-month stock market volatility (Hentschel 2003). Volatility indices are measure of market expectation of volatility over a short-term period (Bagcchi 2012).

Often referred to as the 'investor fear gauge', the VIX aims to track the market expectation of volatility, giving an indication about how nervous the market is about the future. It reflects investors' consensus view of future expected stock market volatility. When the VIX level is low, it implies that investors are optimistic and complacent rather than fearful in the market, which indicates that investors perceive no or low potential risk. On the contrary, a high VIX reading suggests that investors perceive significant risk and expect the market to move sharply in either direction. VIX generally moves inversely to stock markets, rising when stocks fall and vice-versa. Globally known as a 'fear index', VIX is actually one of the best contrarian technical indicators in the world. The VIX is forward looking (Sarwar 2012).

Volatility can have negative impact on existing portfolio position of investors, may require implementation of costly hedging strategies, and could adversely affect overall investment returns. Traders and portfolio managers incorporate volatility expectations in their investment strategy selections and actively adjust their positions to better manage risk associated with volatility fluctuations.

Financial market participants often use the Implied Volatility Index (VIX) to forecast stock market index's future volatility over a short period of time and may employ it as a hedge against existing positions. There is a general belief that the VIX is a good predictor for the future 30-day volatility of the market index (Whaley 2008). The VIX index affects the expected return of stock markets (Durand, Lim & Zumwalt 2011). The VIX index provides better forecast quality than historical volatility (Carr & Wu 2006; Corrado & Miller 2005).

In India, the National Stock Exchange (NSE) introduced a volatility index for the Indian market in 2008 called the India volatility index (India VIX). India VIX is a measure of implied volatility calculated by the NSE from near-term at-the-money options on the CNX Nifty 50 index, and the methodology to compute the implied volatility is identical to the one adopted for the calculation of CBOE VIX. It represents the level of price volatility implied by the option markets, not the actual or historical volatility of the index itself. This volatility is meant to be forward looking and is calculated from both calls and puts option premiums (Thenmozhi & Chandra 2013). NSE launched India VIX Futures for traders who are willing to bet on volatility on February 26th 2014. The underlying asset for the VIX futures contact is the India VIX. India VIX Futures enables participants to more easily hedge, trade and arbitrage the expected volatility.

The study attempts to investigate the relationship of India VIX index with the volatility of the Indian stock market, to explore the association between these two measures of financial market volatility and to understand the directional influence between them. We anticipated the negative relationship, as higher volatility in the market would reflect the negative sentiment of investors and there could be lower trading, leading to less trading volume and lowering index. On the other hand, a low volatility value could mean a boost in investor sentiment and higher trading participation in the market. We also examine whether India VIX has predictive power in regards to stock market volatility. The study is useful for all financial market stakeholders who want to understand salient features of volatility in Indian stock market predict the volatility and apply investment strategies based on the volatility.

2. Literature Review

There exist abundant empirical studies on relationship between VIX and stock market volatility. Numerous articles have examined the forecasting power of VIX since the Index was introduced by CBOE in 1993 and revised in 2003. Taking VIX as the respective set of implied volatilities, Chernov (2001) concludes that the un-biasedness of VIX cannot be rejected over the sample period from 1986 to 2000 and therefore contains information of future volatility. Poon and Granger (2003) conclude that the construction of VIX is a good tool for model-based forecasting. In contrast, the study of Becker et al. (2006) rejects the notion that VIX contains any information for volatility forecasting. However, after a more detailed study, specifically examining the forecast performance of VIX, Becker and Clemens (2007) conclude that VIX is a superior predictor of market volatility. Based on arguments on the forecasting performance of VIX and the financial markets turmoil in 2008, Whaley (2008) argues that VIX is forward-looking measurement of S&P index volatility, representing expected future market volatility over the next 30 calendar days. Hung et al. (2009) find that combining VIX into a GARCH-type model can enhance the one-step-ahead volatility forecasts while evaluating the forecasting with different types of loss functions.

In the Indian context, Kumar (2012) and Bagchi (2012) studied the India VIX and its relationship with the Indian stock market returns. While Kumar (2012) shows the negative association between the India VIX and stock market returns and the presence of leverage effect significantly around the middle of the joint distribution, Bagchi (2012) constructs value-weighted portfolios based on beta, market-to-book value and market capitalisation parameters, and reports a positive and significant relationship between the India VIX and the returns of the portfolios. Banerjee and Kumar (2011), and Lu et al. (2012) find that the implied volatility measures: the CBOE VIX, the KOSPI volatility index, and the India VIX are sufficiently good predictors of realized volatility in the S&P100 index (U.S.A.), the KOSPI 200 index (Korea), and the Nifty index (India) respectively. Kumar (2010) examines the behaviour of India's volatility index by using linear regressions, autoregressive models and unit root tests. The results of the study show that the volatility index exhibits volatility persistence, mean reversion, negative relationship with stock market movements and positive association with trading volumes. However, the negative relationship between market returns and volatility is observed only during market declines. Thenmozhi and Chandra (2013) examine the asymmetric relationship between the India VIX and stock market returns, and demonstrate that Nifty returns are negatively related to the changes in the India VIX levels; in the case of high upward movements in the market, the returns on the two indices tend to move independently. When the market takes a sharp downward turn, the relationship is not as significant for higher quantiles. They also find that the India VIX captures stock market volatility better than traditional measures of volatility, including the ARCH/GARCH class of models.

3. India VIX

India VIX (IVIX) is a volatility index computed by NSE based on the order book of NIFTY Options. For this, the best bid-ask quotes of near and next-month NIFTY options contracts which are traded on the F&O segment of NSE are used. India VIX indicates the investor's perception of the market's volatility in the near term i.e. it depicts the expected market volatility over the next 30 calendar days. Higher the India VIX values, higher the expected volatility and vice versa. A high India VIX value would suggest that the market expects significant changes in the Nifty, while a low India VIX value would suggest that the market expects minimal change. It has also been observed that historically, a negative correlation exists between the two. Volatility indices like India VIX are often perceived to display mean reverting characteristics by oscillating around a long-term variance.

The India VIX reflects the expected movement in the Nifty index over the next 30-day period, which is then annualized. For example, if India VIX is 16.8025, this represents an expected annualized change of 16.8025% over the next 30 days. Although India VIX is often called the "fear gauge", a high India VIX is not necessarily bearish for stocks. Instead, the India VIX is a measure of market perceived volatility in either direction, including to the upside. India VIX uses the computation methodology of CBOE, with suitable amendments to adapt to the NIFTY options order book. The formula used in the India VIX calculation is:

$$\sigma^2 = \frac{2}{T}\sum \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \ldots\ldots\ldots \text{(i)}$$

Where, T = time to expiration, K_i = strike price of i^{th} out-of-the-money option, R = risk-free interest rate to expiration, $Q(K_i)$ = midpoint of the bid ask quote for each option contract with strike K_i, F = forward index taken as the latest available price of Nifty future contract of corresponding expiry and K_0 = first strike below the forward index level F.

4. Methodology

4.1 Nature of Data

The study examines the relationship between the India VIX (IVIX) and stock market volatility in India. Hence, the study is based on time series data of IVIX and CNX Nifty Index. The CNX Nifty is a well diversified 50 stock index accounting for 23 sectors of the Indian economy. It is used for a variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds. The index represents about 66.85% of the free float market capitalization of the stocks listed on NSE as on June 30, 2014.

The total traded value for the last six months ending June 2014 of all index constituents is approximately 50.39% of the traded value of all stocks on the NSE. IVIX's historical data is available from 2nd March, 2009. Hence, the study is based on daily data of IVIX and closing values of CNX Nifty Index from 2nd March, 2009 to 31st December, 2014 comprising a total of 1448 observations. The trend of IVIX and the Nifty index is shown on appendix II. To examine the forecast ability of IVIX for predicting stock market volatility, in-sample-estimation period from 2nd March, 2009 to 30th September, 2014 and out-of-sample forecast period from 1st October, 2014 to 31st December, 2014 is constructed.

4.2 Model Specification

The study empirically examines the relationship between IVIX with Nifty return and Nifty Index volatility. The fluctuation in nifty index is operationalized by returns of nifty index (NI) and rolling standard deviation. The daily nifty returns (NR) is calculated as logarithmic difference:

$$\text{NR} = Ln\left(\frac{NI_t}{NI_{t-1}}\right) x\ 100 \ldots\ldots\ldots \text{(ii)}$$

As VIX is a measure of future volatility during one-month period, Nifty forward return (NFR) is calculated as 22 days forward NR. The 22 days is taken to account for trading closure on weekend holidays. The Nifty forward volatility (NFV) is used as a measure of volatility of Nifty index and is calculated as leading 22 days rolling standard deviation of the daily NI. The study employs Vector Auto-regression (VAR) model to analyze dynamic interrelationship between IVIX and Nifty volatility. All variables to be included in the VAR are required to be stationary in order to carry out joint significance tests on the lags of the variables. Hence, all variables are subjected to unit root tests. The Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests are employed to test for stationarity. The presence of unit root implies non-stationary time series. The simple equation of unit root test is:

$$y_t = \alpha + \rho y_{t-1} + \varepsilon_t \ldots\ldots\ldots \text{(iii)}$$

Where ε_t, is the error term with zero mean, constant variance and α is the intercept. If $\rho = 1$, means unit root is present. The popular ADF unit root test of the null hypothesis of non-stationary is expressed as:

$$\Delta y_{kt} = \alpha_0 + \alpha_1 t + \rho_0 y_{kt-1} + \sum_{k=1}^{q} \rho_i \Delta y_{kt-k} + \varepsilon_{kt} \ldots\ldots\ldots \text{(iv)}$$

Where, y_{kt} denotes the k^{th} variable at time t and $\Delta y_{kt} = y_{kt} - y_{kt-1}$, ρ are coefficients to be estimated, q is the number of lagged terms, t is the trend term, α_1 is the estimated coefficient for the trend, α_0 is the constant, and ε is white noise. MacKinnon's critical values are used in order to determine the significance of the test statistic associated with ρ_0. The unit root tests the null hypothesis H_0 : ρ = 1 against the one-sided alternative H_1: $\rho < 1$. The null hypothesis of a unit root is rejected in favour of the stationary alternative in each case if the test statistic is more negative than the critical value. The PP test is similar to ADF tests, but they incorporate an automatic correction to the DF procedure to allow for auto-correlated residuals. The variables with unit root and first order integration should be first differenced and used in VAR.

The vector auto-regression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR is represented as:

$$y_t = \mathbf{A}_1 y_{t-1} + \mathbf{A}_2 y_{t-2} + \ldots\ldots + \mathbf{A}_p y_{t-p} + e_t \ldots \ldots \ldots (v)$$

Where y_t is a k vector of endogenous variables, $\mathbf{A}_1$, ….., $\mathbf{A}_p$ are matrices of coefficients to be estimated and e_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

The study models the dynamic interrelationship between Nifty index and Nifty volatility (NV) with IVIX. As Nifty is found to be non-stationary, Nifty returns which is stationary is used in analysis. The VAR contains lagged values of the endogenous variables and only a constant as exogenous variable. Unrestricted VAR with same number of lags of all of the variables is used. In order to determine the appropriate lag lengths, information criterions are used. The Granger's causality is also employed in bivariate VAR framework. The model will be specified as two-equation system given below:

$$NV_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i \, NV_{t-i} + \sum_{i=1}^{k} \beta_i \, VIX_{t-i} + \varepsilon_t \ldots \ldots \ldots (vi(a))$$

$$VIX_t = \gamma_0 + \sum_{i=1}^{k} \gamma_i \, VIX_{t-i} + \sum_{i=1}^{k} \theta_i \, NV_{t-i} + \nu_t \ldots \ldots \ldots (vi(b))$$

One of the fundamental weaknesses of the VAR approach to modeling is that it's a-theoretical nature and large numbers of parameters involved make the estimated models difficult to interpret. In order to partially alleviate this problem, three sets of statistics are constructed for estimated VAR models: block significance tests, impulse responses and variance decompositions. Within the framework of the VAR system of equations, the significance of all the lags of each of the individual variables is examined jointly with Block exogeneity Wald test. The test establishes whether all of the lags of a particular variable are jointly significant. In order to consider effect of IVIX on stock market volatility, the impulse responses are also calculated for the estimated VAR models. The forecast error variance is also decomposed to determine the proportion of the movements in the stock market volatility that are a consequence of its own shocks rather than shocks to other variable.

The forecasting accuracy of the VAR models are evaluated using Root mean squared error (RMSE), Mean absolute error (MAE), Mean absolute percentage error (MAPE) and Their inequality coefficient. The in-sample estimation period is 3/03/2009 to 9/30/2014, which includes 1389 observations. The remaining three months period with 58 observations is used as out-of-sample forecast evaluation period to construct forecasts for and to test forecast accuracy.

5. Results Discussion

5.1 Descriptive Analysis

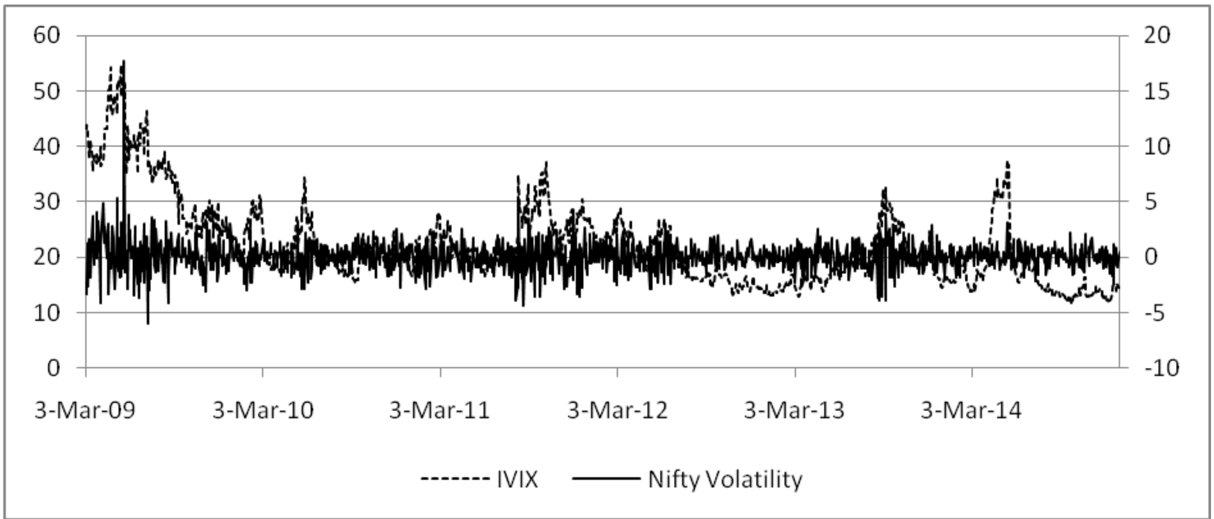
The study empirically examines the relationship between IVIX and Nifty index volatility. Table I given below exhibits the trend of IVIX, Nifty returns and stock market volatility measure. It shows the annualized average figures of the IVIX, Nifty index, logarithmic Nifty index returns (NR), standard deviation of Nifty index (ANV) and 22 days forward rolling standard deviations of Nifty index (NFV).

Table I: IVIX and Nifty Volatility

Year	IVIX	Nifty	NR	ANV	NFV
2009	35.2	4354.4	0.33	726.3	155.3
2010	21.3	5461.2	0.07	422.9	106.4
2011	23.6	5344.8	-0.09	351.2	129.9
2012	19.7	5342.8	0.09	304.9	93.4
2013	18.7	5919.4	0.03	226.2	115.4
2014	17.1	7360.6	0.11	789.7	123.8
Correlation with IVIX		- 0.685	0.040	0.371	0.424

Table I and Figure I show that the volatility of the Indian stock market is in decreasing trend. Negative correlation is observed between IVIX and Nifty. The figure in appendix II displays the negative relationship between the variables. It indicates that lower volatility in the Indian stock market attracts investors and drives the market upward. On the contrary, IVIX has positive correlation with NR, ANV and NFV. However, the correlation with NR is nearly zero. The results support the usefulness of IVIX as a measure of stock market volatility. Moreover, the highest correlation observed with NFV reveals that IVIX is associated with short-term stock market volatility. Figure I exhibits the trend of Nifty volatility calculated as first differenced Nifty index and IVIX. It is seen that periods of higher volatility is accompanied by higher IVIX values and vice-versa. Moreover, it also exhibits that volatility is time varying and displays volatility clustering. The years 2009 and 2011 have experienced higher volatility and have higher IVIX values. The findings indicate that IVIX and stock market volatility are related. Appendix III graphically illustrates the positive relationship between IVIX and NFV.

Figure I: Trend of IVIX and Nifty Volatility



5.2 Results of VAR Analysis

The study employs VAR technique to model dynamic relationship between IVIX, Nifty Index and stock market volatility. VAR requires that all variables in the system to be stationary. Table II displays the output of the two unit root tests: Augmented Dickey Fuller and Philips-Perron tests. The null hypothesis of unit root is accepted for Nifty index series at level for. However, the series is found to be stationary when first difference is taken implying the series is integrated in order of one.

Hence, first difference of Nifty should be used in VAR. However, Nifty return is used in the study as it has better interpretability than first differenced Nifty. The series IVIX, NFR and NFV are all stationary in level form. The results of both unit root tests are similar.

Table II: Results of Unit Root Tests

Variable	ADF		PP		Integration Order
	t-stat		Adj. t-stat		
	Level	1st Diff	Level	1st Diff	
IVIX	-3.564 (0.006)		-3.722 (0.003)		I(0)
Nifty	-1.682 (0.439)	-38.268 (0.000)	-1.680 (0.441)	-38.268 (0.000)	I(1)
NFR	-38.382 (0.000)		-38.402 (0.000)		I(0)
NFV	-9.074 (0.000)		-5.679 (0.000)		I(0)

ADF and PP test critical values are -3.434, -2.863, and -2.5677 at 1%, 5% and 10% level of significance respectively. Values in parentheses are MacKinnon one-sided p-values.

The study uses bivariate unrestricted VAR models to analyze interrelationship between Nifty index and IVIX and determine the usefulness of IVIX as a technical indictor for forecasting Nifty index volatility. All the variables in VAR models are used in stationary form as for applying hypothesis tests, either singly or jointly, to examine the statistical significance of the coefficients, it is essential that all of the components of VAR are stationary. The study uses three VAR models. The endogenous variables in the first VAR model are IVIX and Nifty return. Similarly, IVIX and Nifty forward return, IVIX and Nifty forward volatility are the endogenous variables in the second and third VAR models respectively. Only constant is used as exogenous variable in all models. Lag selection criteria is minimum value of information criterions. The number of lags minimizing information criterions are 3, 4 and 5 for VAR models I, II and III respectively. Table III presents the output of the VAR models.

Table III: Output of VAR Models

VAR I			VAR II			VAR III		
	IVIX	NR		IVIX	NFR		IVIX	NFV
IVIX(-1)	0.878*	0.003	IVIX(-1)	0.884*	0.007	IVIX(-1)	0.884*	-0.032
	[32.146]	[0.13021]		[33.183]	[0.296]		[33.501]	[-0.290]
IVIX(-2)	-0.018	0.031	IVIX(-2)	-0.025	0.069**	IVIX(-2)	-0.030	0.279**
	[-0.484]	[0.96560]		[-0.717]	[2.228]		[-0.864]	[1.892]
IVIX(-3)	0.122*	-0.016	IVIX(-3)	0.106*	-0.010	IVIX(-3)	0.108*	-0.096
	[4.466]	[-0.64092]		[2.978]	[-0.320]		[3.066]	[-0.653]
			IVIX(-4)	0.017	-0.057*	IVIX(-4)	-0.011	0.085
				[0.641]	[-2.456]		[-0.325]	[0.574]
						IVIX(-5)	0.027	-0.146
							[1.017]	[-1.326]
NR(-1)	-0.067**	-0.021	NFR(-1)	0.072*	-0.023	NFV(-1)	0.017*	1.739*
	[-2.148]	[-0.75508]		[2.353]	[-0.881]		[2.738]	[65.891]
NR(-2)	-0.001	0.010	NFR(-2)	0.065**	-0.008	NFV(-2)	-0.022	-0.796*
	[-0.037]	[0.34750]		[2.139]	[-0.297]		[-1.738]	[-15.026]
NR(-3)	-0.035	-0.026	NFR(-3)	0.048	-0.039	NFV(-3)	0.006	0.001
	[-1.174]	[-1.00985]		[1.572]	[-1.458]		[0.462]	[0.015]
			NFR(-4)	-0.050**	0.018	NFV(-4)	-0.008	0.095
				[-1.649]	[0.667]		[-0.664]	[1.784]
						NFV(-5)	0.009	-0.073*
							[1.443]	[-2.772]
C	0.363*	-0.337*	C	0.397*	-0.128	C	0.233	2.104*
	[3.012]	[-3.15101]		[3.215]	[-1.193]		[1.819]	[3.932]
R^2	0.963	0.013		0.962	0.015		0.963	0.988
Adj. R^2	0.963	0.009		0.962	0.009		0.963	0.988
F-Stat	6202.59	3.208		4525.03	2.632		3713.26	11839.78
N	1443	1443		1422	1422		1441	1441
Block Exogeneity Wald Test								
Excluded	NR	IVIX		NFR	IVIX		NFV	IVIX
Wald Stat	6.075	18.182*		15.314*	18.381*		13.328**	19.988*
Forecast Error								
RMSE	0.727	0.844		0.684	0.736		0.718	7.548
MAE	0.530	0.686		0.499	0.580		0.529	5.313
MAPE	3.774	142.50		3.593	110.07		3.792	8.528
Theil IC	0.026	0.913		0.024	0.914		0.025	0.026

*, **, & *** means the coefficient is significant at 1%, 5%, and 10% level of significance respectively.
VAR lag order selection criteria: Akaike information criterion (AIC), Schwarz information criterion (SC), Hannan-Quinn information criterion (HQ) an Final prediction error (FPE).

The large number of parameters involved in above VAR models make the estimated models difficult to interpret. In particular, lagged variables have coefficients, which change sign across the lags. Moreover, with the interconnectivity of the equations, it is difficult to see what effect a given change in variable would have upon future values of the variables in the system just by interpreting the estimated coefficients and their significance. Since several lags of the variables are included in each of the equations of the three VAR systems, the coefficients on individual lags do not appear significant for all lags, and have signs and degrees of significance that vary with lag length. In order to partially alleviate this problem, three sets of statistics have been constructed for the estimated VAR model: block significance tests, impulse responses and variance decompositions.

As all the endogenous variables in the above three VAR models are stationary, the block significance or joint hypothesis has been tested within the Wald test framework. The evaluation of the significance of variables in the context of VAR has been done based on joint tests on all of the lags of a particular variable in an equation, rather than by examination of individual coefficient estimates. The output of the Wald test for VAR I reveals that lags of IVIX causes changes in NR but lags of NR don't have significant influence on IVIX. However, for both VAR II and VAR III models, bidirectional causal relationship of IVIX is indicated with NFR and NFV. The values of Wald test statistics seems to suggest that the direction of causality is stronger from IVIX to NFR and NFV. Therefore, based on Wald test, an initial conclusion is that there exist significant lead-lag interactions of IVIX with NFR and NFV. In addition, it is revealed that IVIX has significant explanatory power for Nifty index volatility.

Block significance test suggest which of the variables in the model have statistically significant impacts on the future values of each of the variables in the system. However, its results are not, by construction, able to explain the sign of the relationship or how long these effects require to take place. That is, Wald test results do not reveal whether changes in the value of a given variable have a positive or negative effect on other variables in the system, or how long it would take for the effect of that variable to work through the system. Such information is obtained from analysis of variance decompositions and impulse responses of the VAR, which have been discussed in following sections.

Variance decompositions offer a method for examining VAR system dynamics. They give the proportion of the movements in the dependent variables that are due to their own shocks, versus shocks to the other variables in the system. A shock to one of the endogenous variable will of course directly affect that variable, but it will also be transmitted to all of the other variables in the system through the dynamic structure of the VAR. For calculating variance decompositions and impulse responses, the ordering of the variables is important. As IVIX is a tool devised to forecast stock market volatility, financial theory suggests that movement in stock market volatility is likely to follow IVIX, rather than precede it. Hence, Cholesky ordering of IVIX followed by other endogenous variables is used. Table IV presents the variance decompositions of the three VAR models.

Table IV: VAR Variance Decompositions

Period Lags	VAR I				VAR II				VAR III			
	IVIX		NR		IVIX		NFR		IVIX		NRV	
	IVIX	NR	IVIX	NR	IVIX	NFR	IVIX	NFR	IVIX	NRV	IVIX	NRV
1	100.00	0.00	8.14	91.86	100.00	0.00	0.48	99.52	100.00	0.00	0.12	99.88
5	99.58	0.42	8.32	91.68	98.88	1.12	1.56	98.44	98.99	1.01	0.68	99.32
10	99.46	0.54	8.43	91.57	98.84	1.16	1.57	98.43	98.54	1.46	2.23	97.77
15	99.41	0.59	8.52	91.48	98.82	1.18	1.59	98.41	97.58	2.42	4.01	95.99
20	99.39	0.61	8.60	91.40	98.81	1.19	1.60	98.40	96.45	3.55	5.66	94.34
25	99.38	0.62	8.67	91.33	98.80	1.20	1.61	98.39	95.53	4.47	6.78	93.22
30	99.37	0.63	8.73	91.27	98.80	1.20	1.62	98.38	94.93	5.07	7.48	92.52
Cholesky Ordering:VAR I = VIX LNRNIFTY, VAR II=IVIX NFR, VAR III = IVIX NFV												

The results show that more than 95 percent of variations in IVIX depend on its own shocks. The shocks are highly persistent, as they remain significantly in the system up to 30 lags. Shocks to NR and NFR have very little impact on IVIX. However, innovations to NRV explain around 5 percent variations in VIX. The variance decompositions of VAR I show that IVIX explains around 9 percent movements in NR and the impact is highly persistent. Similarly, shocks to IVIX also have substantial effect on NRV.

To some extent, impulse responses and variance decompositions offer very similar information. Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables in the system. So, for each variable from each equation separately, a unit shock is applied to the error, and the effects upon the VAR system over time are obtained. Table V gives the impulse responses of dependent variable in VAR models associated with separate unit shocks to the endogenous variables for the three VAR models.

Table V: VAR Impulse Responses

Period Lags	VAR I				VAR II				VAR III			
	Response of IVIX		Response of NR		Response of IVIX		Response of NFR		Response of IVIX		Response of NFV	
	IVIX	NR	IVIX	NR	IVIX	NFR	IVIX	NFR	IVIX	NFV	IVIX	NFV
1	1.461	0.000	0.370	1.243	1.464	0.000	0.088	1.271	1.457	0.000	0.211	6.097
5	1.149	-0.099	0.018	0.000	1.133	0.113	-0.013	0.036	1.062	0.130	1.851	16.268
10	1.055	-0.089	0.019	-0.002	1.048	0.117	0.006	0.002	0.993	0.176	3.338	14.262
15	0.977	-0.082	0.018	-0.002	0.972	0.109	0.006	0.001	0.927	0.243	3.489	6.980
20	0.904	-0.076	0.017	-0.001	0.902	0.101	0.006	0.001	0.870	0.275	2.979	1.174
25	0.837	-0.070	0.015	-0.001	0.838	0.094	0.006	0.001	0.815	0.270	2.387	-1.301
30	0.774	-0.065	0.014	-0.001	0.778	0.087	0.005	0.001	0.763	0.245	1.979	-1.335
Cholesky Ordering:VAR I = VIX LNRNIFTY, VAR II=IVIX NFR, VAR III = IVIX NFV												

For each VAR model we have four sets of impulse responses. For VAR I, response of IVIX to a unit shock to IVIX and NR and response of NR to unit shock on IVIX and NR are illustrated. The results show that shock to NR has a negative impact on IVIX, since the impulse responses are negative after first lag, and the effect of the shock are persistent to 30 lags. It indicates that NR and IVIX are negatively related.

As IVIX is considered a leading indicator for stock market volatility, we focus on how a unit shock to IVIX impact response of NR, NFR and NFV. Considering the signs of responses of innovations or shocks to IVIX, it has positive impact on NFR and NFV but negative for NR. The impact of innovations to IVIX on response of NFV is the largest and the effect is persistent. The effect of shock does not die out, even after 30 days.

Table VI: Output of Granger's Causality Test

Model	Direction of Causality	F-Statistic	Lag Length
I	NR →IVIX	2.025	3
	IVIX →NR	6.060*	
II	NFR →IVIX	3.828*	4
	IVIX →NFR	4.595*	
III	NFV →VIX	2.665**	5
	IVIX →NFV	3.997*	

*, **, & *** means the value is significant at 1%, 5%, and 10% level of significance respectively.

Table VI presents the output of the pairwise Granger's causality test applied to examine if one of the endogenous variable Granger-causes another variable in the VAR. In the first model, uni-directional causality is detected from IVIX to NR. The null hypothesis of NR does not Ganger cause IVIX can't be rejected but the null of IVIX doesn't Granger cause NR is convincingly rejected. It appears that lagged values of IVIX have explanatory power for NR. For both II and III models bi-directional causality is found as all four null hypotheses of no causality couldn't be convincingly accepted at conventional significance level. The findings are similar to results of Wald test. The causality is stronger from IVIX to NFR and NFV. Hence, it could validly be stated that movements in NFV, appear to lag those of IVIX.

6. Conclusions

The study examines the relationship of India VIX with stock market return and volatility. India VIX has negative relationship with market index and return. The Indian stock market goes down when volatility is high. Market returns are higher during low volatility periods and vice-versa. There is existence of dynamic interrelationship and lead-lag interactions between India VIX and stock market volatility. Changes in values of India VIX have explanatory power for future market return and volatility. The India VIX is a predictor of future short-term market volatility. Vector auto-regression model has good forecasting ability for stock market volatility.

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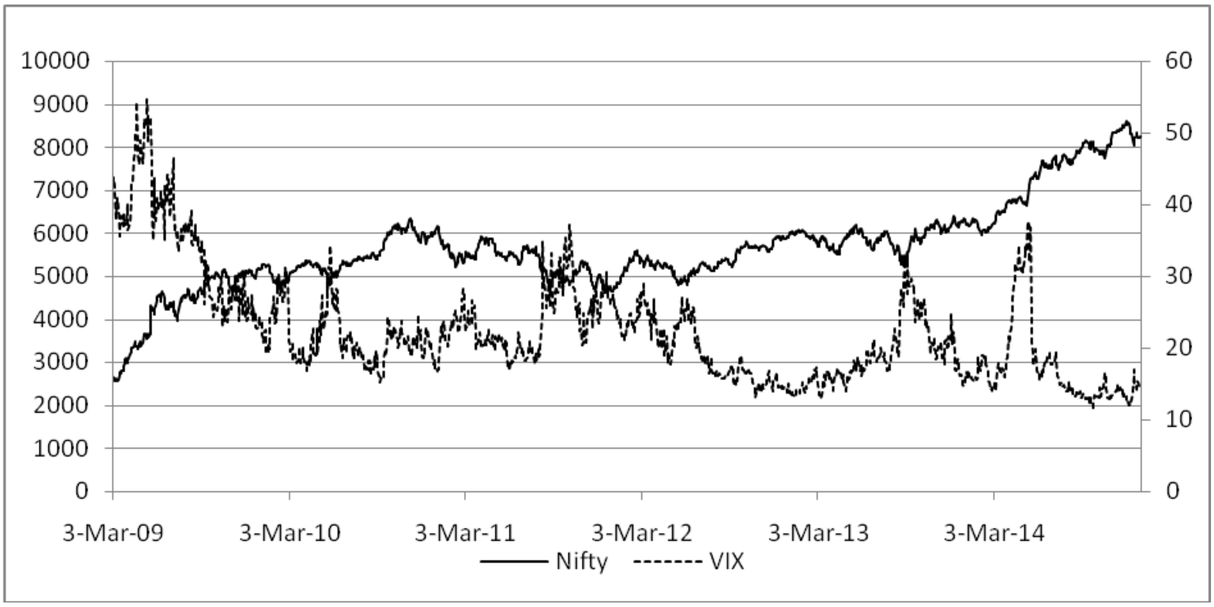
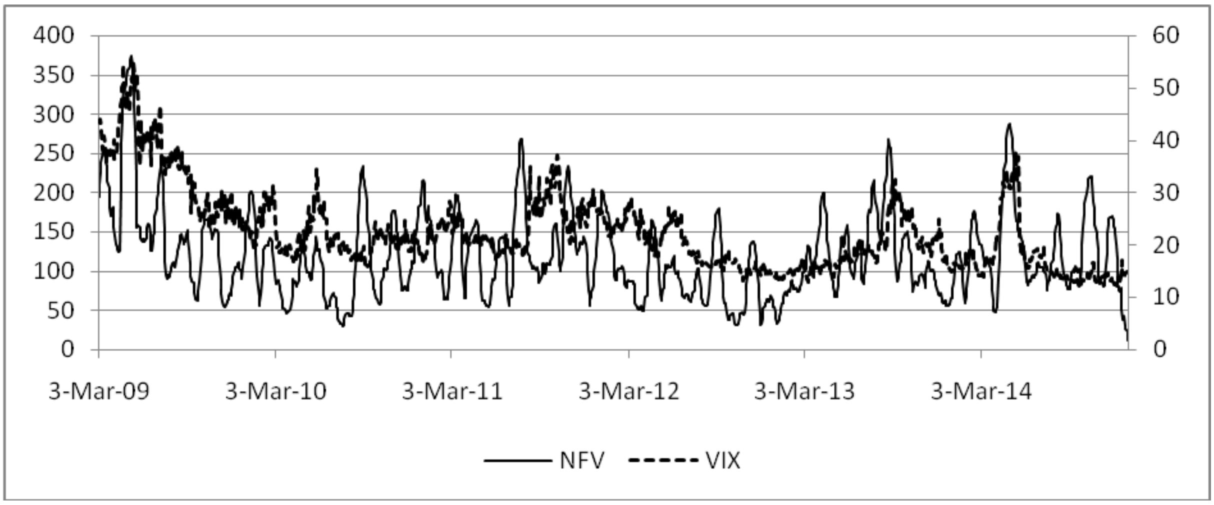
Appendix I: Descriptive Statistics

	IVIX	NFV	NFR	NR
Mean	22.267	119.553	0.069	0.075
Median	20.415	107.098	0.064	0.068
Maximum	54.760	374.386	16.335	16.335
Minimum	11.565	11.596	-6.135	-6.135
Std. Dev.	7.615	55.897	1.287	1.306
Skewness	1.440	1.196	1.3112	1.227
Kurtosis	5.316	5.266	21.464	20.202
Jarque-Bera	822.973	654.741	20666.840	18193.221
Probability	0.000	0.000	0.000	0.000
Observations	1446	1446	1426	1446

Appendix II: Trend of Nifty Index and India VIX



Appendix III: India VIX and Nifty Forward Volatility



Appendix IV: Actual and Forecasted Values of NFV