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On the Linkages between India VIX and US Financial Stress Index

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Abstract

The present study is the first of its kind accounting for linkages among India VIX and US financial stress index by employing vector autoregression model (VAR), Granger causality test, generalized impulse response functions, variance decomposition analysis (VDA) and Diebold and Yilmaz's (2009) spillover index highlighting the impact of cross market variations on each other. The span of monthly data ranges from 2009 to 2015, particularly after the global financial crisis. The results report a unidirectional causality running from the US financial stress to the Indian equity market implied volatility. When a shock is subject to the US financial stress, then the response of implied volatility in the Indian equity market is positive initially, approaching zero after a few months. On an average, 32% of the variations are accounted by cross market shocks whereas rest of the variations are as a result of own market shocks. The contribution of the US financial stress to forecasted error variances in the Indian equity market implied volatility increases over a period of 10 months to 25% approximately. The results have strong implications for the Indian equity market investors.

Keywords

Financial Stress, India, Linkages, US, VIX

1. Introduction

Numerous studies have tried to capture the impact of one financial market on another over the years. The studies are abundant with respect to the equity segment of the financial market (for instance, [1]-[3]). The unprecedented global financial crisis that took place in the years 2007-2009 further exacerbated the concerns of worldwide researchers to account for the impact of one market on another owing to increasing economic integrations among the worldwide markets at an unabatable level. Furthermore, the US subprime crisis reflects spillover of financial sector turbulences to worldwide real sectors problems. Seemingly, information transmissions, financial

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contagion, return-volatility spillovers and financial markets co-movement are well documented events captured over a period of time. However, the present study is an attempt to capture and quantify empirical linkages among India VIX (provided by National Stock Exchange of India Ltd) and US financial stress index, *i.e.* Kansas City Financial Stress Index (KFSI) across the time period 2009 to 2015, particularly after the global financial crisis. India VIX is an implied volatility index that looks into the future based on the prices of NIFTY options. In simple terms, it is a barometer to gauge fear or risk prevailing in the equity market over the next 30 calendar days. It is pertinent to mention that volatility is not always bad for the investors; instead, it is a way to earn abnormal returns in the market through wide fluctuations in asset prices. On the other hand, KFSI captures stress prevalent in the US financial system comprising equity market, debt market, money market, foreign exchange market and banking sector. Due to its magnified construction elements, a priori one would expect a greater degree impact of the US financial system on the Indian equity market.

So, through the present study, an attempt has been made to comprehend the linkages that exist between the US financial stress and India VIX index. Our fundamental objective is to check that whether the stress prevailing in the US financial system has an impact on Indian equity market volatility through diverse transmission mechanisms like international capital flows, real linkages or overall financial linkages in empirical terms. The study employs vector autoregression model (VAR), Granger causality test, generalized impulse response functions, variance decomposition analysis (VDA) and Diebold and Yilmaz's [4] spillover index to account for the said linkages. Overall results report a greater degree positive impact of the US financial stress on Indian equity market volatility. The present study contributes to the literature in two senses. Firstly, the study is the first of its kind capturing linkages among the US financial stress index and Indian equity market volatility index after the financial crisis. Lastly, the study has important implications for financial market participants in the context of movement of Indian equity market volatility with the US financial stress. The rest of the paper is organized as follows: Section 2 spotlights empirical framework; Section 3 presents empirical findings and Section 4 concludes the paper along with implications.

2. Empirical Framework

The monthly data relating to KFSI are collected from the respective website of the Kansas City Fed, whereas historical monthly closing values of India VIX are gathered from the website *Moneycontrol*. The span of monthly data ranges from March 2009 to November 2015 *i.e.* period after the financial crisis. The monthly values, reduce sensitivity and increase reliability of the analysis. The study employs advanced econometric models comprising Vector Autoregression model (VAR), Granger causality test, Generalized impulse response functions and Variance Decomposition Analysis (VDA) to account for linkages among the respective indices. Apart from this, the study also reports a spillover index highlighting the impact of cross market variations on each other; inspired from Diebold and Yilmaz [4]. Sims [5] proposed VAR model to capture dynamic interactions among the endogenous variables. Under the VAR model, each variable is a linear function of its own as well as other variables' lagged values.

$$X_t = \sum_{j=1}^{p} A_j X_{t-j} + u_t \tag{1}$$

where X_t is an $m \times 1$ vector of the endogenous variables and u_t is an $m \times 1$ vector of error terms in Equation (1). The error terms are required to be white noise. As a sub-set of VAR model, impulse response functions capture the response of variables toward one standard deviation shock to the error terms of other variables. However, to overcome the problem of ordering of variables in structural impulse response functions, Pesaran and Shin [6] proposed the Generalized Impulse Response Functions (GIRFs). Now, let us see and denote the generalized impulse response function (G) for a shock to the entire system, u_t^0, as in Equation (2):

$$G_s = E\left(\frac{X_{t+N}}{u_t} = u_t^0, \Omega_{t-1}^0\right) - E\left(\frac{S_{t+N}}{\Omega_{t-1}^0}\right) \tag{2}$$

where the history of the process up to period $t-1$ is regarded as information set Ω_{t-1}^0. Assume $u_t \sim N(0,\Sigma)$ and $E\left(u_t / u_{jt} = \delta_j\right) = \left(\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{mj}\right)' \sigma_{jj}^{-1} \delta_j$, where $\delta_j = \left(\sigma_{jj}\right)^{-1/2}$ denotes a one standard error shock. So, in this way, GIRFs capture response of one variable towards one standard deviation shock to another variable's error term ([7]). Another subset of VAR model is VDA that simply accounts for percentage of variations caused by another variable in an endogenous system. In other words, VDA states that when a shock is given to one variable, then that accounts for how much forecast error variation in another variable.

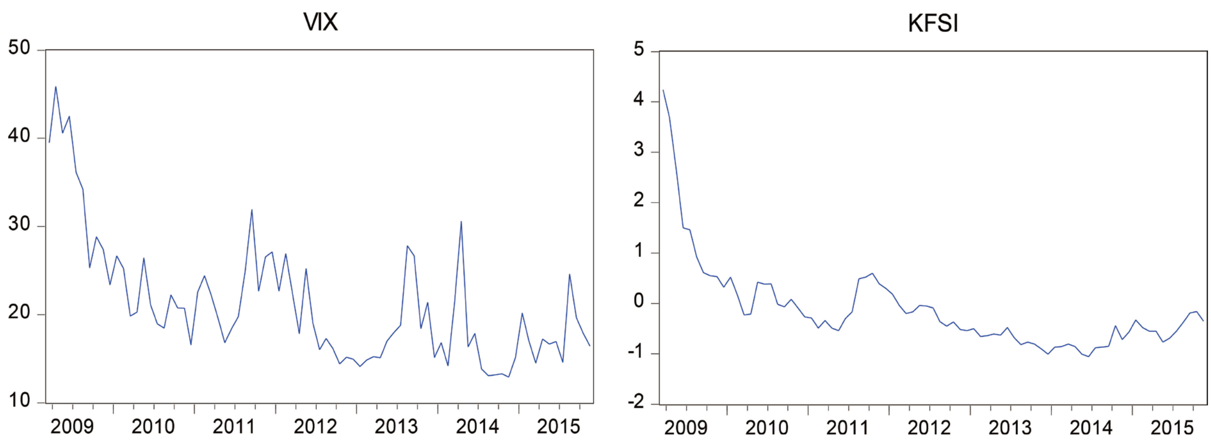
As stated earlier that VAR model captures dynamic interactions among the variables undertaken, so, another advantage of employing the latter framework is to check the cause and effect relationship among the variables under the Block Exogeneity Wald framework. For instance, if past values of one variable, say (X), helps in predicting future values of another variable, say (Y), then it is said that X granger causes Y or Y getting affected by X. Lastly, the study employs Diebold and Yilmaz [4] procedures to come out with a spillover index with the aim to calculate the total contribution of the shocks on an asset market arising from the contribution of all other markets. The index is calculated on the basis of N-variable Vector Autoregression model ([8]). The forecasted error variances calculated under the variance decomposition analysis play a pivotal role in calculating the index values. The forecasted error variances are demarcated into two parts; own variance shocks and cross market variance shocks. Suppose there are two variables, and the possible spillover shock impacts from the first variable to the second and vice versa are $a_{0,12}^{2}$ and $a_{0,21}^{2}$ respectively. The total of the latter can be regarded as the total spillover impact, whereas the average of the same represents as an index value, calculated N step ahead forecasted variances ([9]).

3. Empirical Findings

Figure 1 is the graphical presentation of the financial stress index and the volatility index across the years 2009 to 2015. It is quite interesting to observe that both of the indices are in a decreasing mode after the US financial crisis that got unleashed in the year 2007. This spotlights that there is a strong co-movement between both of the indices. The unconditional correlation coefficient of 0.81 further reports that both the US financial stress index and India VIX index share a strong co-movement with each other.

Table 1 reports the descriptive statistics of both the indices. On an average, monthly implied volatility in the Indian equity market is 21.26 coupled with a standard deviation of 7.03, which is quite high. On the other hand, monthly average stress in the US financial system is favorably negative along with a lower standard deviation of 0.90. It is further confirmed from the maximum and lowest values reported in the context of both of the indices. The skewness values are positive with respect to both of the indices indicating that the probability of a positive value is more in comparison to a negative value. Moreover, the fourth moment values are greater than three thereby indicating leptokurtic distributions of the indices. The Jarque-Bera test values report non linear distribution of the respective indices.

The total number of observations are 81. In financial time series analysis, the dataset is required to be stationary in order to avoid spurious results. So, the present study employs Augmented Dickey Fuller (ADF), Philips-Perron and KPSS tests with trend and intercept in order to check for stationarity of the dataset. Both of the indices are found to be stationary at level and at the 1% and 5% significance level. Lastly, to check independent distribution of the indices, the study employs Ljung-Box test statistics. The results report that none of the indices are independently distributed. This means that both of the indices are significantly influenced by their own past



Source: Computed by the authors.

Figure 1. Graphical presentation of indices.

Table 1. Descriptive statistics.

	VIX	KFSI
Mean	21.26642	−0.108148
Maximum	45.87000	4.240000
Minimum	12.90000	−1.060000
Sigma	7.038491	0.904286
Skewness	1.443934	2.718157
Kurtosis	5.051671	12.16308
Jarque-Bera	42.35331	383.1149
Probability	0.0000*	0.0000*
Observations	81	81
ADF test	−4.2119**	−6.6215**
Philips-Perron test	−3.9706**	−6.4997**
KPSS	0.1331***	0.1788#
L-Box(1)	48.182****	55.306****
L-Box(12)	138.89****	172.39****
L-Box(36)	172.79****	193.02****

Source: Computed by the authors. *Reject null hypothesis of normal distribution at the 5% significance level; **Reject null hypothesis of non-stationary time series at the 5% significance level; ***Accept null hypothesis of stationary time series with asymptotic critical value 0.1460 at the 5% level; #Accept null hypothesis of stationary time series with asymptotic critical value 0.2160 at the 1% level; ****Reject null hypothesis of independent distribution of the indices at the 5 percent significance level.

lagged values, for instance, 1, 12, and 36 month lagged values.

Another important concept in the area of financial economics is cointegration among the variables. In simple terms, cointegration analysis captures that whether the underlying variables share a common stochastic trend over a period of time or not. If they share a common stochastic trend, then it is regarded as long run co-movement among the indices. However, for the existence of cointegration, the time series dataset is required to be integrated of order one, *i.e.* I (1) wherein it should be non-stationary at level but becomes stationary after taking first difference. Contrary to this, the present study shows that both of the indices are integrated of order 0, whereby they are found to be stationary at level per se. So, there is no long run co-movement among the indices. This further highlights and supports the usage of the VAR model to account for short run linkages among the underlying indices.

Table 2 reports VAR model results. The Akaike Information Criteria (AIC) values support the usage of one month lagged values in the VAR framework. One month lagged value of the US financial stress has a statistically significant impact on the current Indian market volatility at the 5% significance level. The magnitude of the impact is quite high as the coefficient value is 3.7021, which means that if the stress in the US financial system increases by 1%, then the volatility in the Indian equity market increases by 3.70% approximately. On the other hand, impact of its own one month lagged value is approximately 0.37%. However, contrary to this, the impact of one month lagged value of Indian equity market volatility on the US financial stress is not found to be statistically significant at the 5% significance level. Consequently, the impact of its own one month lagged value on the financial stress is found to be significant and greater in magnitude (0.83) at the 5% significance level. All of the residual diagnostic tests confirm adequacy of the VAR model.

The inverse roots of AR characteristic polynomial lie inside the unit circle. Furthermore, there is no evidence of serial correlation and heteroskedasticity (bothunivariate and multivariate) in the standardized residuals derived from the VAR model. The residuals are found to be white noise.

Table 3 reports Granger causality results. As expected, the stress in the US financial system Granger causes implied volatility in the Indian equity market. On the other hand, the implied volatility in the Indian equity market does not Granger causes stress in the US financial system in statistical significance terms. Now we move on Generalized impulse responses and VDA part. **Figure 2** reports Generalized impulse responses of the respective variables when shocks are subjected to the error terms of other variables. When a shock is subject to the US financial stress, then the response of implied volatility in the Indian equity market is positive initially. But after

Table 2. Vector autoregression results {standard errors in ( ) & t-statistics in [ ]}.

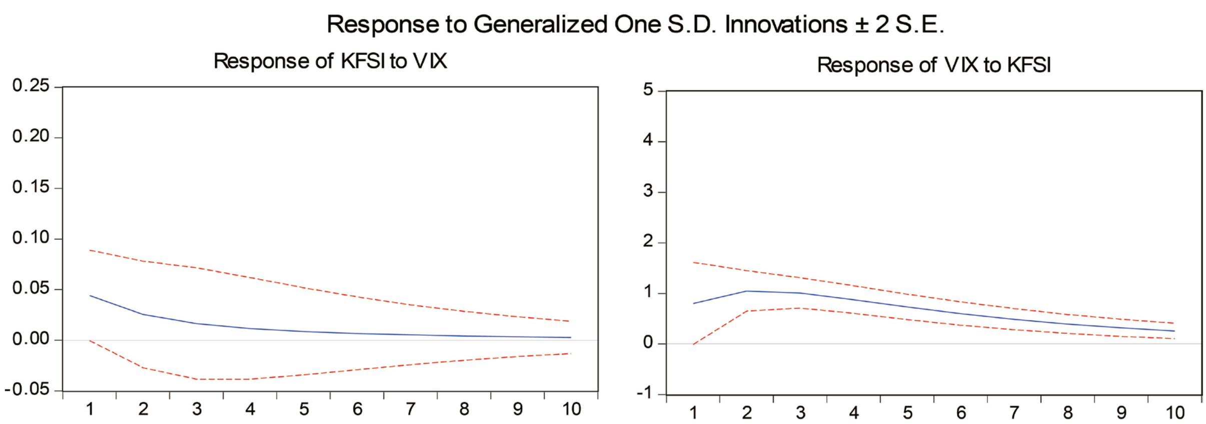
	VIX	KFSI
	0.374932	−0.003100
VIX(−1)	(0.09996)	(0.00552)
	[3.75070]	[−0.56182]
	3.702195	0.831712
KFSI(−1)	(0.77609)	(0.04284)
	[4.77034]	[19.4146]
	13.43168	−0.008951
C	(2.23649)	(0.12345)
	[6.00569]	[−0.07251]
R-squared	0.714961	0.931928
Adj. R-squared	0.707557	0.930160
Sum sq. resids	1033.832	3.150074
S.E. equation	3.664203	0.202262
F-statistic	96.56903	527.0810
Log likelihood	−215.8751	15.86895
Akaike AIC	5.471878	−0.321724
Schwarz SC	5.561204	−0.232398
Mean dependent	21.03863	−0.162500
S.D. dependent	6.775774	0.765357

Source: Computed by the authors.

Table 3. Granger causality results.

Dependent variable: VIX			
Excluded	Chi-sq	df	Prob.
KFSI	22.75615	1	0.0000
All	22.75615	1	0.0000
Dependent variable: KFSI			
Excluded	Chi-sq	df	Prob.
VIX	0.315639	1	0.5742
All	0.315639	1	0.5742

Source: Computed by the authors.



Source: Computed by the authors.

Figure 2. Generalized impulse responses.

three months, it starts following a downward trend and approaches the lowest value in the coming 10 months. However, the response of the US finance stress is positive initially, but with a downward bias. This exhibits that a shock in the US financial system has a greater magnitude impact on the implied volatility in the Indian equity market. The results support strong implications for the Indian equity market investors.

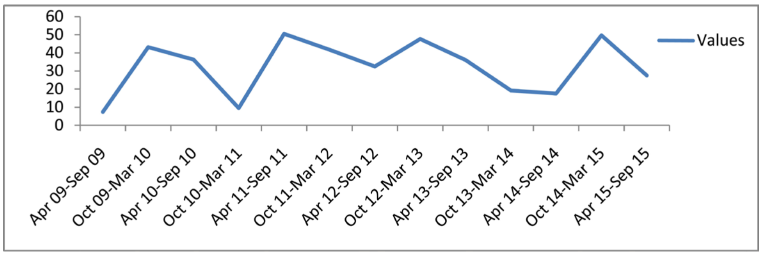
Lastly, **Table 4** reports VDA results. The ordering of the variables is done considering the VAR model results. The results show that when a shock is given to the US financial system, then that contributes around 5% of the forecasted error variations in the Indian equity market volatility index in the first month. However, its contribution increases over a period of 10 months to 25% approximately. On the other hand, when a shock is subject to the Indian volatility index, then that contributes around approximately 0.50% (average) of the variability in the US financial system. This clearly demonstrates the dominant role of the US financial system on the Indian equity market volatility.

To capture time varying interaction behavior among the underlying indices, the study employs Diebold and Yilmaz's [4] spillover index procedures. The spillover plot is computed by taking six month window of the indices collected like April 2009 to September 2009 (one window), October 2009 to March 2010 (second window), April 2010 to September 2010 (third window) and so on. To estimate the spillover index values, two months ahead forecasted error variance values are taken into account. **Figure 3** exhibits the spillover plot for the Variance decomposition for two months ahead forecasted error variance, based on VAR with one lag and a constant. The results exhibit that cross market impact or spillovers are quite high over the years. The respective indices are impacted by own market shocks as well as cross market shocks. On an average, 32% of the variations are accounted by cross market shocks whereas rest of the variations are as a result of own market shocks. Interestingly, during the Euro-zone debt market crisis (late 2011), spillover index value was near to 42 levels, which is again quite high thereby depicting the cross market impact.

Table 4. Variance decomposition analysis results.

Variance decomposition of VIX:			
Period	S.E.	VIX	KFSI
1	3.664203	95.22557	4.774434
2	4.040307	89.33208	10.66792
3	4.189396	84.30112	15.69888
4	4.281751	80.78698	19.21302
5	4.343748	78.49734	21.50266
6	4.385067	77.03337	22.96663
7	4.412249	76.09917	23.90083
8	4.429988	75.50146	24.49854
9	4.441517	75.11777	24.88223
10	4.448995	74.87079	25.12921
Variance decomposition of KFSI:			
Period	S.E.	VIX	KFSI
1	0.202262	0.000000	100.0000
2	0.261731	0.179368	99.82063
3	0.294616	0.347672	99.65233
4	0.314324	0.464999	99.53500
5	0.326534	0.540785	99.45922
6	0.334233	0.588720	99.41128
7	0.339137	0.618964	99.38104
8	0.342280	0.638117	99.36188
9	0.344302	0.650309	99.34969
10	0.345607	0.658107	99.34189

Source: Computed by the authors; Cholesky ordering: KFSI VIX.



Source: Computed by the authors.

Figure 3. Spillover index.

4. Concluding Remarks and Implications

The present study attempts to account for linkages among the US financial stress index and Indian equity market implied volatility index across the years 2009 to 2015 by employing diverse econometric models. The results report a statistical significant impact of the stress in the US financial system on the Indian equity market volatility. With an increase in the stress in the US financial system, volatility in the Indian equity market witnessed a manifold increase accordingly. However, on the other hand, volatility in the Indian equity market does not have a statistically significant impact on the US financial stress. On a similar note, the results are reported by Granger causality test, generalized impulse responses and VDA spotlight greater magnitude impact of the US financial stress on the Indian equity market volatility. There is a uni-directional impact of the US financial stress on the Indian equity market. On an average, 32% of the variations are accounted by cross market shocks whereas rest of the variations are as a result of own market shocks. This shows that spillover impacts across the respective indices are quite pragmatic. Notwithstanding, the results are quite obvious because the US being a dominant economy is expected to have a greater degree impact on the Indian equity market. But through the present study, an attempt has been made to quantify these existing linkages in empirical terms. Moreover, it is quite interesting to observe that the US financial system is still having a greater magnitude impact on the Indian equity market after the financial crisis. The results have strong implications for the Indian equity market investors. Accordingly, an increase in equity market volatility can be hedged by different derivative instruments, like NIFTY VIX futures per se. So, it is quite pertinent to gauge the movement of Indian equity market volatility with the US financial stress. As mentioned earlier, an increased volatility can be considered as an opportunity to earn abnormal returns in the market concerned.

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