

PREDICTABILITY OF INDIA VIX WITH CBOEVIX: A GRANGER CAUSALITY TEST

Abstract

The Volatility Index (VIX) is the most important indicator of the volatility of any stock market. The concept of volatility index was introduced by the Chicago Boards of Options Exchange (CBOE). Thereafter, all the stock markets of the world adopted the concept of VIX, so as to ease down the process of option valuation. The CBOE VIX tracks the S&P 500 index. Literatures show that the US stock markets highly influence the Indian stock markets. The major objective of the study is to test whether there exists a two-sided causality or not between the Indian and US volatility indices. Daily data of Indian and CBOE VIX from January 2013 to December, 2022 was taken under the study, and Granger Causality test was applied in order to check the predictability of Indian VIX with the help of CBOE VIX. The present study finds two-sided causality between India VIX and CBOE VIX.

Keywords: CBOE VIX, Granger Causality test, India VIX, Stationarity, Unit Root test

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I. INTRODUCTION

India VIX or volatility index is the most important indicator of the volatility of the stock market. Usually, the volatility of a particular stock is measured using the beta or standard deviation, whereas the volatility of the entire index (or market) is measured using the volatility index or VIX. The Volatility Index (VIX) is the measure of the volatility in the market, where volatility means dispersion from the actual returns. It is often referred to as the Fear Index as it depicts the level of fear in the market. VIX can provide insights into the market sentiment and volatility. Though VIX is not specifically designed to predict the direction or movements of any individual market, it primarily indicates the expected volatility.

Various indicators have been identified by researchers to measure stock market volatility in the different markets of the world. The first volatility index (VIX) was introduced by Chicago Board of Options Exchange (CBOE) in 1993 based on the expected volatility in the S&P 100 index for the next 30 days. In 2003, CBOE developed further methodologies and changed the underlying index to CBOE S&P 500 index. India VIX is a volatility index based on the NIFTY Index Option prices for the expected market volatility over the next 30 calendar days. India VIX adapted the computation method of CBOE, with amendments to suit the NIFTY options.

The present study is divided into the following sections – Introduction, Literature Review, Objectives of the Study, Research Methodology, Analysis and Interpretations, Recommendations and Conclusions.

II. LITERATURE REVIEW

Banerjee and Kumar (2011) in their study found that forecast error is minimum for VIX, indicating that a model-free estimator of volatility captures the underlying volatility better than an econometric model of volatility. Bagchi (2012) in his study found India VIX yields a positive and significant relationship with the portfolio return. He found that India VIX has higher predictive accuracy over 45-day period. So, India VIX can be regarded as a distinct risk factor that could assist an investor to understand the price discovery mechanism. Mishra (2012) empirically appraised the performance of the Indian capital market and provided the evidence of growing market size, liquidity, greater volatility and weak form inefficiency. Mall et al. (2014) in their study found bidirectional causality from Nifty to VIX. Shaikh and Padhi (2015) analyzed the behavior of implied volatility and results demonstrated seasonal anomalies of the emerging market's volatility index in the form of day, the week, the options expiration and month of the year effects. Naik and Reddy (2016) in their observations to understand the dynamics of linkages between the volatility indices of US(VIX), Germany (VDAX), India (VIX), South Korea (VKOSPI) and China (VXFXI), found that there is a moderate level of influence of the US index on India VIX. Further, the Indian VIX seems to be minimally integrated with its Asian index. Similarly, Singh (2016) in his study indicated the presence of a unidirectional impact of the US financial stress on the Indian equity market. Bantwa (2017) showed that India VIX can be very useful in employing timing strategies in stock market trading. Ramasubramanian and Sophia (2017) in their study on VIX of stock markets found any change in India VIX reflects the change in other markets as well. The study found that Brazilian market has an effect upon the Indian volatility index. The markets that do not relate in the sample markets are USA and Chicago. Patane et al. (2017) found

some significant positive influence of US volatility on German market, however not the vice versa. Pranesh et al. (2017) study showed that factors like business confidence index has positive effect on India VIX while other factors like PMI, FII and DII did not impact India VIX. It also revealed a negative relationship between FII and DII. Saranya and Sudhamathi (2018) examined the asymmetric and temporal relationship between India Volatility Index and select equity index returns where the magnitude of asymmetry is not identical.

Aliyev et al. (2020) in their model tried to estimate the volatility of the nonfinancial, innovative and hi-tech focused stock index, the NASDAQ-100. The index demonstrated leverage effect, and the impact of shocks was asymmetric, whereby the impacts of negative shocks on volatility were higher than those of positive shocks of the same magnitude. Gajera (2020) found movement of stock indices were predictable more for the one's which were opening later based on the one's which were opening earlier. Similarly, stock indices belonging to same continent had higher correlation.

The literature review has revealed a negative and asymmetric relationship between implied volatility and its underlying assets both in developed markets and emerging markets. It also reveals causality of India VIX and Nifty returns.

III. OBJECTIVES OF STUDY

The major objectives of the study based on the above literature review are as follows

1. To analyze the return distribution of daily open, high, low and close data of India and Chicago VIX for the period January 2013 to December 2022.
2. To determine the appropriate lag at where the time series of the open, high, low, and close data become stationary.
3. To test the Granger Causality between the India VIX and Chicago VIX for the period January 2013 to December 2022 at the appropriate lags.

IV. RESEARCH METHODOLOGY

This section discusses the research methodology used to address the research problem. Firstly, the dataset used in the present study is described, followed by the theoretical issues on Granger Causality test.

1. **Data:** Daily data of open, high, low and close (OHLC) on India VIX and Chicago Board Options Exchange (CBOE) were collected from the NSE website for the period of January 2013 to December 2022. The data was collected from the website of National Stock Exchange and Chicago Board Option Exchange website. Since the OHLC data is a time series, Granger Causality test is performed to test whether the India VIX can be used to predict the CBOE VIX or vice-versa.
2. **Theoretical Issues on Granger Causality Test:** One series can be predicted by the use of other, if they are significantly correlated with each other. In a simple cross-sectional data, a correlation analysis is done for scale data (Pearson, 1896). In his paper, it was shown on theory of evolution that the correlation between the two properties of individuals (such as age, gender, height, attractiveness etc.)exists when the mean of one

series is a function of the mean of another series – that mean of one series now can be used to predict the other series.

In order to understand that one time series can be predicted with the other, it is essential to understand that whether one time series causes another, it is necessary to understand, that a “series” must contain some trend, or be free from any fluctuations. In other words, the series should be stationary. This is the first assumption to conduct a Granger Causality test. Granger (1969) mentioned a common specification test for such series, whose error terms were correlated among each other – in other words, the data was the time series data.

Let X_t, Y_t be two time series, having a zero-unit root (i.e., stationary), with mean zero and variance one. Then the simple casual model was stated as –

$$X_t = \sum_{j=1}^m a_j X_{t-j} + \sum_{j=1}^m b_j Y_{t-j} + \varepsilon_t, \quad (1)$$

$$Y_t = \sum_{j=1}^m c_j X_{t-j} + \sum_{j=1}^m d_j Y_{t-j} + \eta_t,$$

where, ε_t, η_t are the two uncorrelated white-noise series, i.e., $E[\varepsilon_t \varepsilon_s] = 0 = E[\eta_t \eta_s], s \neq t$, and $E[\varepsilon_t \varepsilon_s] = 0$ for all t, s . In model (1), m is considered to be finite and shorter than the given time series data. The definition of causality as per Granger (1969) implies that Y_t is causing X_t provided some $b_j \neq 0$. Similarly, X_t is causing Y_t if some $c_i \neq 0$. If both these events occur, then it can be implied that two-way relationship exists between X_t and Y_t .

In order to test the stationarity in the time series, Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) is applied in this study. Unit root is a feature of some random (stochastic) process which may cause hindrance in proper prediction in the time series models. If unit root is present in the data, then the data is said to be non-stationary, and the lagged data is considered to remove the presence of unit root. The ADF test assumes the following alternative hypothesis –

H_a: Unit root is absent in the time series data

The ADF test assumes the following regression model –

$$y_t = c + \beta t + \alpha y_{t-1} + \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} + \dots + \phi_p \Delta Y_{t-p} + e_t \quad (2)$$

In the above regression, the null hypothesis is tested for $\alpha = 1$. If the null hypothesis is accepted, then it is concluded that the unit root is present and the time series is not stationary.

V. ANALYSIS AND INTERPRETATION

Descriptive Statistics In the table 1 (appendix), daily data on OHLC of Indian and Chicago market for the period of 9 years is analyzed. A total of 2332 data points were analyzed. The maximum range in the CBOE market is for the daily high data. The standard deviation is also the highest of the high data of CBOE, whereas the lowest deviation (as observed by range and standard deviation) is observed in the low data. Average open was found to be higher than the average close. All the data points of the CBOE VIX were found to be positively skewed with a standard error of 0.5. The standard deviation between the open, high, low and close was found more or less stable. In the Indian market also, the highest standard deviation was found in the high data and the lowest standard deviation was found in the low data. A high skewness and kurtosis in the India VIX than that of the CBOE VIX revealed a presence of high volatility in the Indian market than that of the CBOE market.

One of the interesting observations in the OHLC data of India and Chicago VIX is that, in the Chicago market, the open, high, low and close data are widely spread, and in the Indian market, the open, high, low and close are not so much widely spread. Therefore, from all the observations of the descriptive statistics, it can be concluded that Indian markets are more volatile than the Chicago markets. One conclusion that can be drawn, that the volatility spillover from the Chicago markets is making the Indian markets more volatile. Therefore, the present study hypothesizes from the literature and the descriptive statistics of the current data that by using the volatility of Chicago markets, Indian volatility can be modelled. From figure 1, it can be observed that the volatility in the Indian market is higher than that of the Chicago market.

Table 2 shows the unit root tests for the stationarity of the data of the OHLC data of the Indian and Chicago volatility index. It also shows the appropriate number of lags at which the data becomes stationary. It can be observed that the Chicago stock market is relatively stable than the Indian stock market in terms of unit root. The high VIX was found to be stable at lag 0, while the low and close VIX was found to be stationary at 2ndlag. The low VIX was found to be stationary at 3rdlag. Regarding Indian volatility, open, low and close volatility was found to be stationary at 5thlag while the high VIX was found to be stable at 8thlag. Table 3 shows the selection of the appropriate lags for conducting the granger causality test. The highest lags (i.e., 5th and 8thlag) were selected to make the time series stationary. Using these lags, the Granger Causality test was carried out to determine the causality between India VIX and Chicago VIX.

After making the data stationary by including the appropriate lags in order to make the time series stationary, the test for two-way Granger Causality was done. Table 4 shows the results of the two-way Granger causality test. 16 pairs of Indian VIX (OHLC) and Chicago VIX (OHLC) was formed (4²pairs). It can be observed from the table that the closing VIX of Indian and CBOE markets has a two-way Granger Causality. This is a clear indicator, that there exists some relationship between the Indian and US volatility and that the Indian shocks can be well predicted with the US markets. However, it can be observed that during the period under study, the Indian open, high and low VIX did not granger cause the CBOE open and high VIX. It was only found to be a unidirectional relationship, similar to the findings of Singh (2016).

VI. RECOMMENDATIONS AND CONCLUSIONS

The present study finds that a unidirectional relationship between Indian Open, High and Low and CBOE Open, High and Close, and bidirectional relationship was found between Indian close VIX and CBOE close VIX. This finding is very important as the US markets close at 01:30 AM IST, and the Indian markets opens at 09:15 AM IST, therefore, a relationship between US VIX and India VIX can be of utmost importance in order to predict the volatility of Indian stock markets. Future research can be undertaken in order to establish the relationship between the CBOE closing VIX and India closing VIX with CBOE closing VIX as the predictor variable and India closing VIX as an outcome variable to understand the bi-directional relationship in order to control the volatility of the Indian stock markets.

REFERENCES

- [1] Aliyev, F., Ajayi, R., & Gasim, N. (2020). Modelling asymmetric market volatility with univariate GARCH models: Evidence from NASDAQ-100. *The Journal of Economic Asymmetries*, 22, e00167. doi:10.1016/j.jeca.2020.e00167
- [2] Bagchi, D. (2012). Cross-sectional analysis of emerging market volatility index (India VIX) with portfolio returns. *International Journal of Emerging Markets*, 7(4), 383-396. doi:10.1108/17468801211264306
- [3] Banerjee, A., & Kumar, R. (2011). Realized volatility and India VIX (688). Indian Institute of Management Calcutta.
- [4] Bantwa, A. (2017). A Study on India Volatility Index (VIX) and its Performance as Risk Management Tool in Indian Stock Market. *Paripex - Indian Journal of Research*, 6(1). Retrieved from <https://ssrn.com/abstract=3732839>
- [5] Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), 427. doi:10.2307/2286348
- [6] Gajera, A. (2020). A study on comparative analysis of major stock indices of world. *IARS International Research Journal*, 10(1). doi:10.51611/iars.irj.v10i1.2020.113
- [7] Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3), 424. doi:10.2307/1912791
- [8] Mall, M., Mishra, S., Mishra, P. K., & Pradhan, B. B. (2014). A study on relation between India VIX and NIFTY returns. *Intercontinental Journal of Banking, Insurance and Finance*, 1(3), 1-7.
- [9] Mishra, P. K. (2012). Global Financial Crises and Indian Capital Market: An Econometric Analysis. *International Journal of Applied Business and Economic Research*, 10(1), 11-29.
- [10] Naik, M. S., & Reddy, Y. V. (2016). Volatility Indices: An International Comparison. *The IUP Journal of Financial Risk Management*, 8(3), 7-19. Retrieved from <https://ssrn.com/abstract=2966588>
- [11] Patanè, M., Tedesco, M., & Zedda, S. (2017). The "Surprise effect" of macro indicators on the options implied volatilities dynamics: A test on the United States-Germany relationship. *Modern Economy*, 08(04), 590-603. doi:10.4236/me.2017.84044
- [12] Pearson, K. (1896). Contributions to the mathematical theory of evolution. III. Regression, heredity, and panmixia. *Proceedings of the Royal Society of London*, 59(353-358), 69-71. doi:10.1098/rspl.1895.0058
- [13] Pranesh, K. K., Balasubramanian, P., & Mohan, D. (2017). The determinants of India's implied volatility index. 2017 International Conference on Data Management, Analytics and Innovation (ICDMAI). doi:10.1109/icdmai.2017.8073532
- [14] Ramasubramanian, H., & Sophia, S. (2017). Relationship Between India VIX and other VIX. *International Journal of Economic Research*, 14(3), 329-337.
- [15] Saranya, P. B., & Sudhamathi, R. K. (2018). On the asymmetric relationship between India VIX and select equity index returns. *Asian Journal of Research in Business Economics and Management*, 8(11), 1. doi:10.5958/2249-7307.2018.00074.9
- [16] Shaikh, I., & Padhi, P. (2015). The behavior of option's implied volatility index: A case of India VIX. *Verslas: TeorijairPraktika*, 16(2), 149-158. doi:10.3846/btp.2015.463
- [17] Singh, A. (2016). On the linkages between India VIX and US financial stress index. *Theoretical Economics Letters*, 06(01), 68-74. doi:10.4236/tel.2016.61009

Appendix

Table 1: Descriptive Statistics of the OHLC Data

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
					Statistic	Std. Error			Statistic	Std. Error	Statistic	Std. Error
CBOE_OPEN	2332	73.68	9.01	82.69	17.76	0.15	7.34	53.87	2.80	0.05	14.14	0.10
CBOE_HIGH	2332	76.16	9.31	85.47	18.81	0.17	8.13	66.12	2.88	0.05	14.58	0.10
CBOE_LOW	2332	61.81	8.56	70.37	16.81	0.14	6.61	43.76	2.58	0.05	11.85	0.10
CBOE_CLOSE	2332	73.55	9.14	82.69	17.64	0.15	7.31	53.41	2.82	0.05	14.33	0.10
INDIA_OPEN	2332	83.61	0.00	83.61	17.79	0.13	6.50	42.31	3.97	0.05	25.50	0.10
INDIA_HIGH	2332	86.64	0.00	86.64	18.54	0.14	6.90	47.58	3.94	0.05	25.26	0.10
INDIA_LOW	2332	75.97	0.00	75.97	16.27	0.13	6.14	37.68	3.91	0.05	25.39	0.10
India_CLOSE	2332	73.16	10.45	83.61	17.81	0.13	6.49	42.18	4.00	0.05	25.57	0.10

Source: Researcher's Computation

Table 2: Augmented Dicky-Fuller tests for unit root

Null Hypothesis	lag	t-stat	p-value
CBOE_CLOSE has a unit root	2	-5.629	0.000
CBOE_HIGH has a unit root	0	-6.207	0.000
CBOE_LOW has a unit root	3	-4.832	0.000
CBOE_OPEN has a unit root	2	-5.601	0.000
INDIA_CLOSE has a unit root	5	-5.800	0.000
INDIA_HIGH has a unit root	8	-6.400	0.000
INDIA_LOW has a unit root	5	-5.858	0.000
INDIA_OPEN has a unit root	5	-5.679	0.000

Source: computed by researcher

Table 3: Selection of Optimum Lags for making data stationary for Granger Causality test

Pair	Particulars		Lags
1	CBOE_OPEN	INDIA_OPEN	5
2	CBOE_OPEN	INDIA_HIGH	8
3	CBOE_OPEN	INDIA_LOW	5
4	CBOE_OPEN	INDIA_CLOSE	5
5	CBOE_HIGH	INDIA_OPEN	5
6	CBOE_HIGH	INDIA_HIGH	8
7	CBOE_HIGH	INDIA_LOW	5
8	CBOE_HIGH	INDIA_CLOSE	5
9	CBOE_LOW	INDIA_OPEN	5
10	CBOE_LOW	INDIA_HIGH	8
11	CBOE_LOW	INDIA_LOW	5
12	CBOE_LOW	INDIA_CLOSE	5
13	CBOE_CLOSE	INDIA_OPEN	5
14	CBOE_CLOSE	INDIA_HIGH	8
15	CBOE_CLOSE	INDIA_LOW	5
16	CBOE_CLOSE	INDIA_CLOSE	5

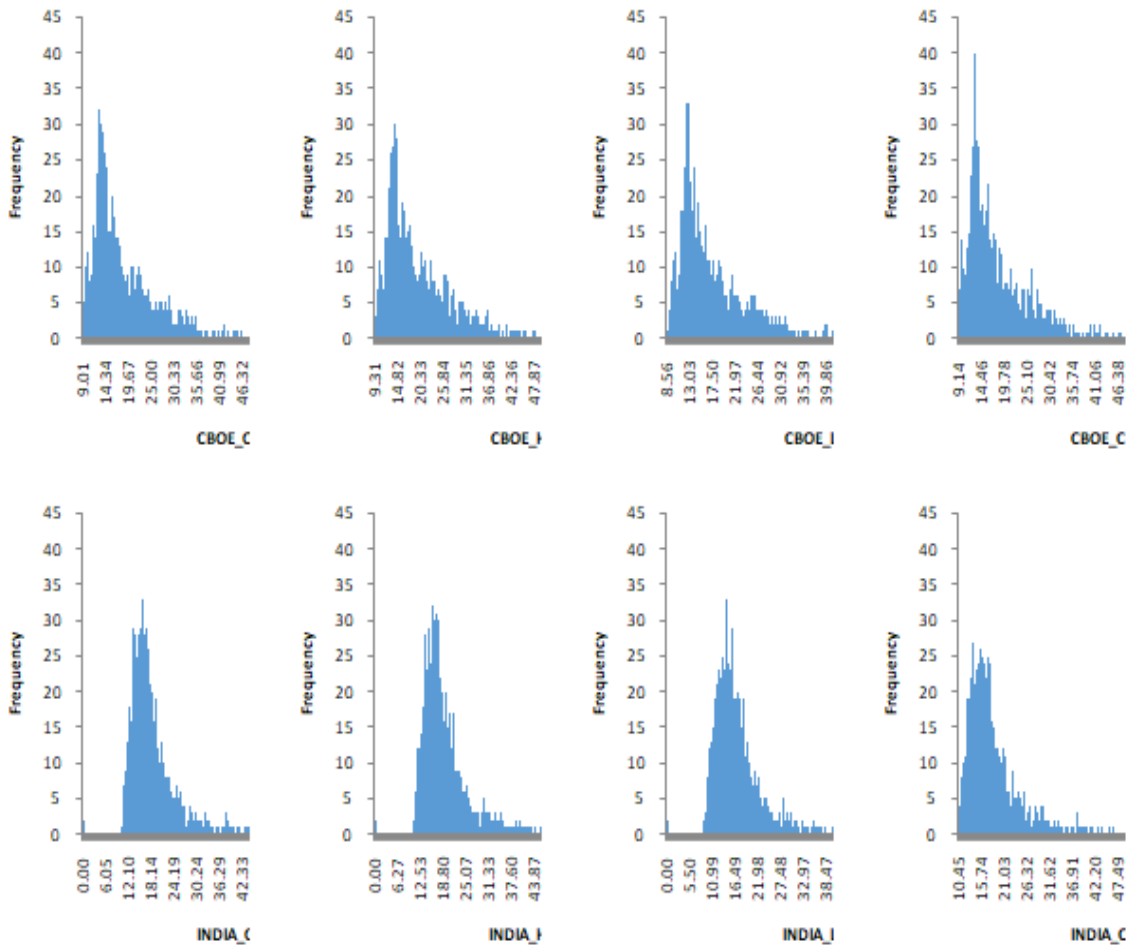
Source: computed by researcher

Table 4: Granger Causality test

Pair	Null Hypothesis	Obs.	F-Stat.	Prob.
1	INDIA_OPEN does not Granger Cause CBOE_OPEN	2327	2.195	0.052
	CBOE_OPEN does not Granger Cause INDIA_OPEN		71.079	0.000
2	INDIA_HIGH does not Granger Cause CBOE_OPEN	2324	2.406	0.014
	CBOE_OPEN does not Granger Cause INDIA_HIGH		13.681	0.000
3	INDIA_LOW does not Granger Cause CBOE_OPEN	2327	2.977	0.011
	CBOE_OPEN does not Granger Cause INDIA_LOW		30.669	0.000
4	INDIA_CLOSE does not Granger Cause CBOE_OPEN	2327	3.274	0.006
	CBOE_OPEN does not Granger Cause INDIA_CLOSE		11.926	0.000
5	INDIA_OPEN does not Granger Cause CBOE_HIGH	2327	1.469	0.197
	CBOE_HIGH does not Granger Cause INDIA_OPEN		72.424	0.000
6	INDIA_HIGH does not Granger Cause CBOE_HIGH	2324	1.814	0.070
	CBOE_HIGH does not Granger Cause INDIA_HIGH		31.014	0.000
7	INDIA_LOW does not Granger Cause CBOE_HIGH	2327	1.319	0.253
	CBOE_HIGH does not Granger Cause INDIA_LOW		47.881	0.000
8	INDIA_CLOSE does not Granger Cause CBOE_HIGH	2327	6.940	0.000
	CBOE_HIGH does not Granger Cause INDIA_CLOSE		24.039	0.000
9	INDIA_OPEN does not Granger Cause CBOE_LOW	2327	3.693	0.003
	CBOE_LOW does not Granger Cause INDIA_OPEN		42.691	0.000
10	INDIA_HIGH does not Granger Cause CBOE_LOW	2324	4.698	0.000
	CBOE_LOW does not Granger Cause INDIA_HIGH		16.954	0.000
11	INDIA_LOW does not Granger Cause CBOE_LOW	2327	3.808	0.002
	CBOE_LOW does not Granger Cause INDIA_LOW		26.043	0.000
12	INDIA_CLOSE does not Granger Cause CBOE_LOW	2327	6.465	0.000
	CBOE_LOW does not Granger Cause INDIA_CLOSE		15.154	0.000
13	INDIA_OPEN does not Granger Cause CBOE_CLOSE	2327	0.987	0.424
	CBOE_CLOSE does not Granger Cause INDIA_OPEN		57.980	0.000
14	INDIA_HIGH does not Granger Cause CBOE_CLOSE	2324	1.365	0.207
	CBOE_CLOSE does not Granger Cause INDIA_HIGH		32.460	0.000
15	INDIA_LOW does not Granger Cause CBOE_CLOSE	2327	1.206	0.304
	CBOE_CLOSE does not Granger Cause INDIA_LOW		47.522	0.000
16	INDIA_CLOSE does not Granger Cause CBOE_CLOSE	2327	0.553	0.736
	CBOE_CLOSE does not Granger Cause INDIA_CLOSE		32.232	0.000

Source: computed by researcher

Figure 1: Histogram of CBOE and Indian VIX (OHLC)



Source: Computed by Researcher