The Behaviour of India's Volatility Index

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Abstract

This study examines the behaviour of India's volatility index (Ivix) that was launched in 2008. By using linear regressions, autoregressive models and unit root tests, the study tries to empirically answer whether Ivix reflects certain characteristics known as stylised facts of volatility. The results of the study show that the volatility index reproduces almost all the stylised facts such as 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. As the index mirrors most of the empirical regularities, the study primarily makes a case for the introduction of exchange traded volatility derivatives in India. Institutional investors can make use of the over-the-counter derivatives such as variance/volatility swaps to gain from portfolio diversification. This is the first study evaluating the performance of a volatility index that is constructed and disseminated by an organised exchange in an emerging market.

Keywords: volatility index, persistence, clustering, mean reversion

1. Introduction

It is quite common, in the realm of economics usage of indices that are summary measures, to gauge macro trends in price rise or exchange rate movements. In stock markets too indices are used to figure out the broad market sentiment whether the mood is positive or negative. In India, the popular stock market indices are BSE Sensex and Nifty. Similarly to gauge the market anxiety there is a requirement for an indicator and that latent need of the market observers and practitioners is addressed by a volatility index.

A volatility index measures the expected volatility in a given market over a 30-day period (in general). It measures the expected fluctuations in the market index and hence serves as the proxy for overall market's riskiness. A higher (lower) value for the volatility index indicates that market expects greater (lesser) fluctuations in either direction over the next 30 days. Just as increases in the Sensex are applauded by the market, an increase in the volatility index alarms the market, since an increase in volatility index means an increase in uncertainty, which results in discomfort for most market participants. In fact this lead to its epithet "the investors fear gauge". Whaley (2008) states two important uses of a volatility index. First, it serves as a reference point of short-term volatility, and second, it allows trading of pure volatility. Construction of a volatility index is a lot more challenging than any other index, since the index is supposed to measure a quantity that is unobservable. This seemingly difficult problem was cracked by the erudite work of Whaley (1993) that laid the foundations for its introduction. In fact the most tractable meaning of the volatility index is given by Whaley (2000) wherein a parallel is drawn with the yield to maturity of a bond.

In 1993, Chicago Board Options Exchange (CBOE) became the first exchange in the world to introduce a volatility index and named it VIX. Towards the end of that decade most of the stock exchanges in Europe and the North America had come up with volatility indices that are predominantly modelled similar to that of CBOE's VIX. The global financial crisis of 2008 clearly and strongly demonstrated the utility and need for volatility indices. Since the volatility indices became the primary indicators of jitteriness in the market, they became quite popular as the financial media reported them side by side with the market indices such as Dow or the S&P 500 index. The only emerging market with a volatility index calculated and disseminated by an organised exchange is India. National Stock Exchange of India Limited (NSE) introduced the country's first volatility index, India Vix (Ivix), in April 2008. The design and construction methodology of Ivix [1] is quite similar to that of the current VIX calculation methodology adopted by CBOE.

A study of the behaviour of Ivix is essential for two reasons. First, it provides feedback on whether the index is fulfilling its purpose. Second, sooner or later trading of products linked to this volatility index may commence and it is quite imperative to examine the index for its performance and characteristics. This paper attempts to evaluate and examine the behaviour of Ivix since its inception. The behaviour of Ivix is evaluated from a different perspective by questioning whether Ivix reflects certain characteristics known as stylised facts [2] of volatility. If Ivix is able to reproduce and replicate most (all) of the predominant empirical regularities, it can reckoned as serving its objective. The most important stylised facts are the following:

1. Volatility clustering and persistence.
2. Volatility is mean reverting.
3. Volatility is negatively related to stock returns.
4. Volatility is positively related to trading volumes.

The next section presents the evolution of volatility indices followed by Section 3 that examines the statistical properties of Ivix. Section 4 investigates empirically the conformance of Ivix to the stylised facts, and Section 5 presents the conclusions.

2. Evolution of Volatility Indices

The idea of a volatility index similar to a stock index was initially mooted by Gastineau (1977) and Galai (1979). Fleming et al. (1995) and Whaley (1993) provided the methodology for the construction of the VIX; however, in over 10 years there is a major change in the computation methodology. Initially VIX was calculated as implied volatility backed out from the Black-Scholes option pricing model. Since Black-Scholes model is based on the assumption of geometric Brownian motion with constant volatility, the implied volatility from this model is at best an approximation of the true risk-neutral volatility. Britten-Jones and Neuberger (2000) provided a method for computing the risk-neutral expectation of the return variance from the prices of European options without resorting to any option pricing model and only assuming that the process is continuous. Especially, they proved that the risk-neutral expected sum of squared returns over a future time period is given by a set of prices of options expiring at a future date (their Proposition 2). An important advantage of this approach is that all available liquid options (in particular out-of-the-money options) are used instead of few options used in the earlier methodology. This approach became the basis for construction of volatility indices, and CBOE was the first exchange to use the model-free methodology to compute VIX. Subsequently this methodology has become the industry standard with almost all the exchanges (barring a few exceptions such as the Montreal Exchange that still uses Black-Scholes model to compute the volatility index) adopting the same.

Carr and Wu (2006) characterise the volatility index (to be precise rather) as an approximation of the variance swap rate of same maturity. A variance swap is an over-the-counter contract which pays off the monetary value of the difference between realised variance over the life of the contract and a fixed variance swap rate. At inception the variance swap has zero market value, and in order to preclude arbitrage, the variance swap rate equals the risk-neutral expectation of the realised variance which a volatility index aims to measure.

3. Statistical Properties

This study examines the empirical behaviour of Ivix over the period November 1, 2007, to February 28, 2010, and the data are obtained from NSE's web site. Figure 1 depicts a time series plot of the Nifty index and Ivix movements over the period November 2007 to February 2010. In conjunction with the descriptive statistics from Table 1 it can be noted that on an average Ivix hovered around 37.36%. The average Ivix is found to be approximately close to the annualised standard deviations of returns (2.39% x $\sqrt{250}$ = 37.79%). Ivix reached the maximum value of 85.13% on November 17, 2008, almost during the peak of the global financial crisis, and a minimum of 20.98% on January 14, 2010. During the period under consideration the median closing level is 35.54%, and 50% of the time it ranged between 43.11% to 29.23% (a range of 13.88 percentage points) and 90% of the observed time it closed between 57.09% and 24.94% (a range of 32.14 percentage points). Looking at the higher moments it can be inferred that Ivix data series is leptokurtic. The Jarque-Bera normality test indicates that the hypothesis of a normal distribution is strongly rejected. The average of daily changes in Ivix (dIvix) indicates that it is not statistically different from zero; hence, it may be concluded that there is no discernable and significant trend in the Ivix changes.

4. Empirical Examination of Stylised Facts

Stylised fact 1: Volatility clustering and persistence. Observed in the early sixties of the past century by Mandelbrot (1963), this refers to the characteristic that large (small) price movements tend to be followed by further large (small) movements. In other words, periods of high volatility will be followed by high volatile periods and tranquil periods followed by tranquil periods. In particular, shocks to volatility are persistent; hence, current information is valuable in forecasting future volatility. This particular feature - volatility clustering - has led to the development of the ARCH/GARCH class models of volatility. Most often cited explanation for volatility clustering is that the information arrives in chunks and hence volatility clusters. The work of Engle et al. (1990) lends support to this hypothesis. Econometrically this can be verified by the autocorrelation function of the volatility series. The statistical significance and slowly decaying autocorrelations at different lags stand testimony to the volatility clustering and persistence.

Table 1: Descriptive Statistics

	lvix	dlvix	Nifty Returns
Mean	37.36	0.02	0.03
Median	35.54	0.11	0.06
Standard deviation	10.44	4.46	2.39
Kurtosis	1.72	22.08	5.52
Skewness	1.16	0.07	0.17
Minimum	20.98	40.00	13.01
Maximum	85.13	34.07	16.33
Jarque Bera	195.47***	11386.2***	714.13***

***Significant at 1%.

lvix is in levels; $dlvix_t = lvix_t - lvix_{t-1}$ and Nifty Return $= \ln\left(\frac{Nifty_t}{Nifty_{t-1}}\right)$.

Figure 1 Evolution of Nifty and Volatility Index (lvix) 2007 - 2010

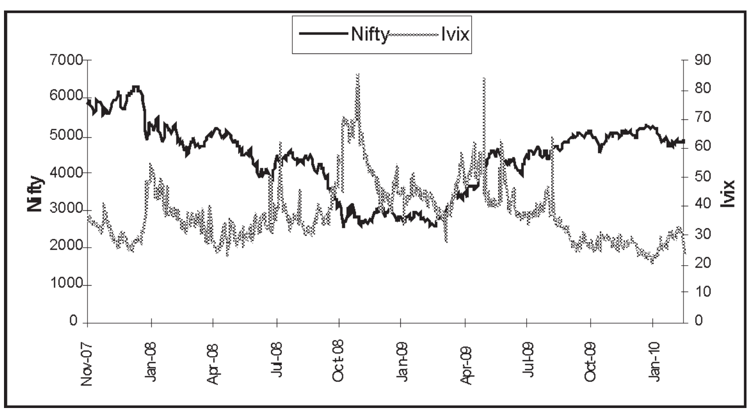

Table 2 presents the autocorrelations of lvix and the values of the standard Ljung-Box portmanteau test for the joint significance of the first 22 autocorrelations (about one month of trading days). The Ljung-Box statistics strongly reject the null hypothesis and holds the presence of autocorrelations. The statistically significant correlation coefficients confirm that the lvix series is positively serially correlated. Therefore, it can be concluded that the volatility persistence and clustering characteristic is manifested by the volatility index.

Table 2: Autocorrelation Coefficients of Ivix in Levels

LAG	ACF	Q-stat	P-value	LAG	ACF	Q-stat	P-value
1	0.9075	471.1083	0.000	12	0.667	4312.2	0.000
2	0.8797	914.5776	0.000	13	0.6423	4553.257	0.000
3	0.8538	1332.98	0.000	14	0.6174	4776.423	0.000
4	0.8322	1731.254	0.000	15	0.5918	4981.818	0.000
5	0.815	2113.86	0.000	16	0.5843	5182.375	0.000
6	0.7984	2481.733	0.000	17	0.5571	5365.079	0.000
7	0.7761	2829.947	0.000	18	0.5466	5541.236	0.000
8	0.7504	3156.051	0.000	19	0.517	5699.104	0.000
9	0.7352	3469.651	0.000	20	0.4995	5846.786	0.000
10	0.7175	3768.885	0.000	21	0.4736	5979.769	0.000
11	0.6982	4052.697	0.000	22	0.4477	6098.816	0.000

Stylised fact 2: Volatility is mean reverting. Mean reversion is generally understood as the tendency of prices to fall (rise) after hitting a maximum (minimum). Similar patterns are observed in stock market volatility too. Though there will be bouts of high/low volatility in due course it will return to its long term average level. In the literature various ways were used to test mean reversion. One approach is to test whether the data are stationary through a unit root test. As a first check a t-test on the unconditional mean of first differences of Ivix is conducted. The t statistic at -0.1145 (P-value = 0.9089) shows that the null hypothesis of zero mean cannot be rejected. This is followed by conducting unit root tests [3], namely Augmented Dickey-Fuller test (ADF) and Phillips-Perron test (PP). The difference between these tests is in the method of dealing with serial correlation and heteroskedasticity in the errors. Phillips-Perron tests are more robust to general forms of heteroskedasticity in the error term. The ADF tests cannot differentiate between unit root and near unit root process; i.e., the power of the tests is low when the process is stationary and the root is close to the non-stationary boundary. ADF and PP tests check for only unit root, and rejection of unit root null hypothesis would not mean the data are stationary. Hence in addition to the unit root tests Kwiatkowski et al (1992) (KPSS) stationarity test is employed for testing stationarity. KPSS tests the null hypothesis that a time series is stationary versus an alternative hypothesis that the series is a unit root process. The results of the tests are presented in Table 3.

Table 3: Unit Root Tests on Ivix Levels Series

Test	Null Hypothesis	Alternate Hypothesis	Test Statistic	Decision
ADF	Unit root process	Stationary process	-2.7707	Reject H0 at 10%
PP	Unit root process	Stationary process	-58.00	H0 is rejected at 5%
KPSS	Mean stationary	Unit root process	0.3635	Accept H0 at 5%

From the test results it may be inferred that Ivix series is stationary, and hence it can be concluded that Ivix exhibits mean reversion. Next the study attempts to compute the mean reversion rate that governs the time taken for the drift to pull the process back to the long-term average. To estimate the mean reversion rate and mean reversion level the following reduced form model is estimated:

$$Ivix_t = \lambda_0 + \lambda_1 \bullet Ivix_{t-1} + \varepsilon_t$$

The above model is an AR(1) model with drift, the unconditional mean is given by the drift and the persistence coefficient as $\frac{\lambda_0}{1-\lambda_1}$. It may be inferred that the past innovation term ε_{t-1} enters today's volatility ($Ivix_t$) at the rate of λ_1 and the next day's volatility at the rate of λ_1^2 so on so forth. The characteristic time to mean revert is given by $\frac{1}{1-\lambda_1}$. The above model is fitted for the unannualised Ivix series, and the results are presented in Table 4.

Table 4: Estimation of Mean Reversion Rate

	Coefficient	Std. error	t-ratio	P-value
Const	0.00088	0.000351	2.5	0.0126
$Ivix_{t-1}$	0.9543	0.0130	73.3	0.0000
Adj R^2 = 0.8434				

From the above results the rate of mean reversion is computed as 21.88 days or around 22 days, which means that the process takes almost one month for half the mean reversion effect to dissipate following a market shock. The mean reversion level is 36.79%. The mean reversion level is close to the unconditional mean of the Ivix at 37.36% (Table 1).

Stylised fact 3: Volatility is negatively related to stock returns. It is observed that volatility is negatively correlated to asset price movements and there is an asymmetric response to favourable and unfavourable news. In particular the increase in volatility following the arrival of bad news is more than the decrease in volatility upon receiving good news. Two competing theories emerged to explain this negative relationship. Black (1976) shows that as the equity prices drop there will be an increase in financial leverage causing the volatility of equity to increase; this is generally known as the leverage effect. Christie (1982) and Schwert (1989) further proved it by documenting an increasing relationship between volatility and financial leverage. The alternate explanation is termed as volatility feedback effect. In the presence of volatility persistence, a positive shock to volatility will have an immediate impact in return to compensate for the additional risk. This translates into a fall in current equity prices. Bekaert and Wu (2000), Wu (2001), Kim et al. (2004), and Mayfield (2004) all find evidence in support of this hypothesis. The relationship between Ivix and stock market returns is examined by running the following regression:

$$Rivix_t = \alpha_0 + \alpha_1 RniftyN_t + \alpha_2 RniftyP_t + \varepsilon_t$$

where $Ivix_t$ measures the daily returns on Ivix series. $Rnifty_t$ measures the daily returns on Nifty series: $RniftyN_t = Rnifty_t$ if the market goes down ($Rnifty_t < 0$) else it is zero; $RniftyP_t = Rnifty_t$ conditional on market going up ($Rnifty_t > 0$) otherwise it assumes a value of zero. If the observed relationship is to hold, the constant term should not be statistically significant, and the coefficients α_1 and α_2 should be statistically significant, their expected sign is negative. For the asymmetric relationship to hold it is expected that $\alpha_1 > \alpha_2$.

Table 5: Relationship Between Ivix and Nifty Returns

	Coefficient	Std. error	t-ratio	P-value
Const	0.0090	0.01	1.6010	0.1099
RniftyN	1.1610	0.47	2.4490	0.0146
RniftyP	0.2105	0.26	0.8140	0.4160
Adj R^2 = 0.03247		F = 5.41; P-value = 0.0047		

The regression results indicate that the constant term is not significant; volatility and stock market returns are negatively related to the volatility changes. Since the constant term is not statistically significant, it is an indication of the absence of deterministic growth further it can be inferred that if the market doesn't move there is no significant change in volatility. Hence, it seems volatility changes can be attributed to market movements. The relationship between Nifty returns and volatility returns are significant only in one direction; i.e., there is a significant negative correlation between Ivix returns and Nifty returns in the down side but no significant relationship is observed in the upside. Hence, it can be inferred that when the markets decline Ivix increases significantly while a rise in the market returns is not associated with a fall in Ivix. Therefore, it can be concluded that Nifty changes and Ivix changes are associated but only during market declines.

Stylised fact 4: Volatility is positively related to trading volumes. Apart from the stock returns-volatility, the other relationship that attracted the attention of researchers is the volume-volatility relationship. Numerous studies have documented a positive relationship between trading volume and volatility. Clark (1973), Karpoff (1987), Lamoureux and Lastrapes (1990), Brock and Lebaron (1996) and Lee and Rui (2002) inter alia have all analysed the relationship between volatility and volume. Hence, this relationship has become a stylised fact. There are two competing hypothesis to explain the relationship between volume and volatility. The first hypothesis is popularly known as mixture of distribution hypothesis (MDH) due to Clark (1973). According to this hypothesis there is a contemporaneous relationship between volume and volatility. The second hypothesis known as sequential information arrival hypothesis (SIAH), first advanced by Copeland (1976), posits that information arrives in a sequential manner and is not received by all traders simultaneously leading to a series of intermediate equilibria before achieving the final equilibrium. Since traded volumes are considered as a proxy for information arrival past values of trading volume contains useful information about future volatility.

The relationship between Ivix and trading volume is examined by the following regression:

$$Ivix_t = \beta_1 + \beta_2\tilde{v}_t + \beta_3\tilde{v}_{t-1} + \beta_4\tilde{v}_{t-2} + \xi_t$$

where $Ivix_t$ is the Ivix on a given day t; $\tilde{v}_t$ is the de-trended trading volume defined as the number of shares traded on a particular day t; to account for the non-linear relationship with past traded volumes two lags of de-trended traded volumes were also included. Since earlier studies such as Lee and Rui (2002) document non-linear trends in trading volume, instead of employing the raw volume figures the study uses the de-trended volume figures obtained as the residuals of the following regression where t is a time trend and v_t is the raw volume: $v_t = \gamma_1 + \gamma_2 t + \gamma_3 t^2 + \tilde{v}_t$

Table 6: Relationship Between Ivix and Trading Volume

	Coefficient	Std. error	t-ratio	*P*-value
Constant	37.3831	1.0264	36.42	0.0000
$\tilde{v}_t$	0.1309	0.0555	2.36	0.0188
$\tilde{v}_{t-1}$	0.0897	0.0524	1.71	0.0875
$\tilde{v}_{t-2}$	0.2590	0.0601	4.31	0.0000
Adj R^2 = 0.083646 F = 18.2216; P-value = 0.000 Breusch-Pagan test = 3.8067; P-value = 0.2831 Hannan-Quinn = 4.6259				

The regression results confirm the positive association between Ivix and traded volume. Hence, it can be concluded that Ivix echoes volume-volatility empirical regularity too.

5. Conclusions and Implications of the Study

India is one of the fastest emerging markets; it has a volatility index calculated and disseminated by an organised exchange, NSE. This volatility index christened as India Vix was launched in April 2008. This study examines the behaviour of the volatility index since inception and empirically tests whether the index reflects the stylised facts of stock market volatility. The study finds that Ivix reflects the stylised facts such as volatility clustering, mean reversion and positive association with trading volumes. However, the market and Ivix returns are significantly negatively related only in one direction specifically during market descends but not when the market moves up.

The study has implications for the regulators and investment fraternity. The study shows that the volatility index Ivix mirrors the empirical regularities normally exhibited by stock returns volatility. Hence, introducing trading products with Ivix as underlying may be contemplated. At present volatility trading is possible in India; as there is an active and liquid market in options trading, launching derivatives based on volatility index will pave way for trading pure volatility in an economical and a convenient way. Volatility trading strategies such as straddles need to be adjusted frequently as prices move else they become directional bets. The study shows a negative relationship between Ivix and Nifty returns which will be quite beneficial to investors, as including Ivix may lead to diversification benefits to investors. More importantly the significant negative relationship indicates volatility products will act as catastrophic hedging tools. In other words, inclusion of volatility index in a portfolio will provide the much needed insurance, particularly in market crashes. This is because volatility peaks during market falls and hence spot market losses could be offset by gains on the volatility front. Even though exchange traded derivatives are not currently available in India at least institutional investors can use the volatility index as the underlying and trade in OTC products such as volatility/variance swaps. To conclude, the study shows that India's volatility index reflects most of the stylised facts of volatility and hence it seems to be serving the purpose. Further studies may examine the predictive power of volatility index and examine the co-movements of Ivix with other global volatility indices.

Notes

1. The computation methodology in detail is provided in "About Volatility Index," National Stock Exchange of India Limited. Available at http://www.nse-india.com/content/vix/India_VIX_comp_meth.pdf.
2. Cont (2001) defines a stylised fact as "a set of properties, common across many instruments, markets and time periods, has been observed by independent studies and classified".
3. For an accessible treatment of the unit root tests see Enders (2003).

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