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India Volatility Index (India VIX) and Risk Management in the Indian Stock Market

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Abstract

This study examines the asymmetric relationship between the India Volatility Index (India VIX)[3] and stock market returns, and demonstrates 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. This property of the India VIX makes it ideal as a risk management tool whereby derivative products based on the volatility index can be used for portfolio insurance against bad declines. We also find that the India VIX captures stock market volatility better than traditional measures of volatility, including the ARCH/GARCH class of models. Finally, we test whether changes in the India VIX can be used as a signal for switching portfolios. Our analysis of timing strategy based on changes in the India VIX exhibits that switching to large-cap (mid-cap) portfolios when the India volatility index increases (decreases) by a certain percentage point can be useful in maintaining positive returns on a portfolio.

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[3] "VIX" is a trademark of Chicago Board Options Exchange, Incorporated ("CBOE") and Standard & Poor's has granted a license to NSE, with permission from CBOE, to use such mark in the name of the India VIX and for purposes relating to the India VIX.

India Volatility Index (India VIX) and Risk Management in the Indian Stock Market

1. Introduction

Investors in financial markets are primarily concerned about the uncertainty in receiving the expected returns as well as the variance in returns. The literature on financial economics has well-documented evidence that the expected returns and variance in returns are negatively related. The variance in returns, also known as volatility, is by its very nature stochastic, and in order to capture the movements in stock price volatility, markets have developed indices that indicate the stock market's perceived volatility over a period. The Chicago Board of Options Exchange (CBOE) was the first exchange to introduce such a volatility index in 1993—the VIX—which is also called the investor fear gauge or the new barometer of investor fear. In India, the National Stock Exchange (NSE) introduced a volatility index for the Indian market in 2008—the India volatility index (henceforth, 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 by the CBOE for calculating VIX on the S&P 100 index options.

In general, VIX is often referred to as the investor fear gauge, mainly because it measures perceived stock market volatility—both upside as well as downside 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. It is largely believed that the stock price volatility is caused solely by the random arrival of new information relating to the expected returns from the stock. Others attribute the cause of volatility to trading. Research suggests that volatility is far larger during trading hours than when the exchange is closed (Fama, 1965; French, 1980). The hypothesis that volatility is mainly caused by new information is questionable; it can be largely attributed to trading (French and Roll, 1986). Further research provides evidence of volatility caused by a host of factors, including information contained in news, the financial performance of organisations, and even investor behaviour. Empirical evidence related to the flow of information contained in macroeconomic news and other public information having a direct impact on stock return volatility is documented widely in financial economics literature (Ross, 1989; Andersen and Bollerslev, 1998; Andersen et al., 2006, among others). Other studies examine the effect of private information—such as the information revealed through informed and liquidity-motivated traders, their orders, and any imbalances in their trades in the securities markets—on the volatility of security prices (Brandt and Kavajecz, 2004; Evans and Lyons, 2008; Jiang and Lo, 2011, among others).

The development of behavioural economics and finance brought in another dimension to the sources of stock market volatility— investors are assumed not to be perfectly rational and their irrational and sentiment-based decisions affect the stock price movements (Kaniel et al., 2008). Investor sentiment as one of the sources of potential stock price volatility has also been studied in the context of the noise trader model (De Long et al., 1990) in order to examine the effect of noise trader risks on stock returns (Lee et al., 1991; Neal and Wheatley, 1998; Baker and Wurgler, 2006, among others).

In this study, we examine whether India VIX is really a fear index that represents the investors' risk aversion, and examine its performance as a sophisticated measure of volatility compared to traditional measures. Specifically, we examine the asymmetric effect of India VIX in the Indian stock market and test whether it captures spot volatility better than standard measures of stock price volatility. We also examine whether a volatility index can be used as an appropriate instrument for timing in the stock market and whether India VIX can be used for risk management and trading rule.

The rest of this report is organised as follows. Section 2 focuses on the theoretical background and literature explaining the volatility-returns relationship. Section 3 discusses the hypotheses and methodology used, and the sample, data, and the measurement of the variables are explained in Section 4. In Section 5, the results of the analysis are discussed, and Section 6 summarises the findings and brings out the practical implications of the study.

2. Theoretical Background

Our study focuses on three major issues. First, we explore whether India VIX represents the true underlying risk aversion of investors in the Indian stock market. Essentially, India VIX documents the level of market anxiety during the ups and downs of the stock market, and it would provide useful benchmark information in assessing the degree of market turbulence being experienced. India VIX was created as an index upon which volatility-based futures and options contracts could be written, and volatility trading has long been considered since it provides a stabilizing effect on an investor's portfolio. The accuracy and the efficacy of a volatility forecast are of immense importance in capital markets. The issue of whether India VIX is a true indicator of the market riskiness is, therefore, quite relevant for risk management and trading activities in the capital market. Second, we evaluate the volatility index for potential uses in spot and derivative markets, for the purpose of risk management as well as for devising efficient and profitable trading strategies. As discussed in Goldstein and Taleb (2007), if volatility is expressed in a particular way, substituting one measure for another will lead to a consequential mistake. This makes our concern of testing India VIX as a true market sentiment indicator more relevant and worth investigating. Finally, we focus on the issue of whether India VIX could be used as an instrument for market-timing in the stock market.

In this section, we review some theoretical and empirical literature relating to investor sentiment, volatility, and relevant trading strategies.

2.1 Risk aversion measures

In modern portfolio theory, risk aversion refers to an investor's tendency to expect an additional marginal reward in lieu of accepting an additional quantum of risk, which is measured as the standard deviation of the return on investment. Risk aversion is a fundamental element in standard theories of asset pricing, decision sciences, lottery choices, contracts, and insurance (Pratt, 1964; Arrow, 1965; Epstein and Zin, 1989, among others). People's attitudes towards risks involving gains may be quite different from their attitudes toward risks involving losses; i.e., when offered a choice formulated in a certain way, they might display risk aversion, but when offered essentially the same choice formulated in a different way, they might display risk-seeking behaviour that is contrary to the first behaviour (Kahneman and Tversky, 1979). This risk aversion of investors and traders plays a crucial role in shaping their preferences in stock market activities. As a result, their preferences concerning possible future payoffs and the probability of obtaining those payoffs are reflected in the prices of assets. In line with the marginal utility theory, the incremental value of a future payoff to an investor reduces with the level of the investor's wealth. Hence, *ceteris paribus*, assets that tend to yield higher payoffs in situations when the investor's wealth is lower are obviously valued more highly. Based on this premise, modern finance theory models asset price as the expectation of future payoffs, calculated not on the basis of their objective statistical likelihood, but rather on the basis of a preference-weighted likelihood measure that filters statistical probabilities by investors' preferences with regard to risk. The ratio of downside risk associated with the two likelihood distributions is directly related to the investor's risk aversion (Tarashev et al., 2003).

Evidence from prior studies suggests that the risk attitudes of investors changes over time. Different time periods are characterised by entirely different collective dispositions of investors vis-à-vis their risk-taking behaviours. Kumar and Persaud (2001) argue that the relatively quick changes in the levels of investors' willingness to bear risk have the capacity to cause or facilitate shifts from one equilibrium to another in capital markets. They further state that the shift in the risk appetite measure could reflect a genuine shift in the degree of risk aversion, or a shift in the relative weight or proportion of different types of investors with different risk appetites. A shift in the degree of risk aversion reflects investor overconfidence, where investors attribute a string of positive returns to their superior skills, and in response, are willing to take on higher risk. Contrarily, a string of negative returns could trigger excessive pessimism and reduce the willingness to take risk (Shiller, 1998). It is observed that risk aversion induces short-term traders to respond to the deteriorating environment by exiting riskier positions and widening bid-offer spreads, which in turn results in investors' further unwillingness to move on the other side of the trades. When there is a shift in the relative weight or proportion of different types of investors with different risk appetites, it may be accompanied by greater price movements than might be suggested by just the flows. In such situations, the rise and fall of hedge funds, or the popularity of emerging market mutual funds, or the use of leveraged derivative instruments could be important elements in the observed change in risk appetite (Kumar and Persaud, 2001). It is important to note that an increase in risk appetite implies a decline in risk aversion, and vice versa.

The change in asset price caused by changes in investors' risk aversion has figured prominently in discussions within the financial community. The fact that it is possible to quantify the price movements attributed to changes in risk aversion gives traders hope to exploit them by adopting momentum and contrarian trading strategies. Financial practitioners use various indices that are constructed in an attempt to capture this relationship between changing risk aversion and subsequently changing asset prices (Illing and Aaron, 2005). Academic research has not focused much on capturing the relationship of price changes with exogenous changes in risk aversion. Although there are a few studies using the approach based on state-dependent preferences, supported by experimental evidence in favour of changing risk aversion, not much empirical work has been done on this issue. Misina (2003) observes that two types of arguments have been made against this approach. First, allowing for changes in risk aversion while modelling changes in asset prices may relax the assumption of constant preferences, which raises the methodological issue of safeguards rigour in economic research. Second, the observational equivalence of changes in prices is stated to be due to changes in asset riskiness, and not due to changes in risk aversion. Exogenous changes in risk aversion, however, have been employed in academic research in order to explain the financial crisis of the late 1990s and to elucidate the mechanisms that lead to financial contagion (Kumar and Persaud, 2001).

Literature in behavioural finance also considers the volatility index as a significant indicator of investor sentiment, and suggests that such an index can be viewed as a market indicator of rises and falls in the underlying index (Olsen, 1998). Shefrin (2007) proposes the dependence theory, which argues that different market scenarios play a crucial role in the decision-making process of investors who might have distinct behaviours depending on the level of fear prevailing in the market. This distinctness of investor behaviour influences the dynamics of the relationship between the investor fear index and the underlying market index.

Our study attempts to fill the gap created by the lack of empirical evidence about whether the volatility index explains the stock market volatility which causes, and to some extent is caused by, shifts in investors' risk aversion. In other words, we seek an answer to the question of whether the India Volatility Index—India VIX—reflects the underlying shifts in investors' risk aversion better than other realised volatility proxies. We also test the accuracy of the India VIX against traditional measures of volatility in the Indian market context.

2.2 Volatility index and stock market returns

Many prior studies in financial economics have dealt with the relationship between the volatility index and stock market returns. Intuitively, when the expected market volatility rises (declines), investors in the market demand a higher (lower) expected rate of returns on stocks and consequently, stock prices go up (fall down). This linkage suggests a simple framework of a proportional relationship between changes in the volatility index and variations in the market index returns. Whaley (2009) argues that an increased demand-to-buy index affects the level of the volatility index, and thus, the change in the volatility index is expected to rise at a higher absolute rate when the stock market falls than when it rises. Empirical evidence supports the volatility index as more a barometer of investors' fear of the downside than as a barometer of investors' excitement (greed) in a market rally.

There is evidence for a large negative contemporaneous correlation between changes in the volatility index and changes in returns on the market index (Flemming et al., 1995). Studying the volatility index (earlier known as VXO) in the U.S. market, Giot (2005a) reports that expected returns are positive (negative) following an extremely upward (downward) movement in the volatility index, implying that an overshooting volatility index indicates oversold markets. Some other major studies examining the properties of the volatility index (either the VXO or the VIX) also report similar findings. Dash and Moran (2005) state that the volatility index VXO is negatively correlated with hedge fund returns, and this correlation is asymmetric in nature. While Guo and Whitelaw (2006) show that market returns are positively related to implied volatility, Blair et al. (2001) find that the VXO is able to explain almost all relevant information about the expected realised volatility of index returns. The volatility index also tends to show an asymmetrical response to positive and negative returns on the market index. Evidence for negative and asymmetric relationship has been provided in the VIX and S&P100 index (Whaley, 2000), the VXN and Nasdaq 100 index (Simon, 2003; Giot, 2005b), the FTSE/ASE 20 index and the Greek volatility index (Skiadopoulos, 2004), and the KOSPI and the KIX in the Korean stock market (Ting, 2007). There is, however, some evidence to the contrary as well. While Dowling and Muthuswamy (2005) report no asymmetric relationship between the volatility index and the market index returns in the Australian market, Frijns et al. (2010) provide mixed evidence for the same. Similarly, Siripoulos and Fassas (2012) find no statistically significant asymmetric evidence for many volatility indices including the VIX, the VXN, and the Montreal volatility index.

Sarwar (2012) examines the efficiency of the CBOE VIX as an investor fear gauge with respect to the stock market indices from a group of developing nations, including BOVESPA (Brazil), AK&M composite index (Russia), SENSEX (India), and Shanghai SE composite index (China). His study reports a strong negative contemporaneous relation between changes in the VIX and the stock market index returns in all the markets, although the evidence in the case of the Indian stock market was found significant only during the period 1993–1997. However, it is noteworthy that this relationship was examined using the CBOE VIX as a measure of investor fear in local markets (such as Brazil, Russia, India, and China), which otherwise is not a convincible argument. Similar results were reported in Sarwar (2011) in the context of U.S. equity market.

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.

[Insert Figure 1 here]

Plotting the India VIX, the VIX (of S&P 500 Index), and the Nifty index shows there is an asymmetric relationship between the India VIX and the Nifty index movement; the India VIX and the VIX are moving in tandem except when the India VIX is visibly more volatile than or is moving in contrast to the VIX (Figure 1). We, therefore, examine the relationship between the India VIX and the Nifty Index.

2.3 Implied and realised volatility

Volatility in assets' expected returns as a crucial input attracts much attention, both from academic researchers as well as practitioners. In financial markets, the volatility in returns is estimated using several approaches, including model-based estimation techniques, such as the conditional volatility models of the ARCH/GARCH family, and the model-free measures of implied volatility, such as the CBOE VIX or the India VIX. Researchers have investigated the differences between implied volatility measures and econometric model-based volatility estimates. Implied volatility indicates a market-determined estimate of volatility, while model-based volatility estimates employ some degree of smoothing past volatility to generate estimates. It is argued that implied volatility measures are able to capture the information that a model-based volatility measure cannot.

The extant literature suggests that various implied volatility measures subsume substantial information—mainly information contained in historical returns data—and use the same for estimating volatility. Fleming (1998) as well as Jiang and Tian (2005) report the efficiency of implied volatility measures in reflecting such information. However, Becker et al. (2006) find weak evidence and state that the S&P500 implied volatility index does not completely subsume a diverse set of information. In a follow-up study (Becker et al., 2009), they find that such implied volatility measures do not reflect information beyond volatility persistence as captured by the model-based volatility estimators that are relevant for forecasting the degree of total volatility. Becker et al. (2009) state that previous studies on the relationship between implied volatility and forecasts of the level of total volatility have completely ignored the fact that volatility may be generated from both continuous diffusion as well as discontinuous jump processes in price. Using the jump components of S&P500 volatility, they find that the VIX both subsumes information relating to past jump contributions to total volatility as well as reflects incremental information pertaining to future jump activity.

Many empirical studies have captured the relationship between the measures of implied volatility and the realised volatility in stock markets. Poon and Granger (2003) provide a comprehensive review of work related to forecasting volatility. Comparing the implied volatility index with historical volatility, Dowling and Muthuswamy (2005) find that the implied volatility measure is not a robust estimator of volatility compared to the historical volatility measure; however, Frijns et al. (2010) find contrary evidence and state that the volatility index contains important information about realised volatility in the Australian market. Carrado and Miller (2005), Maghrebi et al. (2007), and Banerjee and Kumar (2011), and Lu et al. (2012) find that the implied volatility measures the VIX, the KOSPI volatility index, and the India VIX are sufficiently good predictors of realised volatility in the S&P100 index (U.S.A.), the KOSPI 200 index (Korea), the Nifty index (India), and the TAIEX (Taiwan) markets, respectively. Similar evidence is provided for the VIX and the S&P 500 and the Nasdaq 100 indices. Siriopoulos and Fassas (2012) examine the predictive power of 12 volatility indices[4] and find that

[4] The volatility indices included in the study are: CBOE volatility index (VIX), Nasdaq volatility index (VXN), DJIA volatility index (VDX), Russel 2000 volatility index (RVX),

even if implied volatility measures may be biased, they do a better job than the historical realised volatility measures.

In the context of the Indian stock market, although Kumar (2012) provides evidence of the implied volatility measure (India VIX) as an unbiased estimator of future realised volatility, his study uses only one measure of implied volatility, i.e., the India VIX, and one measure of historical volatility. Thus, the results cannot be generalised for other measures of volatility. We, therefore, examine this issue with multiple volatility measures.

Our study differs from the earlier attempts in several ways. First, instead of relying on a single measure, we use multiple measures for both implied as well as realised volatility in the Nifty index returns. For comparing the performance of the India VIX in capturing the actual volatility, we use conditional volatility measures as well as ex-post integrated volatility measures. Further, for the realised volatility estimates, we use standard deviation of returns, daily variance estimates, and realised volatility estimates (following McAleer and Medeiros, 2008). Second, we adopt various criteria to test the efficiency of the volatility estimates. Our criteria include root mean square error, mean absolute error, and mean absolute percent error. Finally, we examine whether the changes in the India VIX can be used for trading strategies in stock markets. Theoretically, we show that the India VIX can be a good tool for portfolio insurance against risk. We also empirically test its use in timing strategies based on size and percentage change in the India VIX.

3. Hypotheses and Methodology

Our study is an empirical attempt to study the India Volatility Index (India VIX) from the perspective of active risk management in the stock market. We first examine the efficiency of the India VIX in explaining the realised volatility computed using various traditional measures, vis-à-vis other measures of conditional volatility such as the ones from the ARCH/GARCH class models. Further, we study the relationship of the India VIX with stock market returns with respect to the CNX Nifty index. We primarily test the following hypotheses:

Deutsche volatility index (VDAX), AEX volatility index (VAEX), BEL 20 volatility index (VBEL), CAC 40 volatility index (VCAC), FTSE 100 volatility index (VFTSE), SWX volatility index (VSMI), Dow Jones EURO STOXX 50 volatility index (VSTOXX), and Montreal exchange volatility index (MVX).

(a) A model-free estimator of implied volatility (India VIX) does not capture the realised volatility in the Nifty returns compared to other measures of conditional volatility from the class of the ARCH/GARCH models.
(b) The India VIX has no significant asymmetric relationship with the Nifty returns.

Moreover, we study the potential implications of the India VIX for trading in spot and derivative markets, and examine whether it can be used for timing and hedging strategies in the stock market.

We mainly use regression-based models to study the India VIX and its association with the Nifty returns. Using daily data from the National Stock Exchange (NSE), we first examine the statistical properties of the India VIX in order to ascertain its dynamics with the stock market returns and its asymmetric relationship with the Indian stock market in general. We also need to ascertain the information content of the India VIX as a predictor of stock price volatility and its performance vis-à-vis other traditional measures such as standard deviation and other realised volatility measures. In the present study, we compare the India VIX performance with the performance of two measures of conditional volatility, namely, the GARCH(1,1)-based conditional volatility measure and the EGARCH conditional volatility measure. We examine how the Nifty index, the India VIX, and the other traditional measures of stock volatility are correlated with one another, and explore whether they are similar, and if not, which one captures spot volatility better. For examining the India VIX-Nifty return relationship, we also use the quantile regression approach for robust estimation.

4. Data and Measurement of Variables

Our study aimed to test a wide spectrum of relationships between the India VIX, stock market returns, and several historical volatility measures. In this section, we present the datasets used in the study and the stylised facts about the data time series. We used financial time-series data with non-overlapping observations on the following variables for a period spanning from March 1, 2009 to November 30, 2012:

(i) Daily closing value of India Volatility Index (INDIAVIX)
(ii) Daily closing value of CNX Nifty index (NIFTY)
(iii) Daily closing value of CBOE Volatility Index (CBOEVIX)

(iv) Daily closing value of CNX Low Volatility Index (LVX)
(v) Realised volatility:
   a. Daily variance estimator (RVOL1)
   b. Realised volatility estimate (RVOL2)
(vi) Conditional volatility measures:
   a. Symmetric conditional volatility measure using GARCH(1,1) (GARCHVOL)
   b. Asymmetric conditional volatility measure using EGARCH (EGARCHVOL)
(vii) Ex-post integrated volatility estimates

India VIX

The India Volatility Index (India VIX) measures the market expectations of near-term volatility, which denotes the rate and magnitude of changes in prices and is a widely-recognised proxy of risk. The India VIX is a volatility index computed by the NSE based on the order book of Nifty options. For this, the best bid-ask quotes of the near and next-month Nifty options contracts that are traded on the F&O segment of the NSE are used. It represents the investor's perception of the market volatility in the near term; i.e., it depicts the expected market volatility over the next 30 days. It is believed that the higher India VIX levels, the higher the expected volatility and vice versa (NSE, 2007). In this paper, we used the daily closing values of the India VIX over the sample period.

Nifty

The CNX Nifty index (NIFTY) consists of 50 stocks representing 22 sectors of the economy, and represents about 67.27% of the free-float market capitalisation of the stocks listed on the NSE (as at the end of September 2012). At the same time, trading in the Nifty stocks involved about 55% of the total traded value of all the stocks on the NSE. We used the daily closing value of the Nifty index as a measure of the market index; we expected it to be inversely related to the India VIX. The Nifty is negatively correlated (-0.830488) with the India VIX. 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. Hence, the Nifty index and the India VIX are inversely related (as can be seen in Figure 1).

VIX

The CBOE Volatility Index (CBOEVIX) is a key measure of the market expectations of near-term volatility conveyed by the prices of the S&P 500 stock index options. Since its introduction in 1993, the VIX has been considered by many (both academicians as well as practitioners) to be the world's premier barometer of investor sentiment and market volatility. The India VIX is significantly positively correlated with the VIX (0.651045) over the sample period. We would, therefore, anticipate a positive relationship between the VIX and the India VIX. The potential arguments for a positive relation between the two are: (i) both the indices follow similar computing methodologies with different underlying prices (the prices of the S&P 500 stock index options in the case of the VIX and those of the Nifty index options in the case of the India VIX); (ii) the global volatility represented by the VIX could be transmitted to the Indian market overnight on a daily basis, with the VIX thereby influencing the India VIX positively and significantly; and (iii) nowadays, Indian companies have significant exposure to the American and European markets, which means highly volatile U.S. and/or European markets would result in increasing uncertainty in the local market, and consequently, high volatility expectations in the Indian market.

Low Volatility Index

The CNX Low Volatility Index (LVX) is a measure of the performance of the least volatile securities listed on the NSE. Of the top 300 companies ranked on the basis of average free-float market capitalisation and aggregate turnover in the last six months, the top 50 securities that remained the least volatile are selected to be included in the LVX. The index is used for various purposes, such as benchmarking fund portfolios, index-based derivatives, structured products, ETFs, and index funds. The weights of the securities in the index are assigned as per their respective volatility, calculated as the standard deviation of the daily log normal price returns for the past one year. This index moves in tandem with the Nifty index, and therefore, has a high positive correlation with the Nifty index (0.913628), whereas it is significantly negatively correlated with the India VIX (-0.873644) and the CBOE VIX (-0.525834). We anticipated an inverse relationship between the LVX and the India VIX because a higher LVX would imply that the top 50 securities trading on the NSE had low volatility and consequently low uncertainty about the top trading stocks. This in turn would mean a low India VIX value.

The descriptive statistics for all the four indices relating to this study—the India Volatility Index (INDIAVIX), the CNX Nifty Index (NIFTY), the CBOE Volatility Index (CBOEVIX), and the CNX Low Volatility Index (LVX)—over the sample period are presented in Panel A of Table 1.

[Insert Table 1 here]

The statistics related to the Nifty Index returns (NIFTYRET) show that the Nifty index maintains a small positive average return during the sample period, with a standard deviation of daily returns of 1.4%. The kurtosis value of the returns series (as well as the other series in consideration) is higher than 3 (the kurtosis of the Gaussian distribution). We can, however, say that the kurtosis values of the INDIAVIX, the CBOEVIX, and the LVX series are closer to normal. The Jarque-Bera statistics of the distribution are much higher than any critical value at conventional confidence levels over the sample period.

The literature suggests that the presence of autocorrelation in the financial time series is inconsistent with the weak form of the market efficiency hypothesis, and therefore, points to a serious issue in modelling volatility directly from daily returns (Pandey, 2005). Panel B of Table 1 presents the correlation among the variables under consideration. We noted that the INDIAVIX is significantly negatively correlated with the NIFTY and the LVX, implying an adverse relationship among the variables. The India VIX, as expected, is significantly positively related to the CBOEVIX. Both the NIFTY and the LVX are negatively related with the CBOEVIX.

Realised Volatility

The literature on financial economics and microstructure talks about several measures of returns volatility. In our study, we used two traditional measures of unconditional realised volatility:

(a) *Daily variance estimator* (RVOL1): Traditionally, the unconditional volatility of an asset return series is estimated using close-to-close returns as follows:

$$- \qquad (1)$$

where P_i is the closing price of the day and n is the number of days used to estimate the volatility (which in our study is taken as 20, assuming the number of trading days in a month). This estimate of daily volatility is assumed to be a proxy of realised volatility and is compared with the other measure of volatility in our study.

(b) *Realised volatility estimates* (RVOL2): Our study used another measure of the realised volatility of the Nifty index return series. Following McAleer and Medeiros (2008), we computed the average daily returns variance by summing all the squared returns over a certain period (20 days, as assumed earlier), rather than calculating the squared daily returns. The methodology for estimating the realised volatility can be expressed mathematically as follows:

(2)

The realised variance thus calculated is a consistent estimator of the integrated variance when there is no microstructure noise. Since our study employed daily data, we expected very little microstructure noise in our sample. The integrated variance is considered the measure of true daily volatility (Andersen et al., 2003).

Table 2 presents the descriptive statistics of the two proxies of realised volatility in the Nifty index returns over the sample period.

[Insert Table 2 here]

From the statistics reported in Table 2, we see that although the average daily volatility estimated by the models RVOL1 and RVOL2 are quite different (with significantly different standard deviations), their distributions are quite similar in nature (as exhibited by skewness, kurtosis, and Jarque-Bera statistics). In our study, we used these two measures along with the standard deviation of daily Nifty returns as proxies of realised volatility for further analysis.

Conditional Volatility Measures

For examining the efficiency of the India VIX in explaining the underlying volatility vis-à-vis other volatility measures, we considered conditional volatility measures, which are widely referred to in academic literature. According to the extant literature, the return series of an index exhibits an ARCH effect over the period. Therefore, we used the following two models for measuring conditional volatility in the Nifty index series:

(a) *Symmetric conditional volatility measure* (GARCHVOL): The first measure of conditional volatility was the GARCH(p,q) model, which is the most used model in the ARCH family. This approach estimates the symmetric conditional volatility of a financial time series—the Nifty index return series, in our case. For the GARCH(p,q) modelling, we estimated the conditional mean μ_t of our daily return series r_t using a simple time-series model, such as a stationary ARMA(p,q) model as follows:

(3)

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where the shock (or mean corrected return) ε_t represents the shock or unpredictable return, and p and q are non-negative integers. Zt is white noise such that (μ=0, σ^2=1) and h_t is the conditional variance of ε_t. This conditional variance can further be modelled in a GARCH(p,q) process as follows:

(4)

where $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$;

with $\alpha_i = 0$, for $i > p$ and $\beta_j = 0$ for $j > 0$.

Empirical evidence shows that a simple GARCH(1,1) process can be fitted adequately in many time financial series (Sharma et al., 1996). Hence, we employed a simple GARCH(1,1) model to measure the symmetric conditional volatility of the Nifty index return series.

Table 3(a) presents the descriptive statistics for the three measures of conditional and integrated volatility, namely, the volatility estimates using the GARCH and the EGARCH approaches, and the ex-post integrated estimates of volatility. The results obtained from the GARCH/EGARCH model are presented in Table 3(b). The sum of the ARCH and the GARCH coefficients (α and β, respectively) estimated by our model was significantly less than 1, which implies that the volatility was mean reverting. However, the volatility during the sample period remained less spiky (lower α) and highly persistent (higher β) during the period covered in our study.

[Insert Table 3(a) here]

[Insert Table 3(b) here]

We also ran the ARCH LM test up to 5 lags in order to test whether our GARCH(1,1) model adequately captured the persistence in the Nifty index return volatility and to test whether there was any ARCH effect left in the residuals obtained from the model. We found that the standardised residuals did not exhibit any further ARCH effect.

(b) *Asymmetric conditional volatility measure* (EGARCHVOL): The conditional volatility of a financial time-series is believed to be dependent on both the magnitude of the error terms or innovations as well as on its signs, which may result in asymmetry. We tested for asymmetric patterns in return volatility, and therefore, estimated an EGARCH(1,1) model for measuring the asymmetric conditional volatility in the Nifty index return series. The EGARCH(1,1) estimates are reported in Table 3(b). From the statistics presented in Table 3(b), we see that the asymmetry term (γ) as well as the other coefficients is significant at conventional significance levels. It is also seen that the standardised residuals are non-normally distributed. The ARCH LM test on residuals further shows that no ARCH effect remained after estimating the model.

Ex-post Integrated Volatility Measure

We constructed a time-series of integrated volatility following Siriopoulos and Fassas (2009) to compare its performance with the India VIX. This measure of volatility was computed as follows:

(5)

where r is the daily Nifty returns and n is the number of trading days in a month. This annualised return variance may serve as a proxy for observed integrated volatility in the Nifty returns. The descriptive statistics of our volatility measure RV is presented in Table 3(a).

5. Results

In this section, we present the empirical results obtained from our analysis. First, we discuss the efficiency of the sample volatility estimates in capturing the realised volatility of the stock market. Next, the relationship between the India VIX and stock market returns is presented and discussed; finally, we present some potential uses of the India VIX as a tool of risk management, including the use of a timing strategy based on percentage change in the India VIX levels.

5.1 India VIX and Volatility Estimates

In this study, we used only two commonly used conditional volatility models from the ARCH/GARCH family to test their performance vis-à-vis traditional and extreme-value unconditional volatility measures. We regressed each of the realised volatility measures—standard deviation of daily Nifty returns (STDEV), daily variance estimator (RVOL1), and realised volatility estimates measured as the sum of squared returns over the past one month (RVOL2)—on the conditional and unconditional measures of implied volatility such as the India VIX (India VIX), the Garch-based conditional volatility measure (GARCHVOL), the EGARCH-based conditional volatility measure (EGARCHVOL), and the annualised estimates of integrated volatility (ex-post volatility estimate), in order to see their linear relationships. The regression estimates are presented in Table 4.

[Insert Table 4 here]

The results indicate that the India VIX as an explanatory variable was associated with our measure of realised volatility-standard deviations of Nifty returns, and the results were statistically significant at the 5% level. The linear association between the India VIX and the other measures of realised volatility (i.e., RVOL1 and RVOL2) was statistically significant. When we estimated the regression with GARCHVOL and EGARCHVOL as explanatory variables, both measures were associated with all the four measures of realised volatility, and the relationship was statistically significant at the 1% level. The regression estimates for the annualised volatility estimates (ex-post volatility estimate) as the explanatory variable were statistically significant at conservative significance levels for all measures of realised volatility. Since the regression estimates provided statistically significant (at traditional level) evidence of the efficiency of the volatility measures used in our study (India VIX, GARCHVOL, EGARCHVOL, and ex-post volatility estimate), we further evaluated these measures for their comparative performance using various performance criteria.

In order to compare the efficiency of the various volatility estimators, we used the following finite sample scale-sensitive performance criteria:

(i) Root mean square error (RMSE)

(ii) Mean absolute error (MAE)
(iii) Mean absolute percent error (MAPE)

The first criterion, RMSE, measures the differences between the values estimated by a model—such as volatility estimated by the GARCHVOL—and the actual values (realised volatility). Being a scale-dependent measure of accuracy, it compares different estimation errors within a dataset, and serves to aggregate the residuals into a single measure of estimation efficiency. The second one, MAE, is also used to measure how close the implied volatility estimates are to the eventual realised volatility. It is an average of the absolute error of estimation. Finally, mean absolute percent error (MAPE) indicates the estimation accuracy in percentage terms. These criteria are measures of efficiency that are less likely to be affected by the presence of outliers in the dataset.The results obtained for RMSE, MAE, and MAPE computed for the India VIX, GARCHVOL, EGARCHVOL, and the ex-post volatility estimate with different measures of realised volatility are presented in Table 5. As evident from the statistics, the EGARCH-based volatility measure had the largest forecast errors followed by the GARCH-based volatility measure, whereas the India VIX had the smallest error. The smaller the value of the scale-sensitive measures of error, the more accurate was the volatility estimate. In the present study, the lower RMSE and MAE values associated with the India VIX indicate that it is relatively more accurate than the other three volatility estimates, namely, the GARCH-based volatility measure, the EGARCH-based volatility measure, and the ex-post volatility measure. However, if the magnitude of the data values were different for these volatility measures, then the error statistics might not be valid. All the four measures of volatility estimates here are apparently of the same magnitude with respect to their statistical properties; thus, we can say that the lower error statistic would imply a better volatility estimate.

Contrary to MAE, MAPE measures the performance of volatility estimate irrespective of the magnitude of data series, and hence, eliminates the problem of interpreting the measure of accuracy relative to the magnitude of the volatility values coming from different measures. Our results show a lower MAPE for the India VIX, which makes it a better volatility estimate compared to the other measures under consideration. At the outset, the India VIX appears to be a better predictor of realised volatility than the GARCHVOL and the EGARCHVOL measures of conditional volatility. The annualised volatility measure appears to be performing better but only in explaining the standard deviations of Nifty returns; for the other measures of realised volatility, it is again the India VIX that captures return volatility better than the other measures. The difference between them is, however, very marginal; yet, the model-free measure of implied volatility (India VIX) is the best of them in estimating realised volatility. The superiority of the India VIX holds for all the measures of realised volatility, be it standard deviation of Nifty returns (STDEV), daily variance estimates (RVOL1), or monthly sum of squared returns (RVOL2).

[Insert Table 5 here]

5.2 India VIX and Stock Market Returns

We first examined how the India volatility index (India VIX) responds to positive and negative Nifty returns by regressing the change of the India VIX ($\Delta IVIX_t$) on positive and negative Nifty returns variables. As documented in Simon (2003), if the underlying index (in our case the Nifty) tends to move upwards significantly, call options prices and their implied volatility may be bid up by investors who prefer to take long positions on calls rather than long delta-equivalent stock positions. One of the possible reasons could be that the existence of any such trend would suggest a greater probability that the underlying index would be considerably higher or lower in future, which would further increase the potential pay-out of options and cause the implied volatility to be bid higher.

According to Simon (2003), a common indicator of trends is the deviation of the current level of the price of a security from a moving average of its recent levels. We used separate variables for each of the positive and the negative percentage deviations of the Nifty index from its 5-day moving average. When traders tend to demand options more, the trends become stronger, leading to a rise in implied volatility. In such situations, the coefficient on the positive and the negative percentage deviations from the moving averages would be significantly positive and negative, respectively. Following a similar approach, we regressed the first difference of the India VIX ($\Delta IVIX_t$) upon the lagged value of the IVIX, contemporaneous Nifty returns, and contemporaneous deviation of the index from the five-day moving average. This approach helped us examine the impact of Nifty returns on variation in implied volatility depending on the extent to which they lead to deviations of the Nifty from its recent central tendency. Our model took the form of multiple regression as follows:

(6)

where is the first difference of the IVIX at time *t*, is the lagged value of the India VIX at time *t – 1*, and are the positive and the negative Nifty returns for same day, respectively, and and are the positive and the negative percentage deviations of the closing Nifty from its five-day moving average, respectively.

Table 6(a) shows the regression results for the different models using the entire sample. Model 1 considered only the past value of the India VIX level as an economic explanatory variable to capture the changes in the India VIX. It was negatively related to the changes in the India VIX with 1% statistical significance level, although it did not have considerable explanatory power as evident from a low *R*-square value.

[Insert Table 6(a) here]

Model 2 was identical to Model 1 except that the positive Nifty return was added as an explanatory variable. We found that the positive Nifty return was significantly positively related to the changes in the India VIX at well beyond the 1% level. However, the past value of the India VIX was not statistically significant. A significant increase in the *R*-square from Model 1 to Model 2 suggests that Model 2 is much better at capturing the changes in the India VIX than Model 1 is.

When we replaced the positive Nifty returns with negative Nifty returns as an explanatory variable along with the past value of the India VIX in Model 3, we found that both variables were negatively related to the changes in the India VIX at statistically significant levels. In addition, the adjusted *R*-square climbed substantially from 0.1054 to 0.2534. Interestingly, the inclusion of negative Nifty returns rendered the past value of the India VIX statistically significant. This shows that negative Nifty returns had more explanatory power than positive Nifty returns with respect to capturing the changes in the India VIX.

Model 4 considered positive Nifty returns and positive deviations of Nifty from its 5-day moving average as economic explanatory variables along with the lagged valued of the India VIX. The moving average term was included to examine the trend in asset price movements. As discussed earlier, the coefficient on positive percentage deviation from the moving average was expected to be positive. Our results reveal that the moving average term was positively and significantly related to the changes in the India VIX level. However, similar to the results from earlier models, the past value of the India VIX and the positive Nifty returns were negatively related with the changes in the India VIX at 5% and 1% significance levels, respectively. Adding the moving average term increased the adjusted *R*-square value from 0.1074 (in Model 2, without the moving average term) to 0.1830 (in Model 4, with the moving average term).

Model 5 was identical to Model 4 except that we used negative Nifty returns and negative deviations of Nifty from its 5-day moving average instead of positive returns and deviations (used in Model 4). We found that apart from the past value of India VIX being statistically negatively related to the changes in India VIX level, the negative Nifty returns were also negatively related to the changes in the India VIX level, and were statistically significant (well beyond the 1% level). As expected, the negative deviations of Nifty from its 5-day moving average were also negatively related to the changes in the India VIX. Moreover, it is evident from a high *R*-square (0.2650) that negative returns and deviations jointly with the past value of the India VIX had significant explanatory power.

The regression estimates through Model 6 considered data over the entire sample period and suggested that the India VIX is mean reverting. All the economic explanatory variables considered in the model jointly have the highest explanatory power (*R*-square being largest at 0.3124). It is evident from the results that an increase (decrease) in volatility index was associated with a subsequent decrease (increase) in the index that was statistically significant at the 1% level. The coefficient values of the positive and the negative Nifty returns suggest a significant directional impact on the India VIX; i.e., higher positive Nifty returns were associated with greater declines in the India VIX, whereas higher negative Nifty returns were associated with greater India VIX increases. The coefficients of both the positive as well as the negative Nifty returns were significant at the 1% level. The results suggest that a 1% decline in the Nifty returns could lead to about 42% point increase in the India VIX, while a similar increase in the Nifty returns could lead the India VIX to an 84% point decline. The *t*-statistics supported the results, which implies that the India VIX responds in equal and in opposite directions to positive and negative Nifty returns.

With respect to the other variables in our multiple regression model estimate, both the positive as well as the negative deviations of the Nifty index from its 5-day moving average had statistically significant impacts on the India VIX (at 5% and 1% levels, respectively). These results indicate that a 1% point change in both the positive and the negative deviations of the Nifty index from its 5-day moving average were associated with about 0.003% and 0.009% points increase in the India VIX, respectively. It is, therefore, evident from the results that while positive Nifty index returns influenced the India VIX adversely, stronger positive Nifty trends affected the India VIX positively.

The results from the multiple regression estimates supported the fact that any positive returns by themselves tended to reduce fear in the market and change investor sentiment to positive. However, it is interesting to note that the negative shocks in the India VIX were mitigated by the positive returns to the extent of positive deviations of the Nifty returns from its 5-day moving average. Simon (2003) suggests one possible explanation for this behaviour—the trending behaviour of the index leads to an increased demand for options because of gamma, which causes the deltas of the options to move in favour of call buyers. The fact that the negative Nifty returns are associated with the negative deviations of the Nifty from its 5-day moving average implies that the downward trend of stock prices reinforces the effect of negative returns and the India VIX increases even more. Assessing only the *p*-values associated with the independent variables suggests that these five independent variables are statistically significant at 1% and 5% levels. The magnitude of *t*-statistics provides a mean to judge the relative importance of the independent variables, namely, lagged India VIX levels, positive and negative Nifty returns, and positive and negative deviations of Nifty from its 5-day moving average.

From the statistics provided in Table 6(a), we can say that the negative Nifty return appears to be the most significant explanatory variable, followed by positive nifty return, negative deviation of Nifty from its 5-day moving average, and positive deviation of Nifty from its 5-day moving average. These findings support the use of the India VIX as an investor fear gauge as the change in the India VIX rises at a higher absolute rate when the Nifty falls than when it rises. This is in contrast to what is usually perceived—the relation between the rate of change in the India VIX should be proportional to the rate of returns on the Nifty index. Our findings show an asymmetric relationship between the two. In short, our model is able to explain much of the variation of the daily India VIX change.

We also tested the relationship between the Nifty index returns and the low volatility index returns (LVXRet) to verify whether it would confirm the hypothesis that low volatility adds to higher Nifty returns. The results are presented in Table 6(b). Model 1 shows that past returns on the Low Volatility Index (LVX) were negatively and significantly related to the current level of the index return, implying a mean-reverting characteristic of returns on the LVX. When we introduced the positive Nifty return as an explanatory variable in Model 2, we found that it was positively related to returns on LVX and was highly statistically significant (well beyond the 1% level). This positive association was consistent with the high positive correlation between the two indices.

[Insert Table 6(b) here]

Model 3 is identical to Model 2 except that the positive Nifty return was replaced with the negative Nifty return. The relationship did not change much; rather Model 3 had lower explanatory power compared to Model 2 (as revealed by the lower adjusted *R*-square of 0.7548 in Model 3 against the adjusted *R*-square of 0.7964 in Model 2). Therefore, it can be said that the LVX return is explained better with the positive Nifty return as the explanatory variable than with the negative Nifty return.

We introduced the positive and the negative deviations of Nifty from its 5-day moving averages as the moving average terms along with the positive and the negative Nifty returns in Model 4 and Model 5, respectively, in order to examine the effect of the trends in Nifty on the LVX returns. Contrary to what we found earlier with positive and negative Nifty returns as the explanatory variables in Models 2 and 3, we found that Model 5 (with negative Nifty returns and negative deviations from its 5-day moving average) had higher explanatory power with a substantially large adjusted *R*-square of 0.8401 (against that of 0.3505 in Model 4). As expected, the moving average term was negatively related to the LVX returns in Model 5 with high significance (well beyond the 1% level).

In Model 6, we considered all the economic explanatory variables for the entire sample and found that this model had the highest explanatory power with an adjusted *R*-square of 0.8554 (which was the highest among all the six models in consideration). Specifically, we found that low volatility was actually associated with the Nifty index in a diametrically opposite way as the India VIX was related to it. The results indicate that an increase (decrease) in LVX returns was not significantly associated with a subsequent decrease (increase) in the index. The coefficient values of the positive and the negative Nifty returns suggest a significant directional impact on the LVX returns, which implies that higher positive Nifty returns are associated with greater advances in the LVX returns, whereas higher negative Nifty returns are associated with greater declines in the LVX returns. The coefficients of both the positive as well as the negative Nifty returns were significant at the conventional significance level. The *t*-statistics supported the results, which shows that the returns on the LVX respond in equal and in opposite directions to positive and negative Nifty returns, respectively.

With respect to the other variables in our multiple regression model estimates, both the positive and the negative deviations of the Nifty index from its 5-day moving average had statistically significant impacts on the LVX returns at conventional significance levels. It can be inferred from the results that while positive Nifty index returns influenced the LVX returns positively, stronger positive (and also negative) Nifty trends affected the LVX returns negatively.

We further examined how the India VIX reacts to the extreme Nifty returns over the sample period (Table 7). Panel A exhibits the ten highest daily percentage losses of the Nifty (averaging to 3.89%), the average India VIX change (reducing nominally by 0.11%), and the average India VIX level during the sample period (39.54%). Panel B presents the ten highest daily percentage Nifty gains (averaging to 5.24%) and the reduction in India VIX by an average of 2.64%, reaching to an average level of 37.99%.

[Insert Table 7 here]

These results show that the India VIX moved in opposite directions in response to large positive and negative Nifty returns. One possible reason for this behaviour could be that the directionality of the volatility index (in our study, the India VIX) is consistent with how the actual volatility of the underlying spot index returns (the Nifty returns, in this context) responds to positive and negative returns. Alternatively, this directionality may be driven by options trading dynamics, particularly by fluctuations in the demand for the defined risk associated with buying options (Simon, 2003).

A preliminary examination of the sample dataset suggests that the distribution of the data series is leptokurtic as are most financial time series. Hence, we decided to use different measures of central tendency and statistical dispersion in order to obtain a more comprehensive picture of the relationship among our sample variables. Therefore, we used quantile regression, which captures the conditional quantile functions instead of the conditional mean functions as in ordinary least square methods.[5] Quantile regression provides more robust results against outliers in the response measurements (Koenker and Hallock, 2001). Following Kumar (2012), we used quantile regression to examine the relationship between the India VIX and the Nifty index.

We began with the standard quantile regression approach as follows. We assumed the τ-th conditional quantile function of volatility index as

(7)

where $IVIX_t$ is India VIX at time t, and $NiftyRet_t$ is the return on the Nifty index at time t. The parameter captures the effect of the returns of the Nifty index at the τ-th quantile of the conditional distribution of the India VIX. We estimated the above model by solving the following:

(8)

where is the standard quantile regression check function (Koenker and Bessett, 1982; Koenker, 2005). The resulting estimator obtained from Equation (8) would be the pooled quantile regression estimator, as we call it.

We estimated the following quantile regression model to test the relationship between returns on the India volatility index (IVIX) and the Nifty index for different quantiles, starting from $q = 0.1$ to $q = 0.9$:

(9)

where is the returns on the India VIX, and are the positive and the negative returns on the Nifty index, respectively.[6]

[5] Quantile regression is a statistical technique intended to estimate and conduct inference about conditional quantile functions. Classical linear regression methods based on minimising sums of squared residuals enable one to estimate models for conditional mean functions; similarly, quantile regression methods offer a mechanism for estimating models for the conditional median function and the full range of other conditional quantile functions. By supplementing the estimation of the conditional mean functions with techniques for estimating an entire family of conditional quantile functions, quantile regression is capable of providing a more complete statistical analysis of the stochastic relationships among random variables.

[6] is $NiftyRet_t$ if the returns on the Nifty index are positive (else, it is 0); and takes the value of $NiftyRet_t$ if returns on the Nifty are negative (else it is 0).

We expected the coefficients of both and to be negative and statistically significant if the returns on the India VIX and the returns on the Nifty index were negatively related, as shown in the earlier analysis. The symmetric relationship could be ascertained if the coefficient of were smaller than that of (*i.e.* <). The quantile regression estimates are provided in Table 8.

[Insert Table 8 here]

The results from the quantile regression model supported our previous findings. The major findings can be summarised as follows:

(i) The sign of the slope coefficients was in accordance with the expectations at all quantiles. Our findings indicate that the relationship between the returns on the volatility index and the Nifty index was significantly negative in either direction, particularly around the centre of the distribution (i.e., at quantile 0.5), which is consistent with the findings of previous studies employing traditional regression models (Flemming et al., 1995; Whaley, 2009, among others) as well as our previous findings obtained from multiple regression estimates.

(ii) The constant term was statistically significant in all quantiles except at q = 0.6 and q = 0.7 at the 1% level, which violated the stylised facts of volatility. Volatility across the markets exhibits the mean reverting trends, and therefore, should not display any significant trend. Our study confirms the presence of a statistically significant trend, similar to the evidence provided by Siripoulos and Fassas (2009) for multiple markets and Kumar (2012) for the Indian market.

(iii) The relationship was statistically significant (at the 1% level) at all quantiles, except in a few cases where the relationship was found to be insignificant. The relationship held more for market declines than for upward movements. In cases involving negative Nifty returns, the effect was sharper for the higher quantiles. Thus, we provide evidence for the presence of statistically significant leverage effect in both the left and right tails, where the left tail has domination over the right tail.

(iv) Our results also show that when the market declined sharply, the changes in the market were significantly associated with the changes in the volatility; similarly, the returns on the India VIX contributed to the upward movements in the Nifty returns, but with less vigour. We, therefore, report that a portfolio with some component of the India VIX would not get adversely affected in sharp upward movements in the stock market, as the India VIX may not fall significantly. However, independence on the right tail at higher quantiles (q = 0.7, 0.8, and 0.9) suggests that smaller gains from upward market movements would not be sufficient to cover the losses caused by the volatility.

(v) The results indicate that the effect of the negative Nifty returns on the volatility was more significant than the effect of the positive returns of similar degree. Earlier, we discussed this relationship between positive and negative returns on the Nifty index and the India VIX. Our quantile regression estimates confirmed those findings.

5.3 India VIX as a Risk Management Tool

This section discusses some potential uses of the India VIX in the Indian stock market. Prior literature as well as our empirical data analysis provided adequate evidence that stock market returns are negatively associated with the implied volatility index. The correlation among equities, bonds, and alternative asset classes tended to be very low before the global financial crisis of 2008. This trend of low correlation across different asset classes reverted during the crisis period, and rose significantly as a variety of assets dropped in value in line with the drop in equities. Consequently, many investors found that their diversified (or at least, perceived-to-be-diversified) portfolios were no longer effectively diversified. In such an uncertain environment, the effectiveness of the diversification of portfolios can be ensured using a long position in the India VIX as a diversifier for an investor's portfolio. A long exposure in the volatility index might result in negative portfolio returns in the long run, but it would provide the much-needed cushion against downturns (already evident from the results in the case of the India VIX and the Nifty returns). Investable and tradable products based on the volatility index in particular may be used to provide the desired diversification during odd times in the market (Szado, 2009).

According to Whaley (1993), a market volatility index provides a reliable estimate of the expected short-term stock market volatility, which is a critical piece of information for many investment decisions such as asset allocation and hedging risks, among others. It also offers a market volatility standard that can be used to develop volatility-based derivative contracts. Since any such market volatility standard should be based on a highly liquid underlying security market, the India VIX can serve the purpose since it is based on the CNX Nifty index, which has remained phenomenally liquid for quite some time. Also, the asymmetric relationship between the India VIX and the Nifty index returns observed through our analysis (and also in some of the prior literature) makes the India VIX a great tool for hedging risky positions in a fluctuating stock market.

It is evident from the findings of our study that an asymmetric relationship exists between the India VIX and the Nifty returns. This implies that on an average, the Nifty returns are negatively related to the changes in the India VIX levels, but in case of high upward movements in the market, the returns on the two indices tend to move independently. When the market takes sharp southward turns, the relationship is not as significant for higher quantiles. This property of the India VIX makes it a strong candidate for use as a risk management tool whereby derivative products based on the volatility index can be used for portfolio insurance against worst declines. When these derivatives on volatility are launched, they are supposed to provide the investors an opportunity to invest in a separate asset class that would carry high diversification attributes.

5.4 India VIX and Timing Strategy

Similar to many previous studies, our study also found that changes in the India VIX provided statistically significant signals about the daily Nifty returns. In this section, we explore whether the India VIX can be used for employing timing strategies with respect to trading in the stock market. Theoretically, capital market equilibrium allows (under the assumption of constant risk aversion of investors) the market risk premium to be positively related to the variance of the market portfolio (Merton, 1980), which implies that any excess returns on the market portfolio over the risk-free rate should be positively related with the risk of the market portfolio. Taking this argument further, French et al. (1987) state that since the market risk premium is positively correlated to the expected volatility (a measure of risk), future discounts used to value a security would also increase in case of any unexpected increase in market volatility. This would further decrease the stock prices. In short, any unexpected increase in volatility would most likely be related to unexpected negative stock returns.

Based on the foregoing theoretical arguments, we assume the changes in volatility as the main driving force for a time-varying risk premium, and following the approach of Copeland and Copeland (1999), we examine the timing strategies based on size. This proposed strategy suggests that an investor shifts his/her portfolio consisting of small-cap stocks to a portfolio of large-cap stocks when the implied volatility goes up, and vice versa following a decline in implied volatility levels. The economic explanation for this strategy is given in the original study as follows: "In general, small-cap stocks earn higher return than large-cap stocks (Basu, 1983; and Fama and French, 1992), but we believe that small-cap stocks perform better when expected volatility decreases and large-cap stocks perform better when expected volatility increases" (Copeland and Copeland, 1999).

In order to explore the relationship between timing strategy based on the India VIX and the size of portfolios, we considered the CNX Nifty index futures as a proxy for the large-cap portfolio and the Nifty Midcap 50 index as a proxy for the mid-cap portfolio. (Due to the paucity of data, we used mid-cap index futures as mid-cap portfolio instead of small-cap ones as suggested in the literature; work on the small-cap portfolio proxy is under way.) These two indices were chosen as representative portfolios based on the assumption that futures contracts written on these two indices are highly liquid and tradable at extremely low costs. The daily returns on the CNX Nifty futures index and the Nifty Midcap 50 futures index were regressed on the percentage change in the India VIX. The percentage change in the India VIX was defined as the difference between the India VIX at time *t* and the 75-day (about 3 months) historical moving average of the India VIX divided by the 75-day historical moving average of the India VIX. The mathematical representation is as follows:

$$\frac{-}{-} \qquad (10)$$

The sample for testing this relationship consisted of daily data from November 2009 through November 2012, as the daily data on the India VIX was available only for this period. After adjustment for 75-day historical moving average, our sample consisted of 697 observations. We then regressed the difference in returns on the Nifty futures index and the Nifty midcap futures index on the percentage change in the India VIX, based on the following regression:

$$(11)$$

where is the returns on the Nifty futures index at time *t*, is the returns on the Nifty Midcap futures index at time *t*, and α, β, and ε are the intercept, the slope coefficient, and the normally distributed random error term at time *t*, respectively. The results from the regression of the difference of future returns on large- and mid-cap portfolio and percentage change in the India VIX are presented in Table 9. The results indicate a statistically significant relationship between current percentage change in the India VIX levels and the difference between the rates of future returns (for different holding periods) on index futures contracts on the CNX Nifty index (representing the large-cap portfolio) and the CNX Nifty Midcap 50 index (representing the mid-cap portfolio).

[Insert Table 9 here]

We further tested for trading strategy based on the percentage change in the India VIX levels. Specifically, we maintained the percentage changes in the India VIX as a signal to switch between the large- and mid-cap portfolios. When the India VIX increased, we shifted our portfolio to a large-cap one, and when it decreased, we shifted to a mid-cap portfolio. We tested for percentage changes in the India VIX level at 10%, 20%, 30%, 40%, 50%, -10%, and -20% levels. For holding periods, we considered only 1, 2, 3, and 10 days of holding for computation of the expected future returns on portfolio. The statistics are provided in Table 10.

[Insert Table 10 here]

The results show that a large-cap portfolio yielded positive cumulative returns in 17 out of 20 cases. We found that switching portfolios based on a 10% change in the India VIX gave negative returns in two cases (one in the 1-day holding period and another in the 10-day holding period). It is evident that a higher percentage change in the India VIX is a useful signal for ensuring positive portfolio returns. Our results were very similar to those reported in Copeland and Copeland (1999): the futures on large-cap portfolios tended to outperform the futures on mid-cap portfolios in most of the cases. Moreover, in cases of volatility declines, the futures on mid-cap portfolios outperformed the futures on large-cap portfolios in all 8 cases. Copeland and Copeland (1999) further confirm the superiority of the trading strategy based on portfolio-size compared to the one based on style, citing Fama and French (1992), who demonstrate that firm size and beta are highly correlated. The correlation between a firm's beta and size is expected to be greater than the correlation between the firm's beta and style. Due to limitations associated with the availability of data, we tested the trading strategy based on only portfolio size, and not on style.

6. Conclusion

In this study, we compared the India Volatility Index (India VIX) with other traditional measures of stock price volatility, such as conditional volatility estimates using the ARCH/GARCH models. For realised volatility estimates also, we considered three different measures such as the standard deviation of historical returns, the daily variance estimates, and the monthly sum of stock returns. Employing the linear regression model and the RMSE, MAE, and MAPE criteria, we found that the India VIX was a better predictor of realised volatility than the GARCHVOL and the EGARCHVOL measures of conditional volatility. The annualised volatility measure seemed to be better performing, but only in explaining the standard deviations of the Nifty returns; for the other measures of realised volatility, the India VIX captured return volatility better than any other measures. Although the difference between them was marginal, the India VIX (which was a model-free measure of implied volatility) was the best among them in estimating realised volatility. The superiority of the India VIX holds for all the measures of realised volatility.

Our results demonstrate a statistically significant negative relationship between the stock market returns and volatility. Using the regression estimations approach and the quantile regression methodology, we showed that the returns on the CNX Nifty index were negatively related to the changes in the India VIX levels; however, in the case of high upward movements in the market, the returns on the two indices tended to move independently. When the market took a sharp downward turn, the relationship was not as significant for the higher quantiles. This attribute of the India VIX makes it a viable risk management tool—derivative products based on the volatility index can be used as portfolio insurance against worst declines.

Finally, we tested whether the India VIX can be used for timing strategy in the stock market. We took the futures on the CNX Nifty index and the CNX Nifty Midcap 50 index as proxies for large- and mid-cap portfolios, respectively, and examined the relationship between the difference in the daily returns on the two portfolios and the percentage change in the India VIX. We found that a higher percentage change in the India VIX could be used as a signal to switch between large- and mid-cap portfolios to ensure positive portfolio returns.

We contribute to the existing literature by examining the asymmetric relationship between a volatility index and stock returns, and supplement our results from linear regression with quantile regression for testing this relationship. We conclude that the India VIX can be used as a tool for portfolio insurance against risks caused by steep downward movements in the market; it can also be used as an indicator for market timing.

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Figure 1: Movement of India VIX (IVIX), VIX, and Nifty

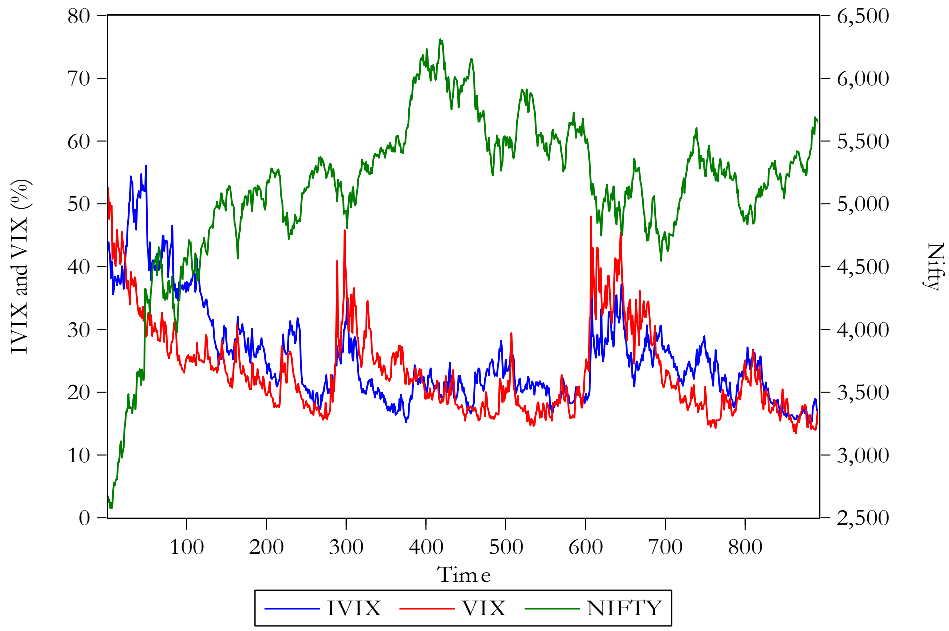

Table 1: Descriptive Statistics of Indices

(A) Descriptive statistics					
	INDIAVIX	NIFTY	NIFTYRET	CBOEVIX	LVX
Mean	25.05361	5146.340	0.000808	23.18010	3683.985
Median	22.96000	5232.050	0.000720	21.28000	3883.895
Maximum	56.07000	6312.450	0.163343	52.65000	4520.700
Minimum	13.04000	2573.150	0.060216	13.45000	1661.870
Std. Dev.	7.940582	624.3712	0.014037	7.208186	610.9529
Skewness	1.376948	-1.534916	1.658820	1.253091	-1.388439
Kurtosis	4.859700	6.723514	22.38263	4.294683	4.4535439
Jarque-Bera	429.7343	906.3077	15048.80	309.6657	392.8145
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Top Decile	37.194	5825.105	0.016727	33.514	4294.918
Bottom Decile	16.979	4512.375	-0.014926	15.99	2774.084
Observations	934	934	934	934	934
(B) Correlation between indices					
INDIAVIX	1.000000				
NIFTY	-0.811718***	1.000000			
NIFTYRET	0.017667	-0.041527*	1.00000		
CBOEVIX	0.677311***	-0.697315***	-0.041527*	1.000000	
LVX	-0.866983***	0.930436***	-0.079389***	-0.619206***	1.000000
* Significant at 10% level; *** Significant at 1% level					

Table 2: Descriptive Statistics of Realised Volatility Measures

	Daily Variance Estimator (RVOL1)	**Realised Volatility (RVOL2)**
Mean	0.000196	0.003911
Median	0.000126	0.002520
Maximum	0.001846	0.036921
Minimum	2.47E-05	0.000494
Std. Dev.	0.000258	0.005156
Skewness	4.715300	4.715300
Kurtosis	27.81013	27.81013
Jarque-Bera	26858.25	26858.25
Probability	0.000000	0.000000
Observations	915	915

Table 3(a): Descriptive Statistics of Volatility Estimates

	GARCH(1,1) Volatility	**EGARCH(1,1) Volatility**	**Ex-Post Volatility**
Mean	0.043845	0.045705	0.041845
Std. Dev.	1.003092	1.004331	0.031999
Skewness	0.446417	0.478095	5.040573
Kurtosis	6.374373	6.511658	67.43339
Jarque-Bera	474.1430	515.4981	165523.9
Probability	0.000000	0.000000	0.000000
Observations	934	934	934

Table 3(b): GARCH/EGARCH Estimates of Conditional Volatility Measures

	GARCH(1,1) Estimates	**EGARCH(1,1) Estimates**
Constant	1.27E-06 (2.563585)*	-0.102117 (-3.051168)**
α	0.042425 (4.036039***)	0.095234 (4.702394***)
β	0.948783 (82.83657***)	-0.032191 (-3.032225**)
γ	-	0.996822 (393.1150***)
Note: The z-statistics associated with each coefficient are reported in parentheses. *Significant at 1% level ; **Significant at 5% level; ***Significant at 1% level		

Table 4: Performance of India VIX and other Volatility Measures in Capturing Realised Volatility

Dependent variable	*Constant*	*β*	*Adj. R-square*	*F-Statistic*
(A) Independent variable: India VIX (in percentage terms)				
Std. dev. of Nifty returns (STDEV)	-0.002241 (0.000398) [0.0000]	0.059930 (0.001534) [0.0000]	0.625191	1525.576
Daily variance estimator (RVOL1)	-0.000360 (2.11E-05) [0.0000]	0.002245 (8.12E-05) [0.0000]	0.455032	764.1617
Realised volatility (RVOL2)	-0.007205 (0.000421) [0.0000]	0.044891 (0.001624) [0.0000]	0.455032	764.1617
(B) Independent variable: Return on GARCH volatility estimates				
Std. dev. of Nifty returns (STDEV)	0.012610 (0.000194) [0.0000]	0.004906 (0.002747) [0.0728]	0.002391	3.190272
Daily variance estimator (RVOL1)	0.000196 (8.51E-06) [0.0000]	0.000230 (0.000121) [0.0475]	0.002867	3.627976
Realised volatility (RVOL2)	0.003920 (0.000170) [0.0000]	0.004591 (0.002410) [0.0425]	0.002867	3.627976
(C) Independent variable: Return on EGARCH volatility estimates				
Std. dev. of Nifty returns (STDEV)	0.012606 (0.000194) [0.0000]	0.002424 (0.002938) [0.9638]	-0.000349	0.680891
Daily variance estimator (RVOL1)	0.000196 (8.53E-06) [0.0000]	5.92E-05 (0.000129) [0.8732]	-0.000864	0.210898
Realised volatility (RVOL2)	0.003914 (0.000171) [0.0000]	0.001184 (0.002579) [0.9608]	-0.000864	0.210898
(D) Independent variable: Ex post volatility estimates				
Std. dev. of Nifty returns (STDEV)	0.010466 (0.000256) [0.0000]	0.052056 (0.004401) [0.0000]	0.131916	139.8933
Daily variance estimator (RVOL1)	0.000113 (1.14E-05) [0.0000]	0.002012 (0.000196) [0.0000]	0.102031	104.8527
Realised volatility (RVOL2)	0.002262 (0.000228) [0.0000]	0.040232 (0.003929) [0.0000]	0.102031	104.8527

Note: Standard errors and *p*-values are reported in parentheses and square brackets, respectively.

Table 5: Performance of Volatility Measures

	India VIX (%)	GARCH volatility estimates	EGARCH volatility estimates	Ex post volatility
(A) Root Mean Square Error (RMSE)				
Std. dev. of Nifty returns (STDEV)	0.003592	0.005861	0.005869	0.005467
Daily variance estimator (RVOL1)	0.000190	0.000257	0.000258	0.000244
Realised volatility (RVOL2)	0.003802	0.005143	0.005152	0.004880
(B) Mean Absolute Error (MAE)				
Std. dev. of Nifty returns (STDEV)	0.002294	0.003901	0.003903	0.003557
Daily variance estimator (RVOL1)	9.00E-05	0.000131	0.000131	0.000119
Realised volatility (RVOL2)	0.001801	0.002614	0.002615	0.002378
(C) **Mean Absolute Percent Error (MAPE)**				
Std. dev. of Nifty returns (STDEV)	17.72460	32.48665	32.51716	29.2306
Daily variance estimator (RVOL1)	52.53680	99.93958	100.3049	84.30777
Realised volatility (RVOL2)	52.53680	99.9358	100.3049	84.30777

Table 6(a): Impact of Nifty Returns and Deviations of Nifty from its 5-day Moving Average on Changes in India VIX

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.421748 (0.153655) [2.744781]***	0.291226 (0.146569) [1.986960]**	0.300961 (0.133550) [2.253540]**	0.153416 (0.141911) [1.081067]	0.253676 (0.133795) [1.895999]**	0.085257 (0.132001) [0.645881]
Lagged value of India VIX (India VIX_{t-1})	-0.018025 (0.005845) [-3.084024]***	-0.002456 (0.005765) [-0.425984]	-0.030570 (0.005124) [-5.966468]***	-0.010671 (0.005657) [-1.886461]**	-0.034244 (0.005308) [-6.451712]***	-0.024601 (0.005305) [-4.637139]***
Positive Nifty returns (Nifty Ret_t (+))		-48.13079 (4.782851) [-10.06320]***		-32.81898 (4.882665) [-6.721530]***		-42.34883 (5.479945) [-7.727966]***
Negative Nifty returns (Nifty Ret_t(-))			-95.61711 (5.468687) [-17.48447]***		-104.6000 (5.983996) [-17.47995]***	-84.47708 (7.686176) [-10.99078]***
Positive deviation of Nifty from its 5-day moving average ($DevMA5_t$ (+))				0.010245 (0.001106) [9.261779]***		0.003085 (0.001398) [2.205922]**
Negative deviation of Nifty from its 5-day moving average ($DevMA5_t$ (-))					-0.003135 (0.000953) [-3.289066]***	-0.008306 (0.001137) [-7.306667]***
R-square	0.010113	0.107317	0.255005	0.183041	0.265804	0.312451
Adj. R-square	0.009050	0.105398	0.253403	0.180394	0.263426	0.308731
F-statistic	9.511207	55.90176	159.1655	69.15717	111.7480	83.98100

Note: Based on the equation:

Standard errors and t-statistics are reported in parentheses and square brackets, respectively.

** Significant at 5% level; *** Significant at 1% level

Model 1 includes only the lagged value of India VIX as the explanatory variable; Model 2 and Model 3 include the lagged value of India VIX along with positive Nifty returns and negative Nifty returns, respectively; Model 4 includes the lagged value of India VIX along with positive Nifty returns and positive deviations of Nifty from its 5-day moving average; Model 5 includes the lagged value of India VIX along with negative Nifty returns and negative deviations of Nifty from its 5-day moving average; and Model 6 includes the lagged value of India VIX, negative and positive Nifty returns, as well as negative and positive deviations of Nifty from its 5-day moving average, as explanatory variables.

Table 6(b): Impact of Nifty Returns and Deviations of Nifty from its 5-day Moving Average on Returns on Low Volatility Index (LVX)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.000991 (0.000314) [3.156131]***	-0.003234 (0.000224) [-14.40878]***	0.005278 (0.000252) [20.97303]***	-0.014864 (0.002336) [-6.361967]***	0.001087 (0.000274) [3.961921]***	0.000917 (0.000197) [4.656269]***
Lagged value of Low Volatility Index (LVX_{t-1})	-0.951305 (0.032740) [-29.05603]***	-0.935574 (0.020390) [-45.88461]***	-0.973500 (0.022382) [-43.49528]***	2.67E-06 (6.00E-07) [4.444168]***	-1.218399 (0.021029) [-57.93973]***	-0.020485 (0.019391) [-1.056405]
Positive Nifty returns (Nifty Ret_t (+))		0.780068 (0.020336) [38.35925]***		0.860481 (0.039538) [21.76356]***		0.560246 (0.018878) [29.67726]***
Negative Nifty returns (Nifty Ret_t(-))			0.936745 (0.028717) [32.61941]***		0.704027 (0.025450) [27.66307]***	0.571180 (0.025973) [21.99154]***
Positive deviation of Nifty from its 5-day moving average ($DevMA5_t$ (+))				1.54E-05 (8.96E-06) [1.720950]*		-2.42E-05 (5.02E-06) [-4.818278]***
Negative deviation of Nifty from its 5-day moving average ($DevMA5_t$ (-))					-0.000104 (4.61E-06) [-22.62465]***	-1.05E-05 (4.51E-06) [-2.339159]***
R-square	0.475568	0.796904	0.755408	0.752642	0.841419	0.856193
Adj. R-square	0.475004	0.796467	0.754882	0.750545	0.840905	0.855414
F-statistic	844.2528	1824.553	1436.128	2912.386	1637.765	1100.252

Note: Based on the equation:

Standard errors and t-statistics are reported in parentheses and square brackets, respectively.

* Significant at 10% level; *** Significant at 1% level

Model 1 includes only the lagged value of Low Volatility Index (LVX) as the explanatory variable; Model 2 and Model 3 include the lagged value of LVX along with positive Nifty returns and negative Nifty returns, respectively; Model 4 includes the lagged value of LVX along with positive Nifty returns and positive deviations of Nifty from its 5-day moving average; Model 5 includes the lagged value of LVX along with negative Nifty returns and negative deviations of Nifty from its 5-day moving average; and Model 6 includes the lagged value of LVX, negative and positive Nifty returns, as well as negative and positive deviations of Nifty from its 5-day moving average, as explanatory variables.

Table 7: Extreme Nifty Returns and India VIX Changes

(A): Ten highest one-day Nifty losses			
Date	Nifty Return (%)	ΔIVIX	Closing IVIX
06-Jul-2009	-6.022	-0.30	39.7
30-Mar-2009	-4.289	0.39	40.09
17-Aug-2009	-4.286	1.19	41.28
22-Sep-2011	-4.169	-7.4	33.88
17-Jun-2009	-3.644	11.01	44.89
08-Jun-2009	-3.483	-2.83	42.06
16-Apr-2009	-3.346	8.04	50.1
2-Mar-2009	-3.275	0	43.17
24-Feb-2011	-3.265	-14.97	28.2
03-Nov-2009	-3.187	3.84	32.04
Average	**-3.896**	**-0.114**	**39.541**
(B): Ten highest one-day Nifty percentage gains			
Date	Nifty Return (%)	ΔIVIX	Closing IVIX
18-May-2009	16.334	0	52.01
4-May-2009	5.053	-1.5	50.51
2-Apr-2009	4.8069	-13.14	37.37
23-Mar-2009	4.6241	1.22	38.59
13-Mar-2009	3.8156	-3.03	35.56
27-May-2009	3.7978	4.18	39.74
29-Aug-2011	3.5546	-13.67	26.07
12-May-2009	3.4969	26.13	52.20
1-Mar-2011	3.4834	-29.98	22.22
10-May-2010	3.4386	3.4	25.62
Average	**5.2405**	**-2.639**	**37.989**

Table 8: Quantile Regression Estimates: India VIX and Nifty Returns

	Constant			**Nifty Ret (+)**			**Nifty Ret (–)**		
Quantile	Coefficient	Std. Error	*t*-Statistic	Coefficient	Std. Error	*t*-Statistic	Coefficient	Std. Error	*t*-Statistic
0.100	-0.040789	0.004830	-8.445208***	-2.885320	0.622635	-4.634048***	-1.871360	0.589094	-3.176677***
0.200	-0.029041	0.002741	-10.59554***	-2.306564	0.347787	-6.632114***	-2.312653	0.250906	-9.217224***
0.300	-0.020870	0.002360	-8.842491***	-2.114044	0.247809	-8.530949***	-2.527082	0.304024	-8.312119***
0.400	-0.013467	0.002359	-5.709776***	-2.000982	0.279463	-7.160094***	-2.875801	0.347046	-8.286503***
0.500	-0.008562	0.002322	-3.687392***	-1.682696	0.295368	-5.696958***	-3.479595	0.322039	-10.80488***
0.600	-0.002679	0.002287	-1.171526	-1.434995	0.306797	-4.677347***	-3.611749	0.274700	-13.14797***
0.700	0.003456	0.002593	1.332803	-0.725521	0.484944	-1.496091	-3.820224	0.281722	-13.56028***
0.800	0.012304	0.002248	5.474460***	-0.075328	0.083317	-0.904114	-3.890067	0.290346	-13.39802***
0.900	0.031128	0.003186	9.771529***	-0.041410	0.315799	-0.131128	-4.300189	0.453381	-9.484719***

*** Significant at 1% level

Note: Based on the equation:

Method: Quantile regression (Median); Sparsity method: Kernel (Epanechnikov) using residuals

Table 9: Relationship between Future Returns on Large- and Mid-cap Portfolios and Percentage Change in the India VIX

Holding period (in days)	α	β	R-square	F-statistics
1	-0.161193 (0.004484) [-35.95108]***	0.134635 (0.028021) [4.804764]***	0.032194	23.08576
2	-0.161603 (0.004490) [-35.98797]***	0.127837 (0.028044) [4.558404]***	0.029111	20.77905
3	-0.162012 (0.004496) [-36.03410]***	0.121602 (0.028070) [4.332072]***	0.026404	18.76685
4	-0.162373 (0.004506) [-36.03569]***	0.114246 (0.028115) [4.063491]***	0.023338	16.51196
5	-0.162741 (0.004512) [-36.06922]***	0.108393 (0.028137) [3.852310]***	0.021055	14.84029
10	-0.164102 (0.004535) [-36.18846]***	0.093022 (0.028182) [3.300736]***	0.015656	10.89484
15	-0.165538 (0.004548) [-36.39563]***	0.080082 (0.028190) [2.840760]**	0.011728	8.069915
20	-0.166754 (0.004561) [-36.55864]***	0.072786 (0.028218) [2.579402]*	0.009761	6.653317

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Note: Based on the equation , where and are log of daily returns on the Nifty index and Nifty midcap index at time *t*, and is change in India VIX level (in percentage terms).

Standard errors and t-statistics are reported in parentheses and square brackets, respectively.

Table 10: Trading Strategy Results from Shifting between Large- and Mid-cap Portfolios Based on Percentage Change in the India VIX

Holding period (in days)	% change in IVIX	Number of days*	Cumulative returns	Daily average returns
1	10	70	-0.14556	-0.00211
1	20	27	0.09503	0.00336
1	30	16	0.05474	0.00526
1	40	14	0.02636	0.00564
1	50	1	0.01595	0.00485
1	-10	158	0.12651	0.00154
1	-20	77	0.06397	0.00378
2	10	83	0.11856	0.00148
2	20	33	0.10271	0.00294
2	30	22	0.04823	0.00331
2	40	18	0.02705	0.00442
2	50	2	0.01831	0.00452
2	-10	186	0.07491	0.00079
2	-20	99	0.04711	0.00219
3	10	93	0.09503	0.00108
3	20	38	0.10976	0.00271
3	30	27	0.06435	0.00355
3	40	22	0.01739	0.00237
3	50	2	0.01153	0.00245
3	-10	205	0.08783	0.00083
3	-20	117	0.05416	0.00212
10	10	137	-0.02198	-0.00017
10	20	61	-0.01894	-0.00031
10	30	54	0.03297	0.00093
10	40	38	0.02118	0.00164
10	50	3	0.02172	0.00224
10	-10	288	0.04930	0.00034
10	-20	197	0.08001	0.00189

* indicates the number of days the portfolio remains in a given position

Note: Positive percentage change in the India VIX implies long large-cap portfolio, and negative percentage change in the India VIX indicates long mid-cap portfolio.