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Does behavioural theory explain return-implied volatility relationship? Evidence from India

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Abstract: The study investigates whether behavioural theory is a superior explanation for short-term return–volatility relationship than traditional leverage and volatility feedback hypotheses. Using VAR and quantile regression frameworks, the study shows that behavioural theory explains the relationship better than the leverage and feedback hypotheses. The study supports that behavioural biases (representative, affect, extrapolation heuristics, etc.) exist among market participants, and these biases cause India Volatility Index (India VIX) to be an efficient hedge for extreme negative market movements.

Subjects: Economic Theory & Philosophy; Econometrics; Investment & Securities

Keywords: return–volatility relation; leverage hypothesis; volatility feedback hypothesis; affect heuristics; representative bias; extrapolation bias

JEL classifications: G12; G13; G17

1. Introduction

Volatility index (commonly known as VIX) measures the short-term expected volatility of the market. After the introduction of the derivatives contracts on volatility index, market participants can now trade directly on volatility. Following this, empirical investigations about the relationship between return and implied volatility are re-emphasized in recent literature. Negative and asymmetric relationship between return and volatility are well established in the financial literature. Asymmetric relationship posits that negative returns are related to larger volatility than positive returns. Leverage

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PUBLIC INTEREST STATEMENT

We investigated whether the behavioural theory is a superior explanation for short-term return–volatility relationship than traditional leverage and volatility feedback hypotheses. Finance theories propose the relationship between risk and return is positive. However, empirical evidence documents that the short-term relationship between volatility and return is negative and asymmetric. Leverage and feedback hypotheses were proposed to explain the negative relationship, but the asymmetric relationship remained as a stylized fact. We examined the negative and asymmetric relationship in light of three alternative hypotheses namely, leverage, feedback and behavioural theory. Our empirical evidence shows that the negative and asymmetric relationship can be better understood by behavioural theories rather than traditional leverage and feedback hypotheses.

hypothesis and volatility feedback hypothesis are the competing theoretical explanations for negative relationship. Asymmetric relationship remains a stylized fact in the market. Though some recent studies (Hibbert, Daigler, & Dupoyet, 2008; Low, 2004) propose behavioural theory to understand the negative and asymmetric relationship, no consensus exists in the literature in support of the behavioural explanation over the traditional theories (leverage and feedback hypotheses), one of the reasons being a dearth of evidence. The current study seeks to explore the consensus further by investigating the return-volatility relationship for Indian market using theoretical frameworks based on leverage hypothesis, volatility feedback hypothesis and behavioural explanations.

Literature employs three broad categories of volatility proxies for studying the relationship. First, a model-based parameterized volatility process such as ARCH family or stochastic volatility models. Second, realized volatility, which is model-free market-based model. Third, implied volatility, that is, forward-looking volatility calculated from the option prices. Implied volatility index proxy is a recent strand of literature, and most of the work is based on developed markets. The majority of the volatility indices are now adopted to model-free implied volatility (MFIV) framework. The MFIV framework, originally proposed by Demeterfi, Derman, Kamal, and Zou (1999) and Britten-Jones and Neuberger (2000), is devised to replicate the fair price of a variance swap and is a measure of unbiased future volatility. MFIV framework is expected to be more informative than Black-Scholes at-the-money (ATM) implied volatility (BSIV) since MFIV incorporates the option information across all moneyness. In March 2008, National Stock Exchange (NSE) of India introduced India VIX, the volatility index for the Indian market. India VIX¹ is calculated using the best bid and ask quotes of the out-of-the-money (OTM) call options, and OTM put options based on the near and next month Nifty² options order book.

Leverage and feedback are two competing traditional hypotheses that attempt to answer the negative relationship between return and volatility. These two theories differ in the direction of causality between return and volatility. Recently, behavioural explanations have found a place in literature to describe the asymmetric behaviour between return and volatility, though the empirical evidence is mixed in favour of behavioural explanations. For example, Badshah (2013) supports the behavioural theory explanation for the relationship between MFIV and market return for developed markets. On the contrary, Padungsaksawasdi and Daigler (2014) find that behavioural theories offer a weak explanation for understanding the return-volatility relationship for commodities. Our paper is an attempt to explain the market return-MFIV relationship in view of the above findings for Indian market. The study is built on the following objectives: first, the study examines the relevance of the behavioural explanation of return-MFIV in the context of emerging markets. Second, the study intends to examine how behavioural theory explains extreme event behaviour between the return and MFIV.

The study contributes to the literature in three ways: first, previous studies investigate behavioural theories of return-implied volatility relationship in the context of developed markets. This study is the first to investigate behavioural explanation of return-implied volatility relationship in the context of emerging market setting, specifically for India. The study supports behavioural theories of return-implied volatility relationship for emerging markets. Thus, the results are consistent with Hibbert et al. (2008) and Badshah (2013), who support the behavioural explanations over traditional theories for developed equity markets. Second, vector autoregressive (VAR) framework is used to investigate the causal relationship between return and implied volatility. These results provide limitation of VAR to study the relationship, specifically for extreme market conditions. This study is the first to document limitations of VAR for understanding the extreme market behaviour of return-implied volatility relationship. Third, leverage and feedback theories are treated separately in comparing behavioural explanation in a quantile regression framework.

Key findings of the study can be described in the following dimensions. First, return-implied volatility relationship supports behavioural theory over leverage effect and feedback effect for the Indian market. Evidence strengthens the behavioural theory further over traditional theories in defining the

return–volatility relationship. Second, the study documents VAR framework as an incomplete description of the return–volatility relationship. Third, we find that India VIX functions as an effective hedge for extreme negative market conditions.

Section 2 contains a brief literature review and hypotheses development. Data and variable description are given in Section 3. Section 4 contains methodology. Section 5 covers empirical results. Section 6 concludes the paper.

2. Brief literature review and hypotheses development

2.1. The leverage effect and feedback effect explanation for return–volatility relationship

Leverage effect and feedback effect are two traditional theories that explain the return–volatility relationship. Black (1976) and Christie (1982) postulate that innovations in the negative return of a stock diminish the value of the stock, increasing the financial leverage (debt-to-equity ratio) of the stock. Since equities are more exposed to the total risk of a firm, decline in the equity value would increase the volatility of the stock. In contrast, the volatility feedback hypothesis (Bekaert & Wu, 2000; Campbell & Hentschel, 1992; French, Schwert, & Stambaugh, 1987; Poterba & Summers, 1986) suggests that variation in conditional volatility is the cause for the change in stock price. Feedback theory states that risk premium is time-varying and volatility is priced in the market. Therefore, positive innovation in volatility would demand a higher rate of return that, in turn, would cause the stock price to go down. Similarly, a negative innovation in volatility would increase the stock price.

The fundamental difference between these two theories is the direction of causality between the two series. Leverage effect assumes that innovation in return causes a change in volatility or simply, the effect runs from price to volatility. On the other hand, feedback effect assumes that positive volatility innovation causes a negative return, i.e. effect runs from volatility to price. Literature also documents the relative magnitude of these two effects. Some of the studies report dominance of the feedback effect over the leverage effect (Bekaert & Wu, 2000; Wu, 2001).

The above-mentioned traditional theories do not propose any specific volatility measure. Many studies report a negative and asymmetric return–volatility relationship based on different measures of volatility. For example, Engle and Ng (1993), Glosten, Jagannathan, and Runkle (1993) report negative and asymmetric relationship based on autoregressive conditional volatility models. Fleming, Ostdiek, and Whaley (1995), Whaley (2000) and Giot (2005) document negative and asymmetric relationship taking VXO.³ Thus, volatility indices are termed as “fear gauge” (Whaley, 2000) because of the asymmetric relation. Among the many different measures of volatility, literature supports the use of option-implied volatility over the realized volatility. For example, Bollerslev and Zhou (2006) report that option-implied volatility displays stronger asymmetric effect than realized volatility. Several other papers also report the pronounced strength of negative asymmetric relationship of option-implied volatility over other proxies of volatility (Bates, 2000; Eraker, 2004). Moreover, literature documents that stronger asymmetric negative relationship is found in the market index rather than individual stocks (e.g. Andersen, Bollerslev, Diebold, & Ebens, 2001; Bekaert & Wu, 2000; Dennis, Mayhew, & Stivers, 2006; Kim & Kon, 1994). Option-implied volatility has two popular measures, namely, Black–Scholes implied volatility (BSIV) and model-free implied volatility (MFIV). Many studies report the negative and asymmetric relationship between market index return and change in the volatility index that are based on MFIV framework (Badshah, 2009; Sarwar, 2012; Whaley, 2009). Badshah (2013) compares the strength of MFIV and BSIV and reports that MFIV displays pronounced asymmetry compared to BSIV. For the Indian market, Kumar (2012) examines the relationship between Nifty and India VIX and reports negative and asymmetric relationship.

Earlier studies (Badshah, 2009; Lee & Ryu, 2013) use VAR framework in the context of return–volatility relationship. For example, Lee and Ryu (2013) document the characteristics of impulse response functions of MFIV for positive and negative returns in the context of Korean equity market.

Badshah (2009) investigates the volatility spillover and transmission process of volatility indices across different developed markets. In this study, we use VAR to understand the traditional theories (leverage and feedback effect) of return-implied volatility relationship. Moreover, we document the limitations of VAR in the context of understanding the traditional theories. Our exploratory analysis shows the limitation of VAR in capturing the extreme events. We show that VAR framework cannot capture the dynamics of the extreme market conditions in the context of return-implied volatility relationship.

2.2. Behavioural explanation for the return–volatility relationship

The leverage hypothesis and feedback hypothesis are based on fundamental factors of the firms. These theories involve examination of lagged relationship between return and volatility. Hibbert et al. (2008), Badshah (2013) report that the relationship is contemporaneous rather than a lagged phenomenon. Previous study of Dennis et al. (2006) reports that return and systematic volatility (not the idiosyncratic volatility) exhibit asymmetric relationship. Therefore, the asymmetric relationship is attributed to systematic marketwide factors rather than firm-level factors. Thus, explanation of negative and asymmetric relationship for market-level data based on traditional theories would be insufficient. The behavioural theory would be an alternative explanation for the relationship. The behavioural explanations can be associated to the biases that exist among market participants. Representative bias is related to the heuristics principles applied by the market participants to infer quick judgement (Representative heuristics as discussed by Tversky and Kahneman (1974)). Market participants judge high (low) returns and low (high) risk as representative of good (bad) investment grounded on the representative heuristics. Based on the same principles, higher volatility is represented as increased risk. Thus, the nature of return and volatility is negative. Another form of heuristics namely, affect bias or affect heuristics, influences participants to make decisions quickly based on the current state of emotion, i.e. greed, fear etc. One of the implications of the affect heuristics for market participants is that participants relate negative price movement as a form of rising risk and subsequently higher volatility, since higher volatility is related to greater risk. Negative price movement finds greater response as rising risk than positive price movement as lowering of risk (Low, 2004). Kahneman and Tversky (1979) state the particular behaviour as loss aversion theory, where the value function is convex and steeper for losses than concave gains. Extrapolation bias states that market participants relate past events as a representative of a future event and take a decision based on that. Another behavioural explanation is the heterogeneous belief that exists among market participants about the fundamental price of an asset. Different beliefs about fundamentals cause different price forecasts. Accordingly, optimistic (pessimistic) investors overestimate (underestimate) the returns and underestimate (overestimate) the volatility. In addition to that, higher disparity of belief occurs during the bear market than in the bull market. It states that different clusters of investors exist in the market and they react differently to positive and negative market movements. Survey results of Shefrin (2008) confirm the existence of heterogeneous beliefs about the fundamentals. In brief, the above behavioural explanations provide reasons for the negative and asymmetric relationship between market return and volatility.

2.3. Behavioural explanations for the shape of the implied volatility function

In this section, we attempt to reconcile behavioural explanations with the shape of the implied volatility function (IVF). As discussed earlier, volatility index captures information across the moneyness of the option series. Volatility index level is computed using the OTM put index options and OTM call index options. If equity portfolio investors use the derivatives contracts on volatility index for managing downside volatility risk, the success of the contract depends on the biases (affect heuristics, extrapolation bias) that exist among the participants of index options market. For example, higher demand for OTM put index options is argued by Bates (2008), stating that index options market operates in inefficiency since market participants prefer OTM put index options as a hedge against crash risk. Index options market functions as insurance market for covering downside risk rather than two-sided market for disseminating financial risk. So if index options market operates more as hedge market for the decrease in asset prices, by the affect heuristics, we expect higher demand for OTM put index options in times of the downside market movements. Similarly, according to the

extrapolation bias, investors extrapolate past events into future and see recent events as a representation of the future. Thus, investor believes current negative market movement is the representation of future. Accordingly, both affect heuristics, and extrapolation biases influence investors to have a higher demand for OTM put index options during negative market movement. Net buying pressure on OTM put index options during negative market movement overprices the OTM put options beyond its efficiency, and more overpricing would be observed in extreme negative market conditions leading to higher volatility index value. Under this scenario, the futures contracts on volatility index would be an efficient hedge for extreme negative market conditions.

2.4. Hypotheses development

Based on the above literature review, our first objective is to examine the return–implied volatility relationship in the light of two alternative theories namely, leverage effect and behavioural theory. As discussed earlier, if the behavioural theory is more fundamental than leverage effect, we expect the contemporaneous relationship between the change of MFIV and return to be the most significant factor because the leverage hypothesis states that lagged returns would be the most significant factor for current change of MFIV. Accordingly, we propose our first hypothesis as below.

Hypothesis I: Contemporaneous Nifty return is the most significant factor that decides the change of current India VIX.

If the above hypothesis holds, we expect contemporaneous NSE Nifty return as the most significant factor in explaining the changes in India VIX, which in turn establishes the representative bias.

Affect heuristics states that market participants respond more during negative price movement (as a representative of rising risk because of potential loss) relative to the positive price movement and lowering of risk. Also, during negative market movement, the higher disparity of beliefs about the fundamentals occurs, thereby causing higher disparity in pricing forecasts. Based on that, we expect that there would be an asymmetric effect for negative and positive returns on change of volatility. We expect that asymmetric effect to increase with higher quantiles of volatility (which is represented as higher risk). We propose our second hypothesis taking the above into consideration.

Hypothesis II: Asymmetric relationship varies across the quantiles of the India VIX change distribution. Moreover, asymmetry is more pronounced at the uppermost quantiles of India VIX change than the lowermost quantile of the India VIX change.

Another proposition is that negative returns are more closely associated with positive innovation in volatility. According to the affect heuristics, and extrapolation bias, market participants relate negative returns with higher risk and subsequently higher volatility, and make quick judgement based on the current state of emotions, which is predominantly fear in this case. Based on the above, we propose the following hypothesis.

Hypothesis III: Negative returns have much higher impact than positive returns on positive implied volatility innovations; negative returns, in particular, are the most important factor that determines the largest change of the India VIX

We test the above hypotheses II and III based on the quantile regression framework. Quantile regression is used by Badshah (2013) to investigate the return–implied volatility relationship for developed countries. Investigations of hypothesis II and hypothesis III have following implications. First, the increase in asymmetric relationship would imply that India VIX functions as insurance for downside market movement. Second, the increase in asymmetry in extreme negative returns imply that India index options market functions more as an insurance market for covering one directional price movement, precisely negative price movement.

Additionally, we set our second objective to examine the short-term relationship between Nifty return and India VIX change in the light of feedback effect and behavioural theory. In the same way, as mentioned in hypothesis I, if the behavioural theory holds true for the Indian market, we expect a contemporaneous relationship between change in India VIX and Nifty return. Feedback effect would only hold if the lagged changes of India VIX are the most significant factors for current Nifty return. We propose the following hypothesis:

Hypothesis IV: Contemporaneous change in India VIX is the most significant factor for current market return for the entire return distribution.

3. Data and variable description

In this section, we introduce Indian stock market and present the details of data used in the study.

3.1. Indian stock market setting

Indian stock markets operate on nationwide market access, anonymous electronic trading and a predominantly retail market and all this make Indian stock market as the top most among emerging countries in terms of a vibrant market for exchange-traded derivatives. We examine the return-implied volatility relation of one of three stock exchanges trading equity and derivatives in India, the National Stock Exchange (NSE). NSE has the largest share of the domestic market activity in the financial year 2015–16, with approximately 83% of the traded volumes on the equity spot market and almost 100% of the traded volume on equity derivatives. The NSE maintained the global leader position in the category of stock index options, by number of contracts traded, in 2014–15 as per the Futures Industry Association Annual Survey. Also as per the WFE Market Highlights 2015, the NSE figured among the top five stock exchanges globally in different categories of ranking in the derivatives market.

Nifty is used as a benchmark of Indian stock market by NSE, which is a free-float market capitalization weighted index. It consists of 50 large cap stocks across 23 sectors of Indian economy. We use Nifty as a market index in our study. The volatility index, India VIX, is introduced by NSE on 3 March 2008, which indicates the investor's perception of the market's volatility in the near term. Nifty is different from India VIX as the former measures the direction of the market and is computed using the price movement of the underlying stocks whereas the latter measures the expected volatility and is computed using the order book of the Nifty options. The NSE launched futures contracts on the India VIX on 26 February 2014.

3.2. Data-set and descriptive statistics

For the study, daily closing values of Nifty and India VIX are used for the period starting from 3 March 2008 to 31 August 2015. The starting date of our sample period (3 March 2008) represents the introduction of India VIX by NSE. We obtained daily closing values from Thomson Reuters DataStream. The data span more than 7 years and consists of 1854 observations.

Table 1 reports summary statistics of the Nifty return and change in India VIX. Return of Nifty is calculated based on percentage continuous compounding i.e. $RNifty_t = \ln\left(\frac{Nifty_t}{Nifty_{t-1}}\right) \times 100\%$, where $Nifty_t$ and $Nifty_{t-1}$ refer to two consecutive closing values of Nifty on the day t and $t-1$, respectively. Similarly, change of India VIX is calculated based on percentage change i.e. $\Delta IVIX_t = \left(\frac{IVIX_t - IVIX_{t-1}}{IVIX_{t-1}}\right) \times 100\%$, where $IVIX_t$ and $IVIX_{t-1}$ indicate two consecutive closing values of India VIX on the day t and $t-1$, respectively. Significant higher mean of $\Delta IVIX_t$ is observed than $RNifty_t$. The standard deviation results signify that $\Delta IVIX_t$ is more volatile than $RNifty_t$. Test for skewness of $RNifty_t$ and $\Delta IVIX_t$ confirm that they are positively skewed. This signifies that the tail on the right side of the probability density function is longer than the left side and maximum of the values lie on the left side of the mean. Kurtosis test confirms that both time series are leptokurtic, meaning the values are more clustered around the mean, signifying both of them have thinner middles and many extreme values. Test of Jarque-Bera statistics confirms that normality is not observed for both

Table 1. Summary statistics

Summary statistics	$RNifty_t$	$\Delta IVIX_t$
Mean	0.025	0.205
Median	0.049	-0.127
Maximum	16.334	64.358
Minimum	-13.014	-37.512
SD	1.519	6.868
Skewness	0.203	1.551
Kurtosis	14.949	16.918
Jarque-Bera	11043.130	15708.720
ADF	-40.880***	-51.977***
Autocorrelation at lag 1 (ρ_1)	0.051**	-0.187**
Autocorrelation at lag 2 (ρ_2)	-0.023	0.026
Autocorrelation at lag 3 (ρ_3)	-0.012	-0.072**
Autocorrelation at lag 4 (ρ_4)	-0.025	-0.013
Number of observations	1,854	1,854

Notes: This table reports summary statistics of daily percentage continuously compounded returns of Nifty ($RNifty_t$) and daily percentage change of India VIX ($\Delta IVIX_t$) over the period 3 March 2008 to 31 August 2015.

*Indicate rejection of the null hypothesis at 10% significance level.

**Indicate rejection of the null hypothesis at 5% significance level.

***Indicate rejection of the null hypothesis at 1% significance level.

$RNifty_t$ and $\Delta IVIX_t$. Augmented Dickey–Fuller (ADF) unit root test results confirm the rejection of unit root in each series at 1% significance level, meaning that both of them are stationary. Next, we examine the autocorrelation function for $RNifty_t$ and $\Delta IVIX_t$ series. We observe that the first lag, of $RNifty_t$ possesses significant positive autocorrelations, whereas negative autocorrelation is observed for the second, third and fourth lag but neither of them is significant. In case of $\Delta IVIX_t$ series, significant negative autocorrelation is observed in the first and third lag. Second lag of $\Delta IVIX_t$ shows a positive autocorrelation but not significant. The correlation between $RNifty_t$ and $\Delta IVIX_t$ indicates that they maintain a negative relationship. The Pearson correlation coefficient -0.329 is observed between contemporaneous daily Nifty return and change of India VIX.

4. Methodology

First, we examine the relationship by employing atheoretical model. We choose vector autoregressive (VAR) framework to understand the causal relationship between return and change of implied volatility. The details of the model specifications are given below.

4.1. Vector Autoregressive framework (VAR)

VAR is purely atheoretical estimation method to capture the interdependencies between multiple time series. So VAR is a natural choice to capture the causal relationship between $RNifty_t$ and $\Delta IVIX_t$. We use bivariate VAR model to capture the linear interdependency between $RNifty_t$ and $\Delta IVIX_t$ time series. The VAR model is specified below:

$$RNifty_t = \alpha_0 + \sum_{i=1}^n \alpha_i RNifty_{t-i} + \sum_{j=1}^n \gamma_j \Delta IVIX_{t-j} + u_{1t} \quad (1)$$

$$\Delta IVIX_t = \beta_0 + \sum_{p=1}^n \beta_p \Delta IVIX_{t-p} + \sum_{r=1}^n \delta_r RNifty_{t-r} + u_{2t} \quad (2)$$

In Equation (1), we model $RNifty_t$ as a linear function of lagged values of $RNifty_t$ and lagged values of $\Delta IVIX_t$. Similarly, $\Delta IVIX_t$ is modelled as a function of lagged values of $RNifty_t$ and $\Delta IVIX_t$ in Equation (2). The choice of number of lags (n) depends on the specific information criteria (SIC and AIC). The error vector u_{it} ($i = 1, 2$) is assumed to follow white noise and hold normal distribution with zero mean and variance-covariance matrix of $\sigma^2 I$. Next, we specify the quantile regression models to test our hypotheses I to IV.

4.3. Quantile regression framework

Quantile regression yields more robust results for outliers i.e. upper and lower quantiles relative to ordinary least squares (OLS) (Koenker, 2005; Koenker & Hallock, 2001). Similar to OLS, which solves the sample mean by minimizing the sum of squared residuals, quantile regression solves quantile median by minimizing the sum of absolute residuals by symmetric weights. To solve the other quantile functions, absolute residuals are tilted i.e. asymmetric weights are assigned to other quantiles. Minimizing the asymmetrically weighted sum of absolute residuals yields the solution for other quantile functions. So, for a random sample $\{y_1, y_2, \dots, y_n\}$, for a given probability p , the p th quantile of $\{y_i\}$ is achieved by, $\min_{\theta \in \mathbb{R}} \sum_{i=1}^n w_p(y_i - \zeta(x_i, \theta))$ where x_i includes the explanatory variables and θ is the parameter of interest. The weights, $w_p(j)$ is defined as:

$$w_p(z) = \begin{cases} pj & \text{if } j \geq 0 \\ (p-1)j & \text{if } j < 0 \end{cases}$$

In the first hypothesis, we examine if the behavioural theory holds over leverage theory. We specify our quantile regression model as below:

$$M1: \Delta IVIX_t = \phi^{(q)} + \sum_{i=0}^3 \Psi_i^{(q)} RNifty_{t-i} + \sum_{j=1}^3 \gamma_j^{(q)} \Delta IVIX_{t-j} + \varepsilon_t \quad (3)$$

where $\phi^{(q)}$ is the intercept for q th quantile, $\Psi_i^{(q)}$ are coefficients for the lagged $RNifty$ and for $i=0$ denotes the contemporaneous return for q th quantile. Similarly, $\gamma_j^{(q)}$ are the coefficients for lagged changes of $IVIX$ at q th quantile. Quantile regression allows heteroscedasticity in the error terms, therefore coefficients $\phi^{(q)}, \Psi_i^{(q)}, \gamma_j^{(q)}$ would vary according to each quantiles selected within the range of $q \in (0, 1)$. We include three lags following Badshah (2013). If behavioural theory holds true, we expect $\Psi_0^{(q)}$ to be significant for all $q \in (0, 1)$. Moreover, negative relationship predicts negative coefficients of $\Psi_0^{(q)}$. Lagged changes of volatility index are also included in the in equation (3). The coefficients of lagged changes of volatility index have significance in understanding two alternative hypotheses. We should observe insignificant coefficients of lagged changes of volatility, when volatility changes according to the shifts in investor's expectation about volatility. Under this scenario, order imbalance is merely a reflection of shifts in investor's expectation about future volatility. If that is the case, then the changes in implied volatility are permanent and thus changes of implied volatility should be uncorrelated through time. Bollen and Whaley (2004) name this phenomenon as "learning hypothesis", where option market participants continuously learn about the underlying asset dynamics and update option prices accordingly. On the contrary, "limits to arbitrage" (Shleifer & Vishny, 1997) hypothesis predicts the lagged coefficients to be negative. Under this scenario, with the upward-sloping supply curve of options, excess buyer-motivated trades would cause implied volatility to rise, and excess seller-motivated trades would cause implied volatility to fall. Excess trades would have a price impact on options, leading option prices to be below or above efficient level. Thus, part of the impact would be temporary, prompting participants to rebalance their portfolio gradually and prices would move towards its efficient level. The process of partial price reversal would cause the implied volatility to fall (rise) relatively. Thus, we expect negative coefficients of lagged changes in the implied volatility index.

To test hypothesis II and hypothesis III, we define the positive and negative returns as below.

$$RNifty_t^+ = \begin{cases} RNifty_t & \text{if } RNifty_t > 0 \\ 0 & \text{if } RNifty_t < 0 \end{cases} \text{ and } RNifty_t^- = \begin{cases} RNifty_t & \text{if } RNifty_t < 0 \\ 0 & \text{if } RNifty_t > 0 \end{cases}$$

We specify the below model to assess the asymmetric relationship across the quantiles.

$$M2: \Delta IVIX_t = \pi^{(q)} + \sum_{i=0}^3 \theta_i^{(q)} RNifty_{t-i}^+ + \sum_{k=0}^3 \delta_k^{(q)} RNifty_{t-k}^- + \sum_{j=1}^3 \gamma_j^{(q)} \Delta IVIX_{t-j} + \varepsilon_t \quad (4)$$

Similar to Equation (3), we include $\theta_i^{(q)}$ to capture the impact of positive returns and $\delta_k^{(q)}$ to capture negative returns for the entire India VIX change distribution. Here, $i = 0$ signifies the contemporaneous returns coefficients. $\gamma_j^{(q)}$ are the coefficients of lagged changes in implied volatility index.

To test hypothesis IV, we employ the following quantile regression model:

$$M3: RNifty_t = \alpha^{(q)} + \sum_{i=0}^3 \lambda_i^{(q)} \Delta IVIX_{t-i} + \sum_{j=1}^3 \eta_j^{(q)} RNifty_{t-j} + v_t \quad (5)$$

Similar to hypothesis I, we expect that impact of coefficients $\lambda_0^{(q)}$ to be significant on current Nifty returns. If that holds, we propose behavioural theory to be the superior explanation than volatility feedback theory, because feedback theory demands the lagged changes of implied volatility index to be most significant for Nifty returns. Moreover, if behavioural theory holds, the lagged changes of implied volatility do not contain much information for current Nifty return. Thus, it would verify the informational content of India VIX for current market movement. $\phi^{(q)}$, $\pi^{(q)}$ and $\alpha^{(q)}$ are the intercept terms and all the errors terms ε_t , v_t , ε_t are assumed to be independent for each equation and derived from error distribution with q th quantile equal to zero.

5. Empirical results

We present the VAR results along with its limitations to capture the dynamics of entire return and change volatility distribution. The next sub-section presents quantile regression results.

5.1. Vector autoregressive (VAR) results

Table 2 (Panel A) reports the estimated coefficients of Equations (1) and (2). Based on AIC, we choose a VAR model of order four. The results show that $RNifty_t$ series is influenced by its own lags ($RNifty_{t-1}$, $RNifty_{t-2}$, $RNifty_{t-4}$) and by the lags of $\Delta IVIX_t$ series ($\Delta IVIX_{t-2}$, $\Delta IVIX_{t-4}$). Similarly, $\Delta IVIX_t$ is influenced by its own lags ($\Delta IVIX_{t-1}$, $\Delta IVIX_{t-3}$) and lag of $RNifty_t$ ($RNifty_{t-3}$). The magnitude of the first lag of $RNifty_t$ is larger than second lags of $RNifty_t$ with opposite sign. This shows a tendency of correction followed by momentum. Similarly, magnitude of the first lag of $\Delta IVIX_t$ is larger than other lags in the series, all of them with negative signs. The signs show a mean reverting tendency for the $\Delta IVIX_t$ series. We also examine variance decomposition and impulse response analysis of VAR model and for brevity these are not reported. Variance decomposition results indicate that the proportion of the movement of $RNifty_t$ due to its own shocks is approximately 100%. On the other hand, $\Delta IVIX_t$ series shows that 11% of the movement of $\Delta IVIX_t$ can be explained by $RNifty_t$ shocks and 89% by its own shocks. The impulse response function shows that one standard deviation of shock to the errors of $\Delta IVIX_t$ does not have significant influence on $RNifty_t$ series. On the other hand, significant response is observed in the $\Delta IVIX_t$ series due to one standard deviation shock to the $RNifty_t$ errors. $\Delta IVIX_t$ decreases approximately by 2% by one standard deviation shock to $RNifty_t$ immediately, and the effect remains approximately for six days in $\Delta IVIX_t$ series.

Table 2 (Panel B) reports Granger causality test results. The test results show that the $\Delta IVIX_t$ granger causes the $RNifty$ series at 1% significance level. No causality is observed from $RNifty$ to $\Delta IVIX_t$ series. Granger causality results indicate that feedback effect seems to be dominating over leverage effect. The results simply infer how the conditional mean of the response variable changes with the vector of covariates. We verify the validity of Granger causality results in a nonparametric setting i.e. by performing an exploratory analysis to understand the impact of extreme events on Nifty and India VIX relationship. If feedback theory holds, we expect the lagged change of India VIX to indicate current Nifty returns at extremes as well. To verify, we consider the extreme five percentile positive and negative returns of Nifty. For each day of those extreme five percentile returns of Nifty, changes of

Table 2. VAR results

Panel A: VAR results of Nifty return ($RNifty_t$) and change of India VIX ($\Delta IVIX_t$)				
	$RNifty_t$		$\Delta IVIX_t$	
	Co-efficient	t-Statistics	Co-efficient	t-Statistics
$RNifty_{t-1}$	0.072***	2.922	-0.146	-1.334
$RNifty_{t-2}$	-0.049***	-1.990	0.045	0.413
$RNifty_{t-3}$	0.009	0.405	-0.215**	-1.969
$RNifty_{t-4}$	-0.043*	-1.769	0.163	1.498
$\Delta IVIX_{t-1}$	0.007	1.354	-0.201***	-8.152
$\Delta IVIX_{t-2}$	-0.010*	-1.813	-0.023	-0.924
$\Delta IVIX_{t-3}$	0.008	1.521	-0.094***	-3.770
$\Delta IVIX_{t-4}$	-0.011**	-2.038	-0.029	-1.183
Intercept	0.028	0.811	0.286*	1.821
Adjusted R^2	0.008		0.041	

Panel B: Granger causality test between Nifty returns and change of India VIX				
The cause	The effect	F statistics	p-value	Causality direction
$\Delta IVIX_t$	$RNifty$	3.959***	0.003	$\Delta IVIX_t \Rightarrow RNifty$
$RNifty$	$\Delta IVIX_t$	1.853	0.116	

Notes: The VAR model as:

$$RNifty_t = \alpha_0 + \sum_{i=1}^n \alpha_i RNifty_{t-i} + \sum_{j=1}^n \gamma_j \Delta IVIX_{t-j} + u_{1t}$$

$$\Delta IVIX_t = \beta_0 + \sum_{p=1}^n \beta_p \Delta IVIX_{t-p} + \sum_{r=1}^n \delta_r RNifty_{t-r} + u_{2t}$$

$$RNifty_t = \ln\left(\frac{Nifty_t}{Nifty_{t-1}}\right) \times 100\%, \Delta IVIX_t = \left(\frac{IVIX_t - IVIX_{t-1}}{IVIX_{t-1}}\right) \times 100\%$$

and n denotes the optimal lag length based on AIC criteria.

The causality direction $X \Rightarrow Y$ imply X Granger cause Y ; $X \not\Rightarrow Y$ implies there is no causal relationship between X and Y .

*Indicate rejection of the null hypothesis at 10% significance level.

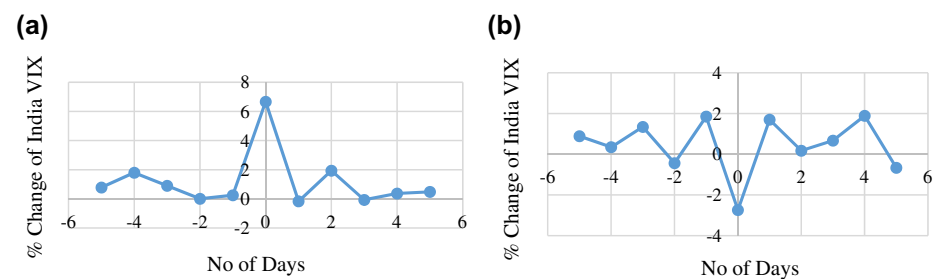
**Indicate rejection of the null hypothesis at 5% significance level.

***Indicate rejection of the null hypothesis at 1% significance level.

India VIX are taken around from -5 to +5 day window. The average of the -5 to +5 days window of change of India VIX is plotted for those extreme five percentile movements of Nifty. This is shown in Figure 1.

The figure shows that for extreme five percentile positive and negative Nifty returns, $\Delta IVIX_t$ is not showing any pattern before the extreme movements. Rather temporary shock is observed in $\Delta IVIX_t$ on the day of the extreme positive and negative Nifty movement i.e. on zeroth day on the above figure. $IVIX_t$ does not show any pattern before the extreme movements of Nifty and quickly comes

Figure 1. -5 to +5 days change of India VIX during extreme five percentile Nifty movements for the period 3 March 2008 to 31 August 2015. Figure 1(a) shows the -5 to +5 days trend of IVIX for extreme five percentile of the Nifty returns. Similarly, Figure 1(b) shows the -5 to +5 days trend of IVIX for extreme five percentile positive Nifty returns.



back to its mean reverting level after the extreme shocks in Nifty. Thus, at extremes of Nifty returns, the relationship is contemporaneous in nature because extreme Nifty movements and India VIX changes occur concurrently on the event date. This analysis indicates that the feedback effect is an incomplete explanation of the relationship and therefore, we employ the quantile regression framework.

5.2. Quantile regression results

We test our hypothesis I by the Equation (3). The coefficients of Equation (3) are reported in Table 3.

The coefficients of the contemporaneous returns (i.e. $RNifty_t$) are consistently significant at 1% level for all quantiles of India VIX change distribution. Also, absolute values of the coefficients of contemporaneous returns for all quantile are higher than all coefficients of all the lagged Nifty returns and all the lagged India VIX changes. Lagged covariates of Nifty returns and India VIX changes are mostly insignificant or mildly significant. For all the quantiles, contemporaneous Nifty return ($RNifty_t$) shows negative coefficients. Negative coefficients indicate that contemporaneous implied volatility changes (India VIX changes) and returns (Nifty returns) are negatively related. Above results confirm hypothesis I. Behavioural theory holds over leverage hypothesis for the entire implied volatility change distribution. Lagged changes of India VIX ($\Delta IVIX_{t-1}$, $\Delta IVIX_{t-2}$, $\Delta IVIX_{t-3}$), specifically the first lagged changes ($\Delta IVIX_{t-1}$), are significant at the lower quantiles (0.05–0.50) of India VIX change distribution. With the increase in quantiles (0.75–0.95) insignificant coefficients are observed for lagged changes of India VIX. All the significant coefficients of the lagged changes of India VIX are

Table 3. Quantile regression results: behavioural theory and leverage hypothesis: Without asymmetric returns

q	Intercept	$RNifty_t$	$RNifty_{t-1}$	$RNifty_{t-2}$	$RNifty_{t-3}$	$\Delta IVIX_{t-1}$	$\Delta IVIX_{t-2}$	$\Delta IVIX_{t-3}$
0.05	-8.028*** (-17.109)	-1.159*** (-4.455)	0.197 (0.703)	0.232 (0.929)	0.344 (1.369)	-0.264*** (-3.731)	-0.135** (-2.247)	-0.059 (-0.941)
0.10	-5.441*** (-22.403)	-1.341*** (-11.047)	0.317** (2.126)	0.057 (0.439)	0.238* (1.658)	-0.156*** (-4.681)	-0.114*** (-4.159)	-0.081*** (-2.849)
0.15	-4.079*** (-20.914)	-1.517*** (-13.334)	0.346*** (3.103)	0.051 (0.407)	0.176*** (2.774)	-0.079*** (-4.753)	-0.089*** (-3.334)	-0.065*** (-2.672)
0.20	-3.237*** (-22.488)	-1.621*** (-22.946)	0.365*** (4.697)	0.009 (0.109)	0.132** (1.987)	-0.080*** (-4.042)	-0.105*** (-4.911)	-0.042** (-2.517)
0.25	-2.612*** (-21.478)	-1.745*** (-24.593)	0.332*** (4.687)	0.064 (1.106)	0.162** (2.262)	-0.080*** (-6.518)	-0.082*** (-5.636)	-0.039*** (-2.682)
Median	-0.151 (-1.365)	-1.822*** (-27.917)	0.332*** (5.702)	0.149** (2.083)	0.132** (2.516)	-0.056*** (-3.377)	-0.032* (-1.820)	-0.021 (-1.337)
0.75	2.549*** (15.958)	-1.841*** (-18.543)	0.404*** (4.303)	-0.008 (-0.081)	0.051 (0.494)	-0.010 (-0.413)	0.009 (0.419)	-0.009 (-0.558)
0.80	3.336*** (18.490)	-1.832*** (-17.605)	0.377*** (3.986)	-0.114 (-1.031)	-0.112 (-0.974)	0.000 (0.015)	-0.001 (-0.046)	-0.018 (-0.763)
0.85	4.566*** (16.505)	-1.690*** (-11.493)	0.294*** (2.794)	-0.179 (-1.185)	-0.183 (-1.142)	-0.036 (-1.101)	0.017 (0.456)	-0.004 (-0.186)
0.90	6.339*** (21.388)	-1.601*** (-12.224)	0.188 (1.218)	-0.267** (-2.216)	-0.372** (-2.360)	-0.073** (-2.130)	0.046 (1.550)	-0.008 (-0.253)
0.95	10.161*** (15.823)	-1.223*** (-4.220)	-0.090 (-0.369)	-0.520 (-1.425)	-0.911*** (-2.683)	-0.105 (-1.421)	0.089 (1.031)	-0.048 (-0.765)
OLS	0.312** (2.118)	-1.463*** (-14.982)	-0.046 (-0.444)	-0.016 (-0.162)	-0.185* (-1.799)	-0.193*** (-8.149)	-0.031 (-1.278)	-0.062*** (-2.648)

Notes: The quantile regression equation as $\Delta IVIX_t = \phi^{(q)} + \sum_{i=0}^3 \Psi_i^{(q)} RNifty_{t-i} + \sum_{j=1}^3 \gamma_j^{(q)} \Delta IVIX_{t-j} + \epsilon_t$; wherein, $\Delta IVIX_t$ is the response variable, which is regressed against contemporaneous and three lagged Nifty returns, and three lagged changes of India VIX. In the equation, q denotes the q th quantile function. R^2 and Adjusted R^2 values are 0.145 and 0.142 are respectively for OLS regression.

*Indicate rejection of the null hypothesis at 10% significance level.

**Indicate rejection of the null hypothesis at 5% significance level.

***Indicate rejection of the null hypothesis at 1% significance level.

with negative sign. These results indicate that at lower quantiles (0.05–0.50) of India VIX change distribution (when changes in India VIX are negative), the implied volatility tends to reverse itself. Explanation of the phenomenon could be, excess seller-motivated trades impact option prices below efficient level, prompting the implied volatility to fall sharply. Option prices tend to adjust to efficient level by subsequent trades when market gradually adjusts portfolio, causing the change of the implied volatility to reverse. At upper quantiles (0.75–0.95), the lagged changes of the implied volatility are uncorrelated. Thus, with positive innovations of implied volatility, “learning hypothesis” appears to be prevailed. When changes of India VIX are positive, uncorrelated lagged changes of implied volatility signify that changes of implied volatility is driven by the shifts of investors’ expectation about future volatility and changes of volatility is observed to be permanent. That means, investors learn about the underlying asset dynamics in times of negative market return and set option prices accordingly.

Table 4 reports the results of Equation (4). Impacts of contemporaneous returns ($RNifty_t^+$, $RNifty_t^-$) are observed to be significant across the quantiles of India VIX change distribution. Also, absolute values of the coefficients of contemporaneous returns are higher than all the lagged covariates. Impacts of positive contemporaneous return ($RNifty_t^+$) and negative contemporaneous return ($RNifty_t^-$) vary across the quantiles of the India VIX change distribution. Differential impact of contemporaneous positive and negative returns across quantiles of India VIX change distribution confirm that asymmetric relationship varies across quantiles. From median to the higher quantiles

Table 4. Quantile regression results: behavioural theory and leverage hypothesis: With asymmetric returns

q	Intercept	$RNifty_t^+$	$RNifty_t^-$	$RNifty_{t-1}^+$	$RNifty_{t-1}^-$	$RNifty_{t-2}^+$	$RNifty_{t-2}^-$	$RNifty_{t-3}^+$	$RNifty_{t-3}^-$	$\Delta IVIX_{t-1}$	$\Delta IVIX_{t-2}$	$\Delta IVIX_{t-3}$
0.05	-4.810*** (-9.019)	-2.910*** (-8.883)	0.562 (0.902)	-1.103 (-1.492)	0.572 (1.323)	-0.370 (-1.641)	0.681 (0.953)	0.145 (0.471)	0.113 (0.252)	-0.223*** (-4.339)	-0.161*** (-3.791)	-0.062 (-1.319)
0.10	-3.436*** (-11.370)	-2.869*** (-15.99)	-0.537* (-1.914)	0.101 (0.428)	0.781*** (3.995)	-0.498*** (-3.220)	0.554 (1.632)	-0.017 (-0.149)	0.033 (0.186)	-0.101*** (-4.451)	-0.094*** (-3.313)	-0.081*** (-3.764)
0.15	-2.189*** (-7.757)	-2.736*** (-10.09)	-0.817** (-2.818)	0.067 (0.442)	0.708*** (3.568)	-0.415* (-1.781)	0.609*** (2.819)	-0.261 (-1.046)	0.364*** (2.594)	-0.075*** (-2.809)	-0.071*** (-2.882)	-0.062*** (-3.104)
0.20	-1.961*** (-7.947)	-2.477*** (-8.406)	-1.243*** (-4.353)	0.102 (0.445)	0.691*** (2.866)	-0.278 (-1.500)	0.357 (1.297)	0.072 (0.322)	0.432*** (2.777)	-0.069*** (-2.707)	-0.061** (-2.448)	-0.021 (-0.845)
0.25	-1.688*** (-7.795)	-2.141*** (-8.687)	-1.387*** (-5.918)	0.345* (1.858)	0.474* (1.935)	-0.311* (-1.780)	0.316* (1.707)	0.030 (0.268)	0.539*** (2.910)	-0.070*** (-3.077)	-0.062*** (-2.901)	-0.016 (-0.757)
Median	-0.514** (-2.566)	-1.401*** (-6.202)	-2.357*** (-9.749)	0.789*** (4.018)	-0.069 (-0.626)	-0.074 (-0.547)	0.449** (2.366)	-0.014 (-0.174)	0.303* (1.940)	-0.068*** (-3.334)	-0.034* (-1.699)	-0.015 (-0.984)
0.75	0.453* (1.703)	-0.297 (-1.121)	-3.740*** (-12.75)	0.968*** (5.744)	-0.229 (-0.990)	0.132 (0.654)	0.092 (0.345)	0.105 (0.438)	-0.112 (-0.317)	-0.035 (0.195)	0.013 (0.471)	-0.007 (-0.302)
0.80	0.784*** (2.802)	-0.228 (-0.887)	-3.984*** (-13.02)	0.913*** (4.114)	-0.176 (-0.701)	0.187 (1.182)	-0.133 (-0.461)	0.264 (0.923)	-0.535 (-1.347)	-0.044* (-1.789)	0.033 (1.035)	-0.020 (-0.671)
0.85	1.177*** (3.498)	-0.029 (-0.082)	-4.205*** (-10.01)	0.864*** (3.244)	-0.465 (-1.082)	0.069 (0.277)	0.010 (0.043)	0.574** (2.038)	-1.159*** (-2.592)	-0.083** (-2.558)	0.044 (1.148)	-0.063* (-1.828)
0.90	1.601*** (5.169)	0.177 (0.675)	-4.836*** (-9.467)	0.996*** (3.684)	-1.017* (-1.725)	0.283 (1.209)	-0.007 (-0.023)	0.542** (2.231)	-1.603*** (-4.151)	-0.141*** (-4.146)	0.074*** (2.780)	-0.058** (-2.341)
0.95	2.812*** (4.642)	1.009 (0.975)	-5.511*** (-7.219)	1.389** (2.198)	-1.597*** (-2.689)	-0.053 (-0.138)	0.386 (0.686)	1.399 (1.623)	-2.077*** (-3.171)	-0.116* (-1.784)	0.151*** (2.698)	-0.064 (-0.918)
OLS	-0.724*** (-2.844)	-0.988*** (-5.809)	-1.972*** (-11.45)	0.548*** (3.218)	-0.604*** (-3.375)	-0.251 (-1.482)	0.323* (1.788)	0.068 (0.402)	-0.387** (-2.140)	-0.197*** (-8.324)	-0.036 (-1.484)	-0.069*** (-2.950)

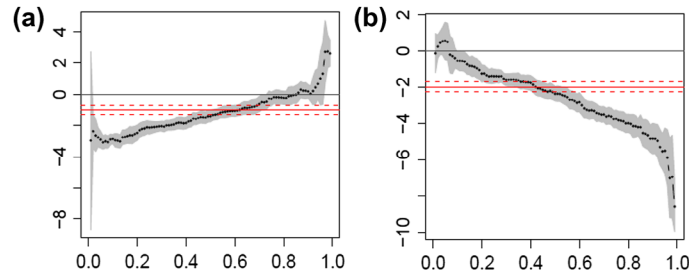
Notes: The quantile regression equation as $\Delta IVIX_t = \pi^{(q)} + \sum_{i=0}^3 \theta_i^{(q)} RNifty_{t-i}^+ + \sum_{k=0}^3 \delta_k^{(q)} RNifty_{t-k}^- + \sum_{j=1}^3 \gamma_j^{(q)} \Delta IVIX_{t-j} + \varepsilon_t$; wherein, $\Delta IVIX_t$ is the response variable, which is regressed against contemporaneous and three lagged positive and negative Nifty returns, and three lagged changes of India VIX. In the equation, q denotes the q th quantile function. R^2 and Adjusted R^2 values are 0.165 and 0.160 are respectively for OLS regression.

*Indicate rejection of the null hypothesis at 10% significance level.

**Indicate rejection of the null hypothesis at 5% significance level.

***Indicate rejection of the null hypothesis at 1% significance level.

Figure 2. Impact of contemporaneous positive and negative Nifty returns on India VIX change distribution. Figure 2(a) plots the impacts of positive contemporaneous return on India VIX change distribution. Y-axis measures impact in percentage change (%); X-axis measures quantiles $q \in (0, 1)$; Impact of $RNifty_t^+$ in percentage change (%) across quantiles is plotted in the above figure. Figure 2(b) plots the impacts of negative contemporaneous return on India VIX change distribution. Y-axis measures impact in percentage change (%); X-axis measures quantiles $q \in (0, 1)$; Impact of $RNifty_t^-$ in percentage change (%) across quantiles is plotted in the above figure.



of India VIX change distribution (0.50–0.95), absolute values of the coefficients indicate that impact of negative contemporaneous returns ($RNifty_t^-$) are higher than positive contemporaneous returns ($RNifty_t^+$). Thus, the effect of negative contemporaneous returns on positive innovations of implied volatility. These confirm hypothesis II and hypothesis III that affect heuristics; extrapolation bias exists among Indian market participants. Market participants respond differently to positive and negative returns. Negative returns are more closely associated with positive innovations of volatility and negative returns are the most important factors that determine the largest change of the India VIX. The impacts of positive and negative contemporaneous returns are shown in Figure 2.

The impact of negative contemporaneous returns increases monotonically from median to higher quantiles of India VIX change distribution. The above finding has implications for the Indian market. The increase in change of India VIX is related to the incremental increase in negative returns. Thus, India VIX functions as an efficient hedge for downside market movement. The absolute values of the coefficients of negative contemporaneous returns from median to higher quantiles (0.50–0.95) are higher than the coefficients of positive contemporaneous returns from median to lower quantiles (0.50–0.05) of India VIX change distribution. The explanation could be that excess seller-motivated trades are lower in times of positive returns than excess buyer-motivated trades in times of negative market returns. In other words, the excess supply of options in times of positive market returns are lower than the excess demand of options in times of negative market returns. That shows Indian index options market functions more as insurance or hedge market for downside market movement. Unlike Equation (3), Equation (4) shows that first lagged changes in India VIX ($\Delta IVIX_{t-1}$) are now significant across the quantile of changes of implied volatility and all the coefficients are negative in sign. When we regress the India VIX change distribution with positive and negative contemporaneous returns, reversal trend of implied volatility change comes into picture. This is because, at higher quantiles (0.50–0.95) of implied volatility change, negative returns prompt excess buyer-motivated trades. In times of negative returns, the excess buyer-motivated trades impact the options prices beyond its efficient level, causing the implied volatility to rise sharply. With the gradual rebalance of portfolio, the prices tend to come back to their efficient level, making implied volatility to fall partially.

Hypothesis IV is tested by Equation (5). The results are reported in Table 5. The coefficients of cotemporaneous India VIX change ($\Delta IVIX_t$) are found to be significant across all the quantiles of Nifty returns at 1% level. No other covariate is significant across all the quantiles. Most of coefficients of the lagged changes of India VIX ($\Delta IVIX_{t-1}$, $\Delta IVIX_{t-2}$, $\Delta IVIX_{t-3}$) are either insignificant or marginally significant. This confirms hypothesis IV that behavioural theory holds. The lagged changes of India VIX are not significant to explain contemporaneous Nifty returns. That has two implications. First, feedback theory does not hold true, and second, India VIX does not subsume information for current market movement.

Table 5. Quantile regression results: behavioural theory and volatility feedback hypothesis

q	Intercept	$\Delta IVIX_t$	$\Delta IVIX_{t-1}$	$\Delta IVIX_{t-2}$	$\Delta IVIX_{t-3}$	$RNifty_{t-1}$	$RNifty_{t-2}$	$RNifty_{t-3}$
0.05	-1.819*** (-16.455)	-0.081*** (-5.266)	-0.020 (-1.135)	-0.016 (-0.929)	-0.013 (-0.862)	0.121* (1.742)	-0.008 (-0.103)	0.054 (0.881)
0.10	-1.240*** (-20.365)	-0.087*** (12.275)	-0.019** (-2.288)	-0.014* (-1.947)	-0.007 (-0.781)	0.102*** (3.881)	0.003 (0.064)	0.015 (0.416)
0.15	-0.948*** (-19.431)	-0.099*** (-15.977)	-0.006 (-0.711)	-0.015** (-2.575)	-0.011* (-1.713)	0.110*** (3.940)	0.009 (0.352)	-0.001 (-0.038)
0.20	-0.731*** (-19.667)	-0.105*** (-22.664)	-0.005 (-0.831)	-0.013** (-2.506)	-0.009* (-1.755)	0.097*** (4.162)	-0.032 (-1.501)	-0.016 (-0.765)
0.25	-0.566*** (-17.562)	-0.109*** (-40.438)	0.003 (0.638)	-0.012** (-2.341)	-0.007 (-1.542)	0.129*** (6.214)	-0.027 (-1.277)	0.011 (0.602)
Median	0.000 (0.000)	-0.106*** (-29.955)	-0.002 (-0.609)	-0.010*** (-2.893)	0.005 (1.583)	0.089*** (5.373)	-0.044*** (-3.056)	0.002 (0.105)
0.75	0.606*** (14.414)	-0.087*** (-14.564)	0.000 (0.025)	-0.004 (-0.842)	0.012** (2.031)	0.041* (1.766)	-0.035* (-1.763)	-0.010 (-0.634)
0.80	0.825*** (16.834)	-0.079*** (-15.397)	0.001 (0.083)	-0.010** (-2.066)	0.017*** (3.009)	0.008 (0.397)	-0.090*** (-4.003)	0.005 (0.200)
0.85	1.123*** (20.002)	-0.076*** (-9.566)	-0.001 (-0.186)	-0.008 (-1.028)	0.015** (2.259)	0.019 (0.528)	-0.130*** (-3.614)	0.008 (0.241)
0.90	1.528*** (23.691)	-0.055*** (-7.515)	0.007 (0.867)	-0.012 (-1.358)	0.019** (2.236)	-0.007 (-0.162)	-0.167*** (-5.171)	-0.009 (-0.259)
0.95	2.174*** (20.090)	-0.036*** (-2.848)	0.017** (2.061)	-0.009 (-0.735)	0.010 (0.775)	-0.014 (-0.289)	-0.124*** (-2.964)	-0.040 (-0.761)
OLS	0.044 (1.312)	-0.074*** (-14.982)	-0.007 (-1.272)	-0.011* (-1.935)	0.004 (0.689)	0.061** (2.628)	-0.041* (-1.765)	-0.006 (-0.249)

Notes: The quantile regression equation as $RNifty_t = \alpha^{(q)} + \sum_{i=1}^3 \lambda_i^{(q)} \Delta IVIX_{t-i} + \sum_{j=1}^3 \eta_j^{(q)} RNifty_{t-j} + v_t$; wherein, $RNifty_t$ is the response variable, which is regressed against contemporaneous and three lagged India VIX changes, and three lagged changes of Nifty returns. In the equation, q denotes the q th quantile function. R^2 and Adjusted R^2 values are 0.116 and 0.113 are respectively for OLS regression.

*Indicate rejection of the null hypothesis at 10% significance level.

**Indicate rejection of the null hypothesis at 5% significance level.

***Indicate rejection of the null hypothesis at 1% significance level.

6. Conclusion

We investigate the short-term relationship between Nifty return and India VIX change using theoretical frameworks based on leverage effect, feedback effect and behavioural explanation. We employ VAR and quantile regression to examine the relationship. We use VAR to understand the causal relationship between return and implied volatility. Although VAR results indicate that feedback effect dominates over the other theories, our exploratory analysis on extreme events shows that the relationship is contemporaneous. Thus, we document that VAR results are an incomplete description of the relationship. We use quantile regression models to study the effect of returns across the quantiles of implied volatility change distribution and the effect of change in implied volatility across the quantiles of return distributions. The previous study of Badshah (2013) uses quantile regression models and concludes the consistency of behavioural theories over leverage effect for developed markets. In this study, we treat the leverage and feedback effects separately while comparing with behavioural theory. Our study also shows that the relationship is consistent with behavioural theory over the leverage and feedback hypothesis. Thus, the study produces more evidence in support of behavioural theory over leverage and feedback hypothesis, and even for emerging markets. In the course of understanding the relationship, we find asymmetric effect is monotonically increasing from median to higher quantiles of India VIX change distribution. That implies that India VIX is an effective hedge for downside market movement. This result has implications for recently introduced India VIX futures.

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Notes

1. Refer NSE white paper for the details of IVIX calculation methodology (https://www.nseindia.com/content/vix/white_paper_IndiaVIX.pdf).
2. Nifty is the name of the equity market index of India. Nifty is provided by National Stock Exchange (NSE) of India Limited.
3. In 1993, Robert E. Whaley developed VIX index (Called VXO) in CBOE. The VXO was computed using a linear combination of eight at-the-money S&P100 Black and Scholes (1973) ATM implied volatilities.

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