Commonality in volatility risk premium

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Abstract

This study examines the existence of commonality in the volatility risk premium of National Stock Exchange of India, an open electronic limit order book market. The study includes market and stock-specific characteristics that may influence the commonality relationship. The key result of the study is that it produces empirical evidence of commonality in volatility risk premium. The commonality relationship is robust and significant even in the presence of market and stock-specific characteristics.

Keywords: Commonality; Model free implied volatility; Realized variance; Volatility risk premium

JEL Classifications: G12; G13; G14

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1. Introduction

Extant literature defines volatility risk premium (VRP) as the difference between implied volatility and realized volatility. Despite the growing body of literature on market VRP, very little is known about the individual stock VRP and its relationship with market VRP. Only a few studies (e.g., Bakshi and Kapadia, 2003; Carr and Wu, 2008; Cao and Han, 2013; Duan and Wei, 2009; Duarte and Jones, 2007) have investigated the pricing mechanism and implications of individual stock VRP. However, these studies do not explore the relationship of individual stock VRP to market VRP.

The central hypothesis of this study is the co-movement of individual stock VRP with market VRP. The hypothesis is motivated by the recent growing literature on commonality. For example, an extensive literature has documented significant commonality in liquidity among stocks (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Krishnan and Mishra, 2012; Syamala et al., 2014). These studies have concluded that liquidity among stocks covary significantly, and there are some common underlying determinants that drive the commonality in the liquidity. In this study, we aspire to investigate the commonality in individual stocks VRP to the market VRP of National Stock Exchange (NSE) of India, which is an open electronic limit order book (LOB) market.

The intuition of the primary hypothesis of the study is as follows. As noted by Chordia et al. (2000), trading activity exhibits a correlated trading pattern in response to market-wide volatility shocks. Volatility shocks induce the investors to create time-varying net demand of volatility in the options market. Broadly, liquidity demanders of volatility in options market could be the informed players who trade on their private information about volatility. Otherwise, they could be only hedgers who demand volatility in the options market to protect their portfolio from volatility shocks. Liquidity suppliers, on the other hand, supply volatility after covering up their asymmetric information cost of volatility, apart from all other costs borne by them. Thus, liquidity suppliers mitigate the net demand of market-wide volatility by a "volatility markup" process, as described by Green and Figlewski (1999). In this process, liquidity suppliers set option prices such that the implied volatility of options exceeds the realized volatility rate to cover up all the costs borne by liquidity suppliers. Under the common market-wide volatility shocks, the volatility markup process is implemented for the individual stock options as well as for the index options. Thus, the plausible reason for commonality in VRP could be the "volatility markup" process set by liquidity suppliers in options market because of the market-wide volatility shocks. The co-movement, or the commonality in VRP, has option pricing implications although this study focuses only on the commonality in VRP, which is the main contribution of the study.

We test the commonality hypothesis by employing pooled regression on individual stock VRP with market VRP. We compute individual stock VRP by the difference of model-free implied volatility (MFIV) of stocks and realized volatility of stocks. The calculation procedure of MFIV is same as the India VIX methodology used by National Stock Exchange (NSE) of India. MFIV methodology measures the expected volatility of thirty calendar days. Realized volatility is computed by two scaled realized volatility (TSRV) measure for past thirty calendar days. The difference between these two measures is taken as VRP of individual stocks.

Empirically, we find the existence of commonality between stock VRP and market VRP. The commonality relationship is robust across the other market-specific characteristics and stock specific characteristics. We consider market volatility level, changes in market volatility, as market-specific characteristics that may influence the commonality relationship. In the analysis, we also consider the stock-specific characteristics, e.g., stock volatility level, recent changes of stock volatility, firm size, stock liquidity, and stock open interest of put options. Empirical results show that both market-specific characteristics and stock specific characteristics influence the stock VRP significantly, but commonality in VRP results are robust even in the presence of market and stock-specific characteristics.

The study proceeds as follows. Section 2 describes the data used in the study. Section 3 discusses the methodology adopted in this study to test the proposed hypothesis. Section 4 discusses the results and main findings of the study. Section 5 concludes the paper.

2. Data

The study uses proprietary NSE data from 30 July 2015 to 30 December 2016. NSE is anonymous open electronic limit order book market by design and the has the largest share of domestic market activity in the financial year 2016-17, with approximately 84% of the traded volumes on equity spot market and almost 100% of the traded volume on equity derivatives[2]. The "Futures and Options" and "Equity" segment of the NSE have the same trading hours. Nifty is the leading stock index of NSE consisting of 50 stocks with highest capitalization and liquidity. During the calendar year 2016, NSE was ranked 1st in Index Options and 9th in single stock options in terms of volume of contracts traded[3]. Index options contribute approximately 77.14% turnover, and individual stock options market contribute approximately 6% turnover of the India derivatives market segment[4]. This study uses 44 individual stocks that are part of the Nifty index. These stocks are chosen in terms of their liquidity in options market.

MFIV of the individual stocks is computed using derivatives snapshot order book data of NSE at 15:00:00 i.e., thirty minutes before the market closure. Order book data of options consists of the expiry date, price, quantity, time stamp, buy/sell indicator, book type of every strike price of each option traded in the derivatives segment of NSE. Realized volatility of the

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[2] 25th Annual Report 2016-1017, NSE India Limited
[3] 25th Annual Report 2016-1017, NSE India Limited
[4] Discussion Paper on Growth and Development of Equity Derivatives Market in India, Security and Exchange Board of India, July 12, 2017

individual stocks is computed using equity market trades data provided by NSE. Trades data of NSE consists of the time stamp, price, and quantity traded on every symbol traded in spot market of NSE. The study also uses "bhavcopy" data provided by NSE to compute open interest of put options for all the stocks and index used in the research.

3. Methodology

VRP is calculated as the difference between the model-free implied volatility (MFIV) to the model-free realized volatility. In the subsequent sections, we discuss the calculation procedures of all the variables.

3.1 Model-free implied volatility of individual stocks

Calculation procedure of India VIX by NSE is employed to compute MFIV of individual stock options. India VIX computation procedure represents the MFIV methodology. India VIX follows the Chicago Board of Options Exchange (CBOE) computation methodology with suitable adjustments to acclimate Nifty Options order book. In a way similar to India VIX[5] methodology, we compute the individual stock option's MFIV, taking the best bid-ask prices of near and next month contracts that are traded in the F&O segment of NSE. The following formula is used to calculate MFIV of individual stock options.

$$stock\_mfiv_{j,t}^2 = \frac{2}{T} \sum_i \frac{\Delta K}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T} (\frac{F}{K_0} - 1)^2$$

$stock\_mfiv_{j,t}$= MFIV of jth stock options

T = Time to expiration

F= Forward level of individual stock as the latest available price of jth stocks future contract of the corresponding expiry

K_0= First strike below the forward level

K_i=Strike price of ith out-of-money option; a call if $K_i > F$ and a put if $K_i < F$

[5] https://www.nseindia.com/content/indices/white_paper_IndiaVIX.pdf

ΔK_i= Interval between strike prices i.e. half the distance between the strikes on either side of K_i (For the lowest strike, ΔK_i is the difference between lowest strike and the next higher strike. Similarly, for the highest strike, ΔK_i is the difference between highest strike and the next lower strike)

R= Risk free interest rate to corresponding expiration

$Q(K_i)$= Midpoint of the bid-ask quote for each option contract with strike K_i

Two differences can be noted between CBOE and NSE computation of MFIV. CBOE computes forward level by the put-call parity relation at a strike where the absolute difference between call and put prices is the smallest. NSE computes MFIV by taking latest available futures price of the underlying. Second, CBOE uses observed midpoint to compute $Q(K_i)$. But liquidity of far month traded options is a problem for the Indian market. Thus, a natural cubic spline interpolation is used to fill the midpoint prices where the bid-ask spread is more than thirty percent. Additionally, to handle liquidity issues individual options, we follow Grover and Thomas (2012) and assign zero weight for strikes where bid or ask or both do not exist. Further, we compute the daily MFIV of individual stocks at 15:00:00 o'clock (thirty minutes before market closing) from the NSE order book. Apart from individual stock MFIV, we use closing value of the India VIX, provided by NSE, as market index MFIV.

3.2 Model-free realized volatility of individual stocks

Two-scaled realized volatility (TSRV) is employed as the model-free realized volatility in the study. We follow Vipul and Jacob (2007) to calculate TSRV, which is as follows.

$$stock\_rv_{j,t}^2 = \frac{N}{(N-\bar{n})}[\bar{\sigma}_{lowfrequency,t}^2 - \frac{\bar{n}}{N}\sigma_{highfrequency,t}^2]$$

$stock\_rv_{j,t}$= Model-free realized volatility measure of j[th] stock

$\bar{n}$=Average number of returns across subsamples at the low frequency

N= Total number of returns at the high frequency

$\bar{\sigma}_{lowfrequency,t}^2$= Average variance at low frequency; low frequency is calculated with five minutes

$\sigma^2_{highfrequency,t}$= Variance at high frequency; high frequency is calculated with one second

The above measure of realized volatility calculates only open market volatility. To calculate realized volatility for the entire day, we need to calculate close market volatility. Thus, we scale up the volatility mentioned above by the ratio of daily close-to-close to daily open-to-close variances following Koopman et al.(2005), Garg and Vipul (2015). The scaling factor ρ_j for j[th] stock is calculated as mentioned below.

$$\rho_j = \sum_{t=1}^{T} r^2_{cc,j} \Big/ \sum_{t=1}^{T} r^2_{oc,j}$$

$r^2_{cc,j}$=Daily close-to-close return of the j[th] stock

$r^2_{oc,j}$=Daily open-to-close return of the j[th] stock

We employ the above-mentioned TSRV measure to calculate both individual stock and market index (Nifty) VRP.

3.3 Volatility risk premium

The traditional definition of VRP is the difference between the expected risk-neutral measure of volatility and expected objective measure of volatility.

$$VRP_{t=} E_t^Q\left(Var_{t,t+1}\right) - E_t^P(Var_{t,t+1})$$

We calculate MFIV of individual stocks as a measure of expected risk-neutral volatility. The MFIV measure calculated by the above procedure is the expected risk-neutral volatility of the next thirty calendar days. Thus, the next focus is to forecast the realized volatility (calculated from the scaled TSRV measure) to the next thirty calendar days. Garg and Vipul(2014) document that in the Indian market , for the monthly forecast, random walk model dominates the other forecasting models (Like EWMA, ARFIMA, HAR) based on the efficiency and bias criteria. Following them we use random walk model to forecast thirty calendar days realized volatility, which would be comparable to the MFIV measure. Under the random walk model measure, the scaled TSRV values are added up to for past thirty calendar days, and next thirty calendar days' forecast is made by the random walk model specified below.

$$\hat{\sigma}_t = \sigma_{t-1}$$

σ_{t-1}=estimate of the volatility at time t-1
$\hat{\sigma}_t$=forecast of volatility at time t

We calculate VRP for individual stocks and market index as specified below. Daily market VRP is calculated based on the difference between daily closing India VIX value and forecasted realized volatility (scaled TSRV as mentioned above) of Nifty. Similarly, the individual stock VRP is measured as the difference between calculated MFIV and forecasted realized volatility for each stock.

$$Market\_VRP_t = IVIX_t - RV_{t,t-30}$$
$$stock\_vrp_{j,t} = stock\_mfiv_{j,t} - stock\_rv_{j,t}$$

3.4 Market and stock specific characteristics

In the study, we control for market specific and stock specific characteristics, which we discuss below.

3.4.1 Market specific characteristics

In the market-specific factors, we control the market volatility and change of the volatility. The intuition behind controlling for the market volatility is that the level of volatility affects the VRP of the stocks. The volatility of an asset is mean reverting in nature so as for market volatility. As trading activity exhibits correlated trading patterns in response to market-wide volatility shocks (Chordia et al., 2000), high (low) level of market volatility would induce individual stocks to exhibit high (low) level volatility. When volatility level is high (low), the "volatility markup" process would yield lower (higher) VRP. This is because VRP is the difference between implied and realized volatility; when realized volatility level is high (low), the difference between these two volatility levels would decrease (increase). Thus, "volatility markup" process that sets implied volatility over and above realized volatility would yield lower (higher) VRP in times of high (low) volatility levels. The single stock VRP and market volatility level exhibit negative relationship if the above intuition holds true. We calculate the daily level of volatility by the difference of Nifty's intraday high and low price divided by the Nifty closing price of the day.

We also control for change of the market volatility following Goyal and Saretto (2009). Although Goyal and Saretto (2009) explain that deviations of implied volatility from realized volatility are signs of volatility mispricing, we have a different explanation for the deviation. We argue that liquidity suppliers set option prices such that implied volatility exceeds the realized volatility rate to cover up all the costs borne by the liquidity suppliers. According to Stein (1989) and Poteshman (2001), investors overreact (underreact) to recent high (low) changes of volatility and pay high (low) premium for high (low) volatility shocks. We differ from this set of explanation, and we argue that liquidity suppliers set higher (lower) implied volatility to recent high (low) change of volatility. Thus, the level of VRP (the difference between implied and realized volatility) would be positively related to the recent changes in the volatility. We compute the recent changes of volatility by the difference between today's volatility and previous trading day's volatility scaled by the previous trading day's volatility.

3.4.2 Firm-specific characteristics

Similar to market volatility level and recent changes of market volatility, we control for the individual stocks volatility level and recent changes in individual stocks volatility. As argued above (Chordia et al., 2000), correlated trading patterns would induce high (low) volatility to individual stocks in tandem to market volatility. Thus, control for stocks volatility and changes of volatility become necessary. Similar to market volatility level, stocks volatility levels should exhibit a negative relationship with the stocks VRP level. Additionally, the recent changes of volatility should exhibit positive effect with stock VRP for similar arguments as discussed above.

Apart from the level of volatility and changes of volatility, we also control for firm size and stock liquidity. Firm size and firm liquidity may affect VRP of stocks. It is a common belief that information asymmetry is lower for larger sized firms because of high analyst coverage and forecast. As VRP is a measure of expensiveness of options, which is related to information asymmetry that the liquidity supplier assumes, it would be a function of the size of the firm. The larger the size of the firm, lower would be the VRP because of less information asymmetry. Stock liquidity might also affect VRP. Highly liquid firms often enjoy less information asymmetry because of the high trading volumes. On the other hand, less liquid firms often suffer from more information asymmetry. Thus, liquidity suppliers would tend to set higher (lower) volatility markup for less (high) liquidity stocks because of higher (lower) information asymmetry. We calculate the size of a firm by the total number of equity outstanding for the stock multiplied by their daily closing prices. We use natural logarithm of the size as our independent variable in the primary regression. Additionally, we also take the squared size of a firm as control variable assuming that there may exist a non-linear relationship between the size of the firm and stock VRP. Further, we calculate daily stock liquidity by the natural logarithm transformation of the number of shares traded.

We include the daily open interest of put options as a proxy for option demand pressure. Previous studies emphasize the role of constrained financial intermediaries (Cao and Han, 2013; Garleanu et. al, 2009; Fan et. al, 2016) in an imperfect market. Studies document that option prices are affected by the demand of the options (Bollen and Whaley, 2004; Garleanu et al., 2009) and when there are limits to arbitrage (Shleifer and Vishny, 1997), because of costly hedge or replication of the option, liquidity suppliers supply options with higher prices. Thus, option demand affects option prices positively. Put options provide investors to hedge against volatility crash. Thus, open interest of put option provides a natural proxy for hedging volatility demand. We include the daily open interest of put options for individual stocks as a proxy for tail risk demand.

3.5 Descriptive statistics

Descriptive statistics of stock VRP and market-specific characteristics are reported in Table 1. The mean of average stock VRP is noticeably negative for the period of study whereas the mean of market VRP is positive. Further, the standard deviation of average stock VRP is very high compared to that of market VRP. All the variables are stationary.

Figure 1 shows that the average single stock VRP is considerably lower than market VRP. Further, average market VRP is negative in most of the time periods. Descriptive statistics of the stock-specific characteristics are reported in Table 2. Noticeably, all the variables in Table 2 are stationary except firm size. Although the variable is not stationary, we do not de-trend the variable following Lo and Wang (2000), where they advised to take a shorter period (typically five years) since de-trend cannot be achieved without removing adequate serial correlation. In the descriptive statistics, the Jarque-Bera test has a null hypothesis of normality and ADF test has a null hypothesis of stationarity. We report the *t*-statistics of these tests.

Table 1: Descriptive statistics of the stock VRP and market-specific characteristics.

Below table reports the descriptive statistics of average stock VRP, market VRP, market volatility level and change of market volatility. Jarque-Bera test has a null hypothesis of normality. ADF test has a null hypothesis of stationarity.

	$stock\_vrp_{j,t}$	$Market\_VRP_t$	$Market\_Volatility_t$	$\Delta Market\_Volatility_t$
Mean	-0.093	1.255	1.141	0.167
Standard Deviation	1.346	0.631	0.621	0.718
Skewness	-0.745	-0.202	2.449	2.111
Kurtosis	3.113	4.187	13.045	10.408
Jarque-Bera (*t*-statistics)	31.611	22.283	1769.088	1030.060
ADF test (*t*-statistics)	-5.440	-5.228	-6.949	-17.705
#Obs	340	340	340	340

Figure 1: Plot of average stock VRP and market VRP

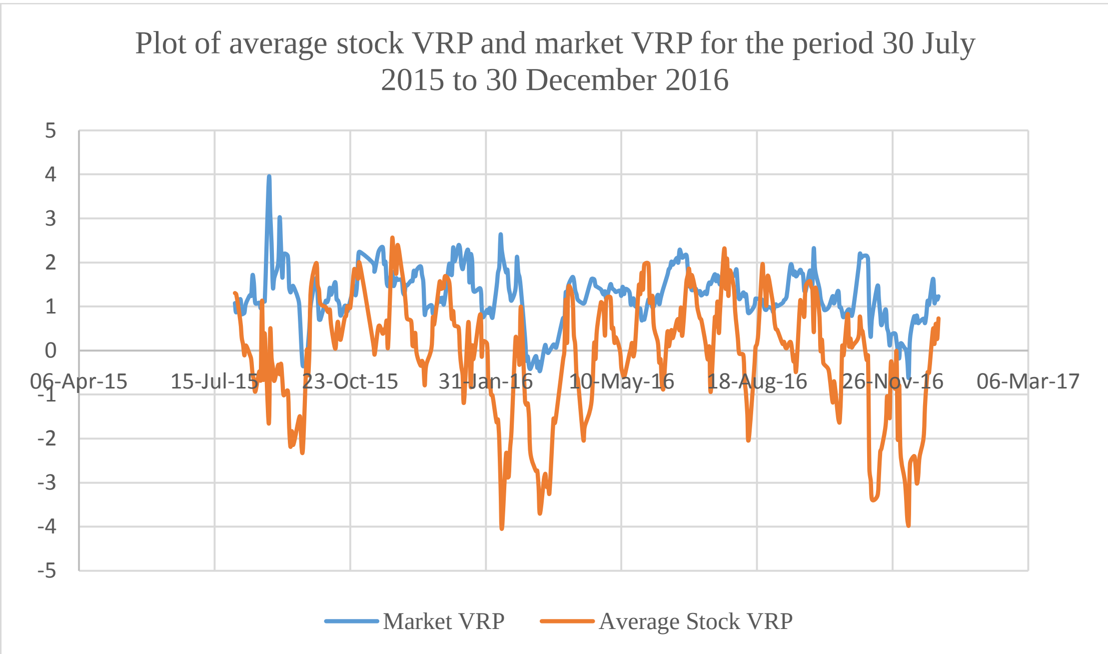

Table 2: Descriptive statistics of the stock-specific characteristics.

Below table reports the descriptive statistics of average stock volatility, average changes of stock volatility, average firm size, average firm liquidity and average open interest of put options of individual stocks. Jarque-Bera test has a null hypothesis of normality. ADF test has null hypothesis of stationarity

	$stock\_volatility_{j,t}$	$\Delta stock\_volatility_{j,t}$	$stock\_size_{j,t}$	$stock\_liquidity_{j,t}$	$stock\_putoi_{j,t}$
Mean	2.625	0.147	10.247	14.388	13.447
Standard Deviation	0.808	0.299	0.101	0.268	0.370
Skewness	2.889	2.884	0.266	0.659	-0.584
Kurtosis	17.372	18.473	2.812	5.278	3.173
Jarque-Bera (*t*-statistics)	3398	3863	4.519	98.173	19.741
ADF test (*t*-statistics)	-5.333	-24.245	-1.450	-7.015	-7.684
# Obs	340	340	340	340	340

3.6 Primary Regression equation

We employ the following econometric specification to regress stock VRP on the market VRP, and other market and stock-specific characteristics, to understand the extent to which individual stock VRP covary with market VRP. The general regression specification is

$$stock\_vrp_{j,t} = a + \sum_{i=-1}^{+1} b_{i+1} Market\_VRP_{t+i} + \sum_{k=-1}^{+1} c_{k+1} Market\_Volatility_{t+k} + d_1 \Delta Market\_Volatility_t + e_1 stock\_volatility_{j,t} + f_1 \Delta stock\_volatility_{j,t} + g_1\, stock\_size_{j,t} + h_1 stock\_size_{j,t}^2 + m_1 stock\_liquidity_{j,t} + n_1 stock\_putoi_{j,t} + \varepsilon_t \quad (1)$$

We perform pooled regressions and compute *t*-statistics from Newey-West (1987) standard error that corrects for cross-sectional correlations in the data. $stock\_vrp_{j,t}$ represents VRP of stock *j* at time *t*. We compute the daily VRP of stock *j* thirty minutes before the market closing. Similarly, $Market\_VRP_t$ represents the market (index Nifty) VRP at time *t*. Market volatility level is represented as $Market\_Volatility_t$ and change of market volatility as $\Delta Market\_Volatility_t$ We include stock specific factors such as $stock\_volatility_{j,t}$ and $\Delta stock\_volatility_{j,t}$ that represent the individual stock daily volatility level and change of volatility of stock *j* at time *t*. We include firm specific factors such as size of the firm and squared stock size in our regression equation as $stock\_size_{j,t}$ and $stock\_size^2_{j,t}$. Similar to firm size, we include stock liquidity of stock *j* at time *t* as $stock\_liquidity_{j,t}$. Consistent with the demand hypothesis of the options we include open interest of put options of stock *j* at time *t* as $stock\_putoi_{j,t}$ as the representative of hedging tail demand.

We include lead and lag terms of market VRP to capture lagged adjustments of commonality in VRP because of non-synchronous trading. Existence of the commonality in the VRP between individual stock and market would mean that any of the b_{i+1} coefficients would be statistically significant and positive. We also include lead and lag terms of market volatility as control for the commonality relationship between stock and market VRP. Apart from commonality, we also test stock VRP behaviour based on the size of the firm of stock *j* and also on the hedging demand of options by the open interest of put options on stock *j*.

4. Results and Discussion

Potential explanations of the results are presented in this section. We first discuss the results of commonality and market-specific factors as described in Section 3. Then we discuss the results of commonality in VRP , taking stock-specific factors. Lastly, we discuss the overall results of the model.

4.1 Commonality with market-specific factors

First, we examine the commonality between stock VRP and market VRP in Table 3. Table 3 shows that the relationship between individual stock VRP and market VRP is significantly positive for all the models. The significant positive relationship is robust even with market-specific factors such as market volatility and change of market volatility. Instead, in the presence of market volatility and change of market volatility factors (Model 3), the estimated contemporaneous coefficient of market VRP is 0.491 with *t*-statistics of 10.51, which shows contemporaneous market VRP is the most significant factor (in terms of magnitude and significance) in movement of stock VRP among the lag, contemporaneous and lead market VRP. Additionally, all the lead and lag coefficients of market VRP are significantly positive for all the models. Lag and lead of market VRP are included to capture lagged adjustments in commonality in VRP because of non-synchronous trading. The significant positive relationship between stock VRP and market VRP is inferred as the evidence of the existence of commonality in VRP.

The relationship between stock VRP and market volatility is significantly negative in Model 1 and Model 2. In fact, contemporaneous market volatility shows the most negative significant relationship with coefficient -0.958 with *t*-statistics -9.42 in Model 3. Moreover, the lag and lead market volatility coefficients are also negatively significant. It shows commonality in stock VRP depends upon the level of market volatility. In times of high (low) volatility level, the “volatility markup” process yields low (high) level of stock VRP as the difference between MFIV and realized volatility decreases (increases) in time high (low) realized volatility.

Change of market volatility is significantly positive with stock VRP with coefficient 0.323 and *t*-statistics 5.16 in Model 3. Recent change of market volatility induces liquidity suppliers to set option prices in tandem with recent change of volatility. Thus, higher (lower) changes of recent volatility induce liquidity suppliers to keep option prices high (low).

Table 3: Commonality with market-specific factors

This table reports the commonality in stock and market VRP with market-specific factors. Daily stock and market VRP are calculated by the difference of MFIV and realized volatility measured from scaled TSRV. Market volatility for a day is measured by the Nifty's intraday high and low price divided by the closing Nifty price. Change of the market volatility is measured by the change of volatility in two consecutive trading days scaled by the previous day's volatility. The sample period is from 30 July 2015 to 30 December 2016. Robust Newey and West (1987) *t*-statistics are reported in the brackets. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively

Variables	Model 1	Model 2	Model 3
Intercept	-1.057***	0.242	0.235
	(-5.68)	(1.25)	(1.22)
$Market\_VRP_{t-1}$	0.164**	0.329***	0.314***
	(2.43)	(4.57)	(4.37)
$Market\_VRP_{t}$	0.243***	0.458***	0.491***
	(4.92)	(10.02)	(10.51)
$Market\_VRP_{t+1}$	0.418***	0.237***	0.223***
	(6.67)	(3.87)	(3.63)
$Market\_Volatility_{t-1}$		-0.405***	-0.148***
		(-6.62)	(-2.7)
$Market\_Volatility_{t}$		-0.642***	-0.958***
		(-11.47)	(-9.42)
$Market\_Volatility_{t+1}$		-0.315***	-0.301***
		(-5.8)	(-5.67)
$\Delta Market\_Volatility_{t}$			0.323***
			(5.16)
$Adjusted\ R^2$	0.0225	0.0572	0.0581

4.2 Commonality with stock specific factors:

Next, we study how the commonality relationship is affected by the stock-specific characteristics. Table 4 reports the results of a pooled regression of stock-specific characteristics. Table 4 shows that for all the models, the market VRP coefficients (lag, contemporaneous and lag) are all positively significant to the stock VRP. Thus, commonality relationship does not get affected by the presence of the stock-specific factors. Interestingly, the *t*-statistics of contemporaneous market VRP is 7.19 with a coefficient of 0.357 in the Model 7. This *t*-statistic is the highest among all the variables in Model 7, indicating that commonality in VRP is statistically the most significant variable.

First, we include stock volatility level in the commonality relationship. Model 1 shows that, similar to market volatility level, stock volatility level is significantly negative. This result may be explained by similar arguments of market volatility level. “Volatility markup” in which liquidity suppliers set stock option prices to exceed realized volatility rate, yields low (high) VRP level in times of high (low) stock volatility level since VRP level of the stocks is the difference between implied and realized volatility level. When we include recent changes of stock volatility in the regression (Model 2), the coefficient of changes of stock volatility is significantly positive without affecting commonality or stock volatility level results. This result indicates that recent changes in stock volatility affect the stock VRP level. High (low) changes of recent changes of volatility prompt the liquidity suppliers to set option prices higher (lower). This result is also consistent with recent changes in market volatility.

We include firm size in the commonality relationship as shown in Model 3. The result shows that firm size is negatively significant with stock VRP level. The intuition is, larger the size of the firm, greater the analyst coverage and lower the information asymmetry. As VRP level can be thought as the proxy for option’s expensiveness, lower (higher) information asymmetry of a firm produces lesser (higher) expensiveness of the options. This is because, liquidity suppliers set lower (higher) prices of the options with lower (higher) information asymmetry involved with the firm. When we include a quadratic term of the firm size in the pooled regression, it becomes positively significant. Thus, a non-linear relationship exists between the stock VRP level and firm size. Results of pooled regression with firm size and quadratic firm size indicate that there exists a U-shaped relationship between firm size and stock VRP level.

Next, we include stock liquidity in the commonality relationship. The inclusion of stock liquidity does not change the commonality relationship. The coefficient of stock liquidity is negative although not statistically significant. This result is quite intuitive. High(low) liquidity firms will have lower (higher) trading costs (Forster and Viswanathan,1993). Thus, liquidity suppliers suffer from lesser (higher) price impact for high (low) liquidity firms prompting them to set option prices lower (higher). Accordingly, stock liquidity displays negative relationship with stock VRP. When we include firm size and its quadratic variation along with stock liquidity in Model 5, the commonality relationship does not change. All the coefficients are consistent with expected signs.

We include the open interest of put options in the commonality relationship in Model 6. Open interest of put options is a natural proxy of option demand for tail risk and volatility shocks. Constrained financial intermediaries (Bollen and Whaley, 2004; Garleanu et al., 2009) affect the option prices conditional on demand of options. Because of limits to arbitrage, liquidity suppliers of options set prices according to the demand for options. Conditional on high (low) demand of options, liquidity suppliers supply options making option prices high (low). Thus, the stock VRP (the difference between MFIV and realized volatility) varies positively with option demand. Results of Model 6 indicate that open-interest of put options positively affects stocks VRP with statistical significance. This result is consistent with Fan et al., (2016). In Model 7, we include all the stock-specific characteristics. The results are consistent with no meaningful change to any of the stock-specific variables as discussed above.

Table 4: Commonality with stock specific factors:

This table reports the commonality in stock and market VRP with stock-specific factors. Daily stock and market VRP are calculated by the difference of MFIV and realized volatility measured from scaled TSRV. Individual stock volatility for a day is measured by the stock's intraday high and low price divided by the closing stock price. Change of the stock volatility is measured by the change of volatility in two consecutive trading days scaled by the previous day's volatility. Stock size is calculated by the total number of equity outstanding for the stock multiplied by the NSE closing prices for that day. We take the natural logarithm of the size in the regression. The liquidity of a stock is measured by the total traded value of the stock for that day. Stock put open interest is the total number of open interest of put options outstanding for the day. The sample period is from 30 July 2015 to 30 December 2016. Robust Newey and West (1987) *t*-statistics are reported in the brackets. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	-0.404**	-0.318*	9.635***	-0.766	10.101***	-2.436***	8.568**
	(-2.2)	(-1.65)	(2.71)	(-1.22)	(2.74)	(-4.32)	(2.4)
$Market\_VRP_{t-1}$	0.189***	0.229***	0.162**	0.164**	0.163**	0.165**	0.240***
	(2.83)	(3.33)	(2.42)	(2.44)	(2.42)	(2.44)	(3.45)
$Market\_VRP_t$	0.383***	0.351***	0.240***	0.243***	0.241***	0.242***	0.357***
	(7.63)	(7.11)	(4.87)	(4.94)	(4.89)	(4.92)	(7.19)
$Market\_VRP_{t+1}$	0.324***	0.325***	0.421***	0.416***	0.419***	0.416***	0.306***
	(5.5)	(5.51)	(6.74)	(6.69)	(6.76)	(6.62)	(5.19)
$stock\_volatility_{j,t}$	-0.284***	-0.331***					-0.360***
	(-6.03)	(-5.58)					(-5.49)
$\Delta stock\_volatility_{j,t}$		0.192**					0.221**
		(2.2)					(2.27)
$stock\_size_{j,t}$			-1.974***		-1.999***		-1.809***
			(-2.8)		(-2.82)		(-2.63)
$stock\_size^2_{j,t}$			0.089***		0.090***		0.078**
			(2.59)		(2.62)		(2.32)
$stock\_liquidity_{j,t}$				-0.020	-0.024		-0.131*
				(-0.46)	(-0.54)		(-1.71)
$stock\_putoi_{j,t}$						0.103***	0.241***
						(2.58)	(3.72)
$Adjusted\ R^2$	0.0386	0.0406	0.0297	0.0225	0.0297	0.0248	0.0565

4.3 Commonality with market and stock-specific factors

Table 5 reports commonality results with all the market and stock-specific characteristics. The inclusion of all the market and stock specific variables does not change the commonality relationship between stock and market VRP. All the market VRP coefficients are significantly positive, contemporaneous market VRP being the most important in terms of both magnitude and statistical significance. The contemporaneous market VRP coefficient is 0.490 with *t*-statistics being 10.59. All the market-specific characteristics are consistent with the results of commonality with market factors as discussed in Section 4.1. All the commonality and market factors are statistically significant with expected signs. Likewise, stock-specific characteristics are also statistically significant (except stock liquidity) and consistent with the expected signs. There is no meaningful change of the results of the stock characteristics as discussed in section 4.2.

Overall, all the results provide stong evidence of the existence of commonality in VRP. This relationship is robust with all the market and stock-specific characteristics. The commonality in the VRP signifies the correlated market-wide trading activity, specifically in terms of volatility pricing activity by the liquidity suppliers of the options. We find stock VRP has a significant negative relationship with market volatility level and significant positive relationship with recent changes in market volatility. Thus, market-wide volatility level and market-wide volatility shocks influence the stock option suppliers to set the option prices accordingly. Moreover, similar to market volatility level and recent changes in market volatility, individual stock volatility level and recent changes of stock volatility retain significant negative and positive relationships respectively. Additionally, results show that stock VRP maintains a significant U-shaped behavior with firm size. Stock VRP is also negatively related to stock liquidity, although the relationship is hardly statistically significant. Consistent with the constrained intermediaries hypothesis, we also find that open-interest of put options, which is a proxy for option demand, has a significant positive relationship with the stock VRP.

Table 5: Commonality with market and stock-specific factors:

This table reports the commonality in stock and market VRP with stock-specific factors. Daily stock and market VRP are calculated by the difference of MFIV and realized volatility measured from scaled TSRV. Market volatility for a day is measured by the Nifty's intraday high and low price divided by the closing Nifty price. Change of the market volatility is measured by the change of volatility in two consecutive trading days scaled by the previous day's volatility. Individual stock volatility for a day is measured by the stock's intraday high and low price divided by the closing stock price. Change of the stock volatility is measured by the change of volatility in two consecutive trading days scaled by the previous day's volatility. Stock size is calculated by the total number of equity outstanding for the stock multiplied by the NSE closing prices for that day. We take the natural logarithm of the size in the regression. The liquidity of a stock is measured by the total traded value of the stock for that day. Stock put open interest is the total number of open interest of put options outstanding for the day. The sample period is from 30 July 2015 to 30 December 2016. Robust Newey and West (1987) t-statistics are reported in the brackets. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively

Variables	**Overall model**
Intercept	9.990***
	(2.79)
$Market\_VRP_{t-1}$	0.321***
	(4.45)
$Market\_VRP_t$	0.490***
	(10.59)
$Market\_VRP_{t+1}$	0.214***
	(3.48)
$Market\_Volatility_{t-1}$	-0.061
	(-1.13)
$Market\_Volatility_t$	-0.797***
	(-8.67)
$Market\_Volatility_{t+1}$	-0.262***
	(-5.31)
$\Delta Market\_Volatility_t$	0.321***
	(5.27)
$stock\_volatility_{j,t}$	-0.189***
	(-3.23)
$\Delta stock\_volatility_{j,t}$	0.131*
	(1.8)
$stock\_size_{j,t}$	-1.891***
	(-2.74)
$stock\_size^2_{j,t}$	0.083**
	(2.46)
$stock\_liquidity_{j,t}$	-0.123
	(-1.6)
$stock\_putoi_{j,t}$	0.199***
	(3.09)
$Adjusted\ R^2$	0.0739

5. Conclusion

The paper examines the existence of commonality in stock VRP and market VRP. Previous studies document correlated trading activity in the stock market by examining commonality in liquidity. Correspondingly, this study aims to understand the correlated trading activity, both in stock and options market, by examining commonality in VRP, which is a derived measure from both spot and options market.

The key contribution of the study is that it produces evidence of commonality in VRP. Further, the relationship is robust across other control variables. We include market specific and stock specific factors that may influence the commonality relationship. Our findings suggest that the commonality relationship between stock and market VRP is robust and significant both statistically and economically, even in the presence of all the other factors.

The results are consistent with the market-specific factors. In market-specific factors, we find that market volatility affects the stock VRP negatively and significantly. Moreover, we find positive significant relationship between recent changes in market volatility and stock VRP. Among stock-specific factors, similar to market volatility and changes of market volatility, we find a significant negative relationship with stock volatility level and significant positive relationship with recent changes of stock volatility. Firm size shows significant U-shaped behavior with stock VRP. Stock liquidity affects the stock VRP negatively. Further, consistent with the constrained financial intermediaries hypothesis, our results show that option demand affects stock VRP significantly and positively. The overall results suggest that commonality in stock and market VRP exists and the relationship is robust and significant.

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