Options Order Flow, Volatility Demand and Variance Risk Premium

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This study investigates whether volatility demand information in the order flow of Indian Nifty index options impacts the magnitude of variance risk premium change. The study further examines whether the sign of variance risk premium change conveys information about realized volatility innovations. Volatility demand information is computed by the vega-weighted order imbalance. Volatility demand of options is classified into different categories of moneyness. The study presents evidence that volatility demand of options significantly impacts the variance risk premium change. Among the moneyness categories, volatility demand of the most expensive options significantly impacts variance risk premium change. The study also finds that positive (negative) sign of variance risk premium change conveys information about positive (negative) innovation in realized volatility.

Keywords: variance risk premium; volatility demand; model-free implied volatility; realized variance; options contract

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I. Introduction

It is consistently observed that systematic selling of volatility in the options market results in economic gains. Options strategies that engage

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in selling volatility practice are gaining popularity among practitioners. Theories of finance suggest that economic gains by selling volatility can be attributed to variance risk premium (*VRP*). *VRP* is the difference between risk neutral and physical expectation of variance. Many studies investigate the presence of volatility or variance risk premium. For example, Bakshi and Kapadia (2003), Carr and Wu (2008), Bollerslev, Tauchen, and Zhou (2009), and Garg and Vipul (2015) document the presence and stylized facts about volatility or variance risk premium. For example, Bollerslev, Tauchen and Zhou (2009), Bollerslev, Gibson, and Zhou (2011), Bekaert and Hoerova (2014) relate variance risk premium with market-wide risk aversion. Carr and Wu (2008) argue that variance risk is priced as an independent source of risk. Yet, very few studies attempt to understand the determinants of *VRP* and thus they are less understood. We take this up in this study and strive to understand the *VRP* in the context of a demand and supply framework of options. Previous studies of Bollen and Whaley (2004), Garleanu , Pedersen, and Poteshman (2009) demonstrate that the net demand of options influences prices and implied volatility of options. For example, Bollen and Whaley (2004) show that net buying pressure impacts the implied volatility of options. Similarly, Garleanu, Pedersen and Poteshman(2009) document that market participants are net buyers of index options and that demand of options influences prices.

The rationale behind variance risk premium can be explained by the mispricing of options. In an ideal world, options are redundant securities. But in practice, there is a strong demand for them owing to several reasons. Informed investors may prefer options over the underlying assets because of the high leverage provided by the former (Black,1975\, Grossman 1977). On the other hand, presence of stochastic volatility prompts volatility informed investors to trade on volatility by using non-linear securities such as options. These incentives prompt investors to participate in options trading. Previous studies investigate the informational role of the options market and discuss whether informed traders trade use it for trading (Chakravarty, Gulen,and Mayhew (2004)). Informed players may use options to trade directional movement information of the underlying asset and its expected future volatility information, or any other information by taking long, short positions on call or put options or their different combinations. A single underlying asset has a wide range of strike prices and multiple maturities, which make information extraction from options trading difficult. In a recent study, Holowczak, Hu, and Wu (2014) show how to extract a particular type of information by aggregate option transactions. In this study, we are interested to extract directional and volatility demand information of options. A call option is a positive exposure while put option is a negative exposure to the underlying stock price. Delta of an option measures the sensitivity of the option price to the underlying stock price movement. So we assign a positive delta to the call options order imbalance and negative delta to the put options order imbalance for each strike-maturity level. Thus, at an aggregate level, order imbalance of call and put options should take opposite signs and the net aggregated order imbalance of a call and put combination at that strike and maturity would measure the underlying stock price movement exposure. This method is different from Bollen and Whaley (2004) study in which they capture the net buying pressure of options. Bollen and Whaley (2004) used absolute delta as a measure of net buying pressure for call and put options. Bollen and Whaley (2004) argue that net demand of an option contract makes it deviate from its intrinsic values and impacts its implied volatility. Different option contracts for the same underlying stock experience different net buying pressures. Accordingly, the implied volatilities of these option contracts vary and produce apparent anomaly in the market, which is known as volatility smile or smirk or skew. Coming to the calculation of net volatility demand, Holowczak, Hu,and Wu (2013) argue that vega, which is the sensitivity of the option price to the underlying volatility movement, is the same for both call and put options for the same strike price and maturity. That means in an ideal world, traders do not have any reason to prefer one type of options (call or put) over the others in trading volatility. Vega is positive for both call and put options. The net volatility demand of a strike and maturity can then be calculated by the aggregated vega-weighted order imbalance of call and put options at that strike and maturity.

One of the stylized facts of implied volatility is that on an average it exceeds the realized volatilities. Theory suggests that difference is the premium paid by the buyers to the sellers of the options. The buyer of the options pays the premium because of the risk of losses during periods when realized volatility starts exceeding the option implied volatility. Increase in realized volatility coincides with downside market movement and increase in uncertainty in the investment environment (Bakshi and Kapadia 2003). Extant literature documents the presence of volatility/variance risk premium across different financial markets. Many studies have concluded that volatility risk is priced through variance risk premium (Bakshi and Kapadia, 2003; Carr and Wu, 2008; Coval and Shumway, 2001). For example, Bakshi and Kapadia (2003) document the presence of variance risk premium (*VRP*) by delta hedged option gains. Using the difference between realized variance and variance swap rate as variance risk premium, Carr and Wu (2008) show strong variance risk premium for S&P and Dow indices. Further, they argue that the variance risk is independent of the traditional sources of risk. In the context of the Indian market, Garg and Vipul (2015) document the presence of volatility risk premium. They confirm that option writers make consistent economic profits over the life of the options because of the presence of volatility risk premium.

Previous related studies on options trading and volatility include Bollen and Whaley (2004), and Ni, Pan, and Poteshman (2008). Bollen and Whaley (2004) explain the shape of implied volatility function (IVF) by the net demand of options. In the Black-Scholes framework, the supply curve of the options is horizontal regardless of the demand for the options. Bollen and Whaley (2004) argue that the supply curve of the options is upward sloping rather than horizontal because of the limits to arbitrage[1]. The upward supply sloping curve of options make them mispriced from their Black-Scholes intrinsic values. Hence, the net demand of a particular option contract affects the implied volatility of that series and determines the implied volatility function. Bollen and Whaley (2004) measure the net demand of an option contract by the difference between the numbers of buyer and seller motivated contracts traded traded multiplied by the absolute delta of that option contract. The paper concludes that absolute delta-weighted options order flow impacts the implied volatility function. Similarly, Ni, Pan and Poteshman (2008) measure volatility demand by the vega-weighted order imbalance. According to Ni, Pan and Poteshman (2008), net volatility demand contains information about future realized volatility of the underlying asset. They use volatility demand to forecast future realized volatility.

This study is related to the study of Fan, Imerman, and Dai (2016). Fan, Imerman and Dai (2016) investigate determinants of volatility risk premium in a demand and supply framework. Their study argues that the supply of options is related to market maker's willingness to absorb inventory and provide liquidity. On the other hand, demand of options emerges from the hedging requirement of tail risk. Investors use put index to hedge tail risk. The study captures the demand effect by put

1. Shleifer and Vishny (1997) propose limits to arbitrage theory. This theory describes that exploitation of mispriced securities by arbitrageurs is limited by their ability to absorb intermediate losses.

option open interest and also the supply effect by credit spread and TED spread. We argue that volatility demand of options impacts the *VRP* and propose that changes in the expected volatility would change the net demand of volatility in the option marketplace, consequently, affecting the implied volatility of options. Thus, magnitude of the difference between implied variance and realized variance would emerge as a consequence of net volatility demand. Fan, Imerman and Dai (2016) decompose the volatility risk premium (*vrp*) into magnitude and direction components. According to them, magnitude and direction of volatility risk premium contain different information. They argue that magnitude of the volatility risk premium reflects the imbalance in demand and supply, while direction or sign of volatility risk premium reflects the expectation of realized volatility. Building on the same, we decompose the change of variance risk premium into magnitude and direction components. We argue that expectation of future realized volatility changes the volatility demand that drives changes in implied volatility. Thus, magnitude of the variance risk premium reflects the divergence or convergence of implied variance change with respect to realized variance change. On the other hand, the sign or the direction of change of variance risk premium reflects the expectation of realized volatility change. When change in the variance risk premium is positive (negative), trades expect that the expected realized volatility would increase (decrease). We investigate empirically how change in the volatility demand affects the magnitude of the variance risk premium, and whether the sign of the change reflects the expectation of realized volatility. We are interested to understand the change of magnitude of variance risk premium by volatility demand of options. We use vega-weighted order imbalance of options to capture the net demand of options. Moreover, Fan, Imerman and Dai (2016) investigate the level effect of volatility risk premium, whereas we are interested to capture the change in its magnitude in a volatility demand framework. We propose the following testable hypotheses:

H1: Net volatility demand affects the magnitude change in variance risk premium.

H2: The sign of the change in variance risk premium reflects expectation about the realized volatility innovations.

Main findings of our study are as follows. First, we find that volatility demand of options significantly impacts the variance risk premium change. Second, among moneyness categories, volatility demand of the most expensive options significantly impacts variance risk premium change. Third, positive (negative) sign of variance risk premium change conveys information about positive (negative) innovation in realized volatility.

The rest of the paper is organized as follows. Section II describes the methodology that provides calculation details of variance risk premium and volatility risk premium. Further, it explains the decomposition method of directional and volatility order imbalance components. Section III describes the data used for the study and presents the summary. Section IV reports the results of the empirical tests. Section V reports the robustness test results. Section VI concludes the paper.

II. Methodology

This section explains the computation of variance risk premium. Next, the moneyness categories used for the study are explained. The section then explains the calculation details of volatility demand and directional demand information from the option order flows. Next, we explain the empirical specifications employed for the study.

A. Variance risk premium

The formal definition of variance risk premium is the difference between risk neutral and objective expectation of the total return variance i.e., $VRP_t = E_t^Q\left(Var_{t,t+1}\right) - E_t^P\left(Var_{t,t+1}\right)$. Literature employs different proxies for measuring variance risk premium and uses variance risk premium and volatility risk premium interchangeably.

We compute the variance risk premium in a model-free manner. Model-free implied volatility (*MFIV*) framework is proposed by Demeterfi, Derman, Kamal, and Zou (1999), Britten-Jones and Neuberger (2000) and is used to calculate risk-neutral expectation of future volatility. Based on the *MFIV* framework, in 2003, CBOE introduced the volatility index (*VIX*), which measures the short-term expectation of future volatility. The National Stock Exchange of India (NSE) introduced India *VIX* in 2008 based on the *MFIV* framework. We use India *VIX* as risk-neutral volatility expectation. We calculate realized variance in a model-free manner by the sum of squared returns. Previous studies of Bollerslev, Tauchen and Zhou (2009), Drechsler and Yaron (2010) have used five-minute sum of squared returns to calculate realized variance. We also use five-minute sum of squared return to obtain model-free realized variance. Although the definition of variance risk premium says ex-ante expectation of realized variance, we use ex-post realized variance of thirty calendar days while computing *VRP*. This specific way of calculation of variance risk premium makes it observable at time t and also makes it free from any modelling or forecasting bias.

We define variance risk premium as,

$$VRP_t = IVIX_t^2 - RV_{t,t+30}^2 \tag{1}$$

where we proxy risk-neutral measure by squared India *VIX* [2] (after transforming into its 30- calendar days risk neutral variance) and realized variance, taking the sum of five-minute squared returns over thirty calendar days, treating overnight and over-weekend returns as one five-minute interval, following Drechsler and Yaron (2010) and Bollerslev, Tauchen and Zhou (2009). We use ex-post realized variance to avoid forecasting bias. Thus, the above measure gives the thirty calendar-day variance risk premium.

B. Moneyness of options and total traded quantity

We define moneyness of an option as $y = \log(K/F)$, following Carr and Wu (2008), Wang and Daigler (2011). Here, *K* is the strike price and *F* is the futures price of the Nifty index. As we aggregate vega-weighted order imbalance for each strike and same maturity, for both call and put options, we define the following categories of options based on moneyness, for both call and put options.

We employ tick test to calculate the number of traded Nifty options for the period of study and obtain proprietary Nifty options trades data from the NSE. We calculated the number of buy and sell traded options using Nifty options trade data. If the trade price is above the last trade price, it is classified as buyer-initiated. Similarly, when trade price is below the last trade price, it is classified as seller-initiated. If the last trade price is equal to the current trade price, the last state of

2. India *VIX* is the volatility index computed by the National Stock Exchange of India based on Nifty options order book. The above measure of computation is adopted to the model-free implied volatility framework.

TABLE 1. Moneyness categories of options

Category	Label	Range
01	Deep in-the-money call ($DITM_{CE}$)	$y \leq -0.30$
	Deep out-of-the-money put ($DOTM_{PE}$)	$y \leq -0.30$
02	In-the-money call (ITM_{CE})	$-0.30 < y \leq -0.03$
	Out-of-the-money put (OTM_{PE})	$-0.30 < y \leq -0.03$
03	At-the-money call(ATM_{CE})	$-0.03 < y \leq +0.03$
	At-the-money put (ATM_{PE})	$-0.03 < y \leq +0.03$
04	Out-of-the-money call (OTM_{CE})	$+0.03 < y \leq +0.30$
	In-the-money put (ITM_{PE})	$+0.03 < y \leq +0.30$
05	Deep out-of-the-money call ($DOTM_{CE}$)	$y > +0.30$
	Deep in-the-money put ($DITM_{PE}$)	$y > +0.30$

Note: The categories are defined by moneyness of the options, where moneyness is measured as $y=\log(K/F)$, where K= strikeprice of the options and F= Futures price of Nifty index.

classification is kept for the current state of trade price. By tick test, we calculate the number of options bought and sold for each moneyness defined above in the period of study. The results are reported in table 1.

C. Volatility Demand and Directional Demand Information

We calculate the volatility demand and directional demand information by the proprietary snapshot data obtained from the NSE. Proprietary data of the NSE is received for the period of July 2015 to December 2015. This snapshot data is given for five timestamps in a trading day (we discuss data details in the data section). We create the order book for each timestamp from the snapshot data and calculate vega-weighted (as well as delta-weighted) order imbalance for each of the timestamp and average the five-time stamped vega-weighted (delta-weighted) order imbalance to compute daily vega-weighted (delta-weighted) order imbalance for each strike and same maturity. Details of the computation procedure are described below.

Nifty options are European in style and their maturity is identical to those of Nifty Futures. While computing vega and delta of each strike-maturity point, we use Nifty futures prices, following the modified Black (1976)[3] model to avoid dividend ratio calculation of the Nifty index. The vega[4] and delta[5] are calculated as per the standard Black-Scholes model.

We calculate volatility demand by the vega-weighted order imbalance for each strike-maturity point at any time stamp (*ts*) as,

$$VOI_{K,T}^{ts} = [CVI(K,T) + PVI(K,T)]$$

3. In the modified Black (1976), the d_1 is computed as, $d_1 = \left(\ln(F/K) + \left(\sigma^2/2\right)T\right)/\sigma\sqrt{T}$ where F = Nifty Futures Price, K = Strike price of the option. σ = volatility of the underlying, T = Time to maturity. Following Bollen and Whaley (2004), we use the last sixty days realized volatility (based on square root of sum of five minute squared return for the last sixty calendar days) as volatility proxy to calculate d_1.

4. The vega of both call and put is defined as $v_{c,p} = F\sqrt{T}N'(d_1)$, where F = Nifty Futures price, T = time to maturity.

5. Delta of the call option is defined as $\Delta_c = N(d_1)$ where $d_1 = \left(\ln(F/K) + \left(\sigma^2/2\right)T\right)/\sigma\sqrt{T}$. Similarly, put delta is defined as $\Delta_p = N(d_1) - 1$. $N(d_1)$ and $N'(d_1)$ represent the cumulative density and probability density function of the standard normal variable, respectively.

where $$CVI(K,T)=\left(BO_t^j-SO_t^j\right)\cdot\frac{v_c}{Volume_t}$$

and $$PVI=\left(BO_t^j-SO_t^j\right)\cdot\frac{v_p}{Volume_t}$$

BO_t^j and SO_t^j represent the number of buy and sell contracts outstanding for execution in the order book for each strike-maturity point. We identify buy and sell orders that are standing for execution by the buy-sell indicator in the snapshot data. We take the first hundred best bids and ask orders, ignoring the rest. We scale the difference by the volume ($Volume_t$) of total buy and sell contracts up to the first hundred best orders. Volume represents the number of buy and sell orders for the first hundred best orders. v_c and v_p represent the vega of the call and the put option at each strike-maturity point. *CVI* (*K,T*) represents the volatility demand component for the call option at each strike-maturity point. Similarly, *PVI* (*K,T*) represents the volatility demand component for the put option at each strike-maturity point. $VOI_{K,T}^{ts}$ represents the volatility demand at each strike-maturity point. Each strike-maturity point is classified into a moneyness category defined in table 1. In a particular time-stamp, volatility demand is aggregated for each moneyness category based on the all strike-maturity points belonging to the category. Thus, volatility demand for each moneyness category is obtained for a particular timestamp. The same computational process is repeated for five timestamps (namely, 11:00:00, 12:00:00, 13:00:00, 14:00:00, and 15:00:00). The average of the five timestamps volatility demand of each moneyness category is taken to arrive at the volatility demand of each moneyness category for a particular trading day. We denote volatility demand information for each category as $AVOI_t^{cat}$, where *cat*=01,02,03,04,05 as defined in table 1.

Similarly, we calculate the delta-weighted order imbalance[6] (directional demand information) by a similar computational procedure,

6. Delta-weighted order imbalance for each strike-maturity point is denoted as $DOI_{K.T}^{ts}=COI(K,T)+POI(K,T)$ where $COI(K,T)=\left(BO_t^j-ST_t^j\right)\cdot\left(\Delta_c/Volume_t\right)$ and $POI(K,T)=\left(BO_t^j-SO_t^j\right)\cdot\left(\Delta_p/Volume_t\right)$. Similar to the volatility demand information, average of the five timestamps directional demand of each moneyness category is taken to arrive at the directional demand of each moneyness category for a particular trading day.

the only difference being that order imbalance is weighted by the delta of the option instead of vega. We denote directional demand information for each category as $ADOI_t^{cat}$, where *cat*= 01,02,03,04,05 as defined in table 1. The maturity is taken as near month expiry of Nifty options.

D. Empirical Specifications

Magnitude regression equations

As a preliminary regression, we employ the following empirical specification (equation 2) to estimate daily change of variance risk premium with the contemporaneous volatility demand over the moneyness categories of options. The dependent variable is the signed change rather than the absolute change of the variance risk premium.

$$\begin{aligned}\Delta VRP_t = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log\left(Vol_{Nifty}\right)_t + \gamma_1^{02} ADOI_t^{02} \\ + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} \\ + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 \Delta VRP_t + \varepsilon\end{aligned} \tag{2}$$

The rationale behind estimating equation (2) is to compare and understand whether signed change of variance risk premium contains different information than absolute change of variance risk premium. Absolute change is the dependent variable of equation (3) by which we investigate hypothesis H1.

In hypothesis H1, we investigate whether net volatility demand affects the magnitude change in variance risk premium. We test hypothesis H1 by the following empirical specifications (equation 3), where absolute values of daily changes of variance risk premium are regressed with contemporaneous volatility demand.

$$\begin{aligned}\left|\Delta VRP_t\right| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log\left(Vol_{Nifty}\right)_t + \gamma_1^{02} ADOI_t^{02} \\ + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} \\ + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 \left|\Delta VRP_{t-1}\right| + \varepsilon\end{aligned} \tag{3}$$

Equation (3) specification contains the daily magnitude change of variance risk premium ($|\Delta VRP_t|$) as a dependent variable. The absolute change of variance risk premium is considered as the magnitude change of the variance risk premium. Equation (3) is employed to understand whether it provides more insight about H1. If net volatility demand impacts the change of the magnitude of the variance risk premium, in equation (3), we expect that at least one of the slope coefficients $\left(\delta_1^{02}, \delta_1^{03}, \delta_1^{04}\right)$ of the volatility demand would be statistically significant. We also include different control variables that might affect the relationship between magnitude of the variance risk premium change and net volatility demand.

The explanatory variable consists of volatility demand for different categories of options. We ignore categories 01 and 05 options because of the thin-traded volumes. Category 02 consists of in-the-money call (ITM_{CE}) and out-of-the-money put (OTM_{PE}) options. Relationship between volatility demand at category 02 options and absolute change in variance risk premium depends on whether net demand of ITM_{CE} or OTM_{PE} dominates the impact on the magnitude change of variance risk premium. Similarly, category 03 option consists of at-the-money call (ATM_{CE}) and at-the-money put (ATM_{PE}) options. We expect a positive relationship between the demand of ATM_{CE} and ATM_{PE} options and change in absolute variance risk premium. This is because of the fact that at-the-money options are most sensitive to volatility changes. So, increase in demand of the *ATM* options would have positive impact on implied volatility and, in turn, on magnitude of variance risk premium change. Category 04 option consists of in-the-money put (ITM_{PE}) and out-of-the-money (OTM_{CE}). Relationship between volatility demand at category 04 option and absolute change in variance risk premium depends on whether net demand of ITM_{PE} or OTM_{CE} dominates the impact on magnitude change of variance risk premium. Further, to understand the effect of volatility demand on individual categories of call and put options, different regression equations are estimated with magnitude change of variance risk premium as the dependent variable. The lagged term of dependent variables is kept as a control variable in the regression equations to control for serial correlations.

We estimate the regression equations using the generalized methods of moments (GMM), and report Newey and West (1987) corrected t-statistics with 7 lags. Next, we discuss the set of the chosen control variables.

Control variables for magnitude regression equation

First, we chose Nifty returns as one of the control variables. We expect a negative relationship between the magnitude of variance risk premium change and Nifty returns. This is because negative returns of Nifty increase implied volatility. Previous studies (Giot 2005; Whaley 2009; Badshah 2013; Chakrabarti and Kumar 2017) document that a negative and asymmetric relationship exists between return and implied volatility. Extant literature documents that high volatility is a representative of high risk (Hibbert, Daigler, and Dupoyet, 2008; Badshah 2013) and high volatility coincides with negative market returns (Bakshi and Kapadia 2003). So, in times of negative market movement, variance risk premium should go up.

The next control variable is Nifty traded volume. We include traded volume because both traded volume and volatility influence together by information flow. We expect a positive relationship between Nifty volume and magnitude of variance risk premium. This is because an increase of traded volume of Nifty implies lower volatility (Bessembinder and Seguin 1992), and lower volatility, in turn, lowers the magnitude of variance risk premium. Nifty volume is included after taking logarithm transformation.

The next set of control variables consist of directional demand information of the options i.e. $ADOI_t^{02}, ADOI_t^{03}, ADOI_t^{04}$. Control for directional demand information seems important, following Bollen and Whaley (2004) whoshow that absolute delta-weighted order imbalances impact implied volatility.

Empirical test with sign of change of variance risk premium

In the second hypothesis, H2 of the study, we investigate whether sign of the change of variance risk premium contains information about the expectation of realized volatility innovations, as discussed by Fan, Imerman and Dai (2016) and Ait-Sahalia, Karaman, and Mancini (2015). Following a similar line of argument, we test whether sign of variance risk premium change conveys any information regarding the realized volatility innovations.

$$\Delta RV_t = \alpha_0 + \alpha_1 sign\left(\Delta VRP_t\right) + \varepsilon \tag{4}$$

In the equation (4), ΔRV_t represents the innovation of realized volatility that is measured by the daily change of the realized volatility. The sign (ΔVRP_t) represents the positive or the negative sign of the change of the variance risk premium. We expect α_1 to be positive, because when there is a positive (negative) change in variance risk premium, market expectation in realized volatility change would be higher (lower). Equation (4) is estimated by generalized method of moments (GMM), and reports Newey and West (1987) corrected t-statistics with 30 lags due to overlapping data. The next section describes data and sample of the study.

III. Data and Sample Description

In this section, we provide an overview of the Indian equity market. Then we explain data sources. Lastly we present the summary statistics of variables.

A. Indian derivatives market

Indian equity markets operate on nationwide market access, anonymous electronic trading and a predominantly retail market; all these make the Indian stock market the top-most among emerging markets. The NSE had the largest share of domestic market activity in the financial year 2015-16, with approximately 83% of the traded volumes on equity spot market and almost 100% of the traded volume on equity derivatives. The exchange maintained global leadership position in 2014-15 in the category of stock index options, by number of contracts traded as per the Futures Industry Association Annual Survey. Also, as per the WFE Market Highlights 2015, the NSE figures among the top five stock exchanges globally in different categories of ranking in the derivatives market.

Nifty is used as a benchmark of the Indian stock market by the NSE, which is a free float market capitalization weighted index. It consists of 50 large-cap stocks across 23 sectors of the Indian economy. We used Nifty as the market index in the study. The volatility index, India *VIX*, was introduced by NSE on March 3, 2008, and it indicates the investor's perception of the market's volatility in the near term (thirty calendar days). It is computed 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 Nifty options order book.

B. Data Sources

Sample period of the study ranges from 1 July, 2015 to 31 December, 2015. We have obtained proprietary Nifty options trade data from the NSE. This data provides the details of trade number, symbol, instrument type, expiry date, option type, corporate action level, strike price, trade time, traded price, and traded quantity for each trading day. We have used the data to calculate the number of buy and sell trades over the study period i.e., 01 July, 2015 to 31 Dec, 2015 by the tick test, as mentioned in the methodology section. We obtained snapshot data consisting of order number, symbol, Instrument type, Expiry date, Strike price, Option type, Corporate action level, quantity, Price, Time stamp, Buy/Sell indicator, Day flags, Quantity flags, Price flags, Book type, Minimum fill quantity, Quantity disclosed, and Date for GTD. We use regular book as book type section. These are order book snapshots at 11 am, 12 noon, 1 pm, 2 pm and 3 pm on a trading day. We also obtained minutes data of Nifty from Thomson Reuters DataStream and used it to calculate five-minute squared return to find realized variance of the Nifty index. We also obtained daily Nifty adjusted closing prices, Nifty traded volume, and Nifty Futures prices from the NSE database and risk-free interest data from the EPW time series database, as mentioned in the methodology section.

C. Statistics of variables

Trading activity of Nifty options

Table 2 reports the number of Nifty options traded for the period of 01 July, 2015 to 31 December, 2015.

Trading activity of the Nifty options reveals some important aspects. First, total trading activity on call index options (51.59%) is greater than that of put index options (48.41%). Unlike the developed markets, where trading activity in put index options is greater than the call index options (especially S&P 500 index options), the Indian market has greater trading activity on call options than on put options. Second, moneyness-wise, trading activity on *ATM* call and *ATM* put are the largest compared to the other moneyness categories. Moreover, proportion of trading activity on *ATM* call options (34.36%) is substantially greater than *ATM* put options (30.03%). *OTM* put and *OTM* call are the next largest traded options (*OTM* call contributes

TABLE 2. Summary of the number of Nifty options traded for the period of 1 July, 2015 to 31 December, 2015

Category	Buy Call	Sell Call	Buy Put	Sell Put
Category 01 ($DITM_{CE}$ and $DOTM_{PE}$)	337550	334400	19500	23475
Category 02 (ITM_{CE} and OTM_{PE})	46436025	46523975	1499116125	1543271775
Category 03 (ATM_{CE} and ATM_{PE})	2919770975	3001981825	2544880225	2630805125
Category 04 (OTM_{CE} and ITM_{PE})	1417336475	1457551150	61255950	63846525
Category 05 ($DOTM_{CE}$ and $DITM_{PE}$)	18000	22725	44100	36425
Total	4383899025	4506414075	4105315900	4237983325

(Continued)

TABLE 2. (Continued)

Category	Call Contracts		Put Contracts		Call	Put
	No. of contracts	Proportion of contracts	No. of contracts	Proportion of contracts	Net purchase of contracts	Net purchase of contracts
Category 01 ($DITM_{CE}$ and $DOTM_{PE}$)	671950	0.000039	42975	0.000002	3150	–3975
Category 02 (ITM_{CE} and OTM_{PE})	92960000	0.005394	3042387900	0.176538	–87950	–44155650
Category 03 (ATM_{CE} and ATM_{PE})	5921752800	0.343617	5175685350	0.300325	–82210850	–85924900
Category 04 (OTM_{CE} and ITM_{PE})	2874887625	0.166819	125102475	0.007259	–40214675	–2590575
Category 05 ($DOTM_{CE}$ and $DITM_{PE}$)	40725	0.000002	80525	0.000005	–4725	7675
Total	8890313100	0.5159	8343299225	0.4841	–122515050	–132667425

Note: This table summarizes the total number of call purchase, total number of put purchase across categories classified by moneyness of the options. It also presents the net purchase of call and put options across categories. Categories are defined in table 1.

TABLE 3. Table reports summary statistics of all the variables

A. Descriptives

	VRP_t	ΔVRP_t	$\lvert\Delta VRP_t\rvert$	$MFIV_t$	RV_t	$RNiFty_t$
Mean	0.00084*	–0.00001	0.00027***	0.00272***	0.00187***	–0.05123
(t-statistics)	(1.85)	(–0.25)	(3.44)	(7.37)	(4.53)	(–0.55)
Median	0.00117	–0.00004	0.00015	0.00228	0.00146	–0.00995
Maximum	0.00407	0.00305	0.00305	0.00708	0.00482	2.26230
Minimum	–0.00284	–0.00186	0.0000004	0.00143	0.00070	–4.49811
Std. Dev.	0.00162	0.00053	0.00045	0.00115	0.00118	0.82708
Skewness	–0.73731	2.8821	4.4434	1.7141	1.3456	–1.2231
Kurtosis	3.0436	20.983	25.663	5.3637	3.5592	8.8271
Jarque-Bera (p-value)	11.063***	1798***	2987***	88.147***	38.411***	203.029***
	(0.0039)	(0)	(0)	(0)	(0)	(0)
ADF (p-value)	0.082*	0.000***	0.000***	0.396	0.548	0.000***
# Observations	122	121	121	122	122	122

B. Correlations

VRP_t	1.0000					
ΔVRP_t	0.1724*	1.0000				
$\lvert\Delta VRP\rvert_t$	0.2177**	0.4680***	1.0000			
$MFIV_t$	0.6815***	0.3180***	0.5188***	1.0000		
RV_t	–0.7054***	0.0723	0.2051**	0.0379	1.0000	
$RNifty_t$	0.0067	–0.5394***	–0.4449***	0.1734*	–0.177*	1.0000

(*Continued*)

TABLE 3. (Continued)

C. Autocorrelation functions

Lag	VRP_t	ΔVRP_t	$\lvert\Delta VRP_t\rvert$	$MFIV_t$	RV_t	$RNifty_t$
1	0.944**	0.297**	0.477**	0.923**	0.975**	0.343**
2	0.857**	–0.156	0.235**	0.806**	0.941**	0.019
3	0.786**	–0.126	0.056	0.739**	0.902**	–0.055
4	0.727**	–0.052	0.013	0.710**	0.859**	–0.105
5	0.674**	0.093	0.124	0.688**	0.809**	–0.087

Note: Panel A is the descriptive statistics of monthly variance risk premium (VRP_t), daily change of variance risk premium (ΔVRP_t), daily magnitude change of variance risk premium ($\lvert\Delta VRP_t\rvert$), realized variance (RV_t) (monthly), Model free implied variance ($MFIV_t$) (monthly), and daily return of Nifty ($RNifty_t$) for the period 01 July, 2015 to 31 December, 2015. Above we report in parentheses the t-statistics on the significance of mean of VRP, $MFIV$, RV and $RNifty_t$, adjusted for serial dependence by Newey-West method with 30 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% level respectively.

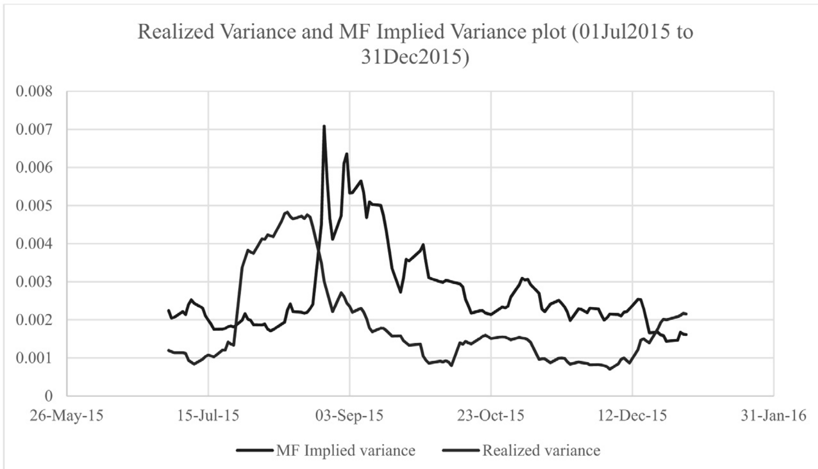

FIGURE 1.— Realized variance and *MFIV* plot (01Jul2015 to 31Dec2015)

16.68% and *OTM* put contributes 17.65%). *ITM* call and *ITM* put come next as contributors to the trading activity. However, percentage-wise their contribution is much less (*ITM* call 0.53% and *ITM* put 0.72%). Third, interestingly, the net purchase shows that the market is a net seller of options across all categories except *DITM* put and *DITM* call. But the proportion of *DITM* put and *DITM* call are negligible. For that matter, the proportion of trading activity proportion in category01 and category05 is negligible. Therefore, we ignore category01 and category05 for all empirical tests.

Variance risk premium

We calculate *VRP* by equation (1) i.e. $VRP_t = IVIX_t^2 - RV_{t,t+30}^2$. We take risk neutral variance by squared India *VIX* (transforming into its one month variance term), which is calculated by the *MFIV* framework, as proxy. We calculate ex-post realized variance by the sum of five-minute squared returns over thirty calendar days. The NSE disseminates India *VIX* in terms of annualized volatility. We square India *VIX* and divide it by 12 to transform it into monthly variance. Below is the summary statistics of $VRP_t, \Delta VRP_t, |\Delta VRP|_t, MFIV_t$ and RV_t, along with Nifty returns $(RNifty_t)$.

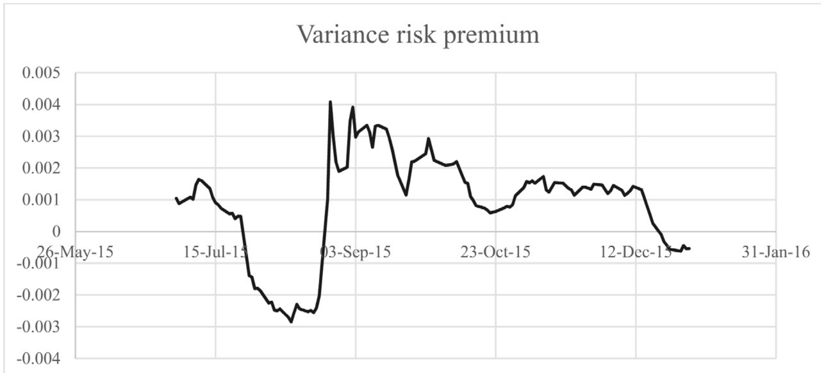

FIGURE 2.— Variance Risk Premium (*VRP*) plot (01Jul2015 to 31Dec2015)

Panel A shows that the mean of the variance risk premium is significantly greater than zero; so are $MFIV_t$ and RV_t. Thus, variance risk premium exists in Indian options and this result is consistent with Garg and Vipul (2015). Further, mean of magnitude change of variance risk premium $(|\Delta VRP_t|)$ is significantly greater than zero, which is not the case for change of variance risk premium (ΔVRP_t). The standard deviation of $|\Delta VRP_t|$ is less than ΔVRP_t. This shows that the magnitude of variance risk premium change is less volatile than signed variance risk premium change. VRP_t $\Delta VRP_t, |\Delta VRP_t|, RNifty_t$ series are significant after removing trend and intercept component from them. This shows that these series are trend and intercept stationary. Panel B shows the correlations among the variables. VRP_t and RV_t have strong negative correlations. On the other hand, VRP_t and $MFIV_t$ have strong positive correlations. But $MFIV_t$ and RV_t do not show significant statistical correlations. Autocorrelation functions of VRP_t, $MFIV_t$ and RV_t show that these series are strongly correlated, and all the reported five lags are significant. We observe that VRP_t maintains autocorrelations up to thirty lags though we do not report the autocorrelation coefficients of VRP_t, $MFIV_t$ and RV_t series here for brevity. ΔVRP_t does not show autocorrelation for more than one lag. Similarly, $|\Delta VRP_t|$ does not show autocorrelation for more than two lags.

Figure 1 shows the realized variance and *MFIV* plot for the period 1 July, 2015 to 31 December, 2015. It is observed that *MFIV* is consistently higher up to mid-July, and after the month of August i.e., from the starting of September, 2015.

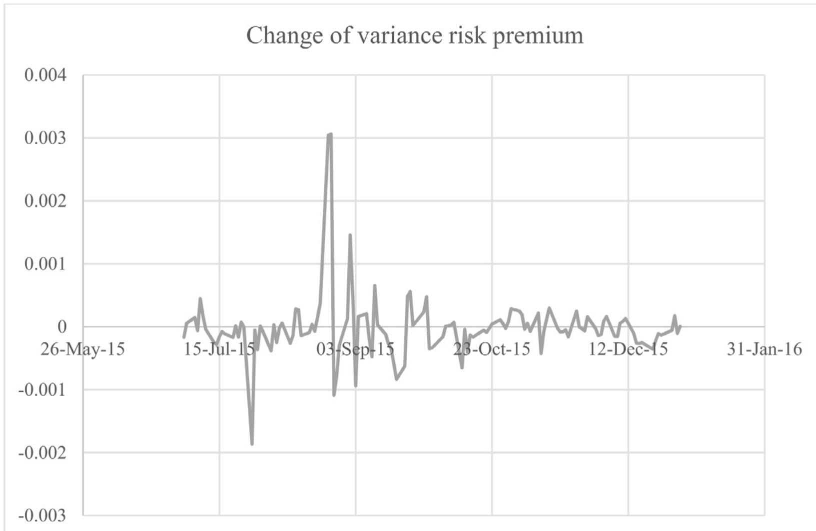

FIGURE 3.— Change of variance risk premium (01Jul2015 to 31Dec2015)

One reason why *MFIV* is less than *RV*, especially during the month of August 2015, could be because of the distress in the market due to the China slowdown that affected the Indian market significantly. We plot the *VRP* (variance risk premium) dynamics for the period 1 July, 2015 to 31 December, 2015 in figure 2. We observe that *VRP* is less than zero during mid-July to August, 2015. This may be due to the reason stated above. Previous studies of Bollerslev, Tauchen and Zhou (2009), Bollerslev, Gibson and Zhou(2011), and Bekaert and Hoerova (2014) relate the variance risk premium with the market-wide risk aversion. Economic intuition is straight forward in case of positive variance risk premium. But what is puzzling is the economic intuition of negative variance risk premium. Fan, Imerman and Dai (2016) argue that the sign of negative volatility risk premium can be related to the delta-hedged gains or losses of volatility short portfolios.

We plot the change of variance risk premium and magnitude change of variance risk premium in figures 3 and 4, respectively.

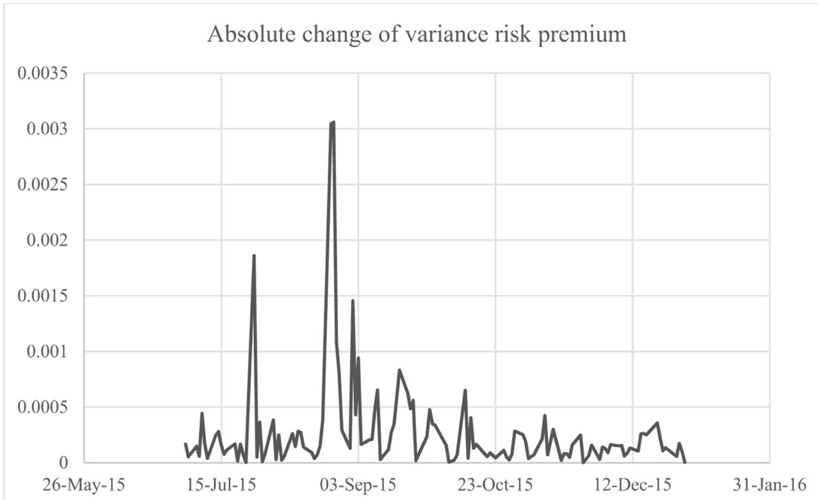

FIGURE 4.— Change of absolute variance risk premium (01Jul2015 to 31Dec2015)

Summary statistics of main variables

Table 4, Panel A represents the correlations among main variables. Here, $ADOI_t^{02}, ADOI_t^{03}$, and $ADOI_t^{04}$ represent the aggregated directional deamnd and $AVOI_t^{02}, AVOI_t^{03}$, and $AVOI_t^{04}$ represent aggregated volatility demand for category 02 (*ITM* call and *OTM* put), category 03 (*ATM* call and *ATM* put), category 04 (*OTM* call and *ITM* put), respectively. We observe that both ΔVRP_t and $|\Delta VRP_t|$ maintain significant negative correlations with Nifty return $(RNifty_t)$. $AVOI_t^{04}$ has negative correlation with $RNifty_t$. Further, $AVOI_t^{04}$ has negative correlation with $|\Delta VRP_t|$. Similarly, $AVOI_t^{03}$ maintains positive correlation with $RNifty_t$ and $|\Delta VRP_t|$. However, these correlations are not statistically significant. Further analysis on correlations for individual call and put option categories are shown in Panel D. Here, we segregate the aggregated demand of each category (02, 03, and 04) into volatility demand components for call and put options. Category 02 consists of ITM_{CE} and OTM_{PE}. Here, $VDOTM_{CEt}$, $VDATM_{CEt}$, and $VDITM_{CEt}$ represent volatility demand for *OTM* call, *ATM* call, and *ITM* call options, and $VDOTM_{PEt}$, $VDATM_{PEt}$, and $VDITM_{PEt}$ represent volatility demand for *OTM* put, *ATM* put, and *ITM* put options,

TABLE 4. Correlations, Autocorrelation function and summary statistics of the variables

A. Correlations

	ΔVRP_t	$\|\Delta VRP_t\|$	$RNifty_t$	$\log(Vol_{Nifty})_t$	$ADOI_t^{02}$	$ADOI_t^{03}$	$ADOI_t^{04}$	$AVOI_t^{02}$	$AVOI_t^{03}$	$AVOI_t^{04}$
ΔVRP_t	1.0000									
$\|\Delta VRP\|_t$	0.4680***	1.0000								
$RNifty_t$	–0.5394***	–0.4449***	1.0000							
$\log(Vol_{Nifty})_t$	0.2956***	0.4212***	–0.1883**	1.0000						
$ADOI_t^{02}$	–0.0800	–0.0875	0.1488	–0.0546	1.0000					
$ADOI_t^{03}$	0.0752	0.0888	–0.2336***	0.1067	0.3790***	1.0000				
$ADOI_t^{04}$	–0.0963	0.0125	0.1549*	–0.1286	0.0827	–0.0382	1.0000			
$AVOI_t^{02}$	–0.0818	–0.0368	0.1438	–0.0247	0.3709***	–0.0201	–0.0046	1.0000		
$AVOI_t^{03}$	0.1338	0.1440	0.0491	0.1912**	–0.3247***	–0.2188**	–0.1059	–0.0070	1.0000	
$AVOI_t^{04}$	0.0517	–0.0569	–0.0903***	0.0901	–0.0595	0.0258	–0.0751	0.1493*	0.3218***	1.0000

B. Autocorrelation function

Lag	$\log(Vol_{Nifty})_t$	$ADOI_t^{02}$	$ADOI_t^{03}$	$ADOI_t^{04}$	$AVOI_t^{02}$	$AVOI_t^{03}$	$AVOI_t^{04}$
1	0.512**	0.062	0.102	0.384**	0.236**	0.253**	0.416**
2	0.432**	–0.018	–0.086	0.137	–0.055	0.129	0.410**
3	0.245**	0.065	0.095	0.339**	–0.034	0.135	0.276**
4	0.193**	–0.063	0.062	0.181**	–0.096	0.047	0.181**
5	0.166**	–0.061	–0.046	0.029	–0.065	0.054	0.134

(*Continued*)

TABLE 4. (Continued)

C. Descriptive statistics of the main variables

Statistics	$\log(Vol_{Nifty})_t$	$ADOI_t^{02}$	$ADOI_t^{03}$	$ADOI_t^{04}$	$AVOI_t^{02}$	$AVOI_t^{03}$	$AVOI_t^{04}$
Mean	18.884***	0.0141**	–0.0045	–0.0709***	9.3939*	36.978***	31.924***
(t-stat)	(476.79)	(2.04)	(–1.46)	(–5.01)	(1.85)	(5.98)	(5.28)
Median	18.860	0.0159	–0.0038	–0.0383	7.1742	33.181	24.131
Maximum	19.590	0.5172	0.1940	0.1312	166.33	183.35	131.06
Minimum	18.327	–0.4598	–0.0998	–0.4143	–362.80	–284.46	–202.05
Std. Dev.	0.2410	0.0780	0.0336	0.0960	54.805	49.566	38.205
Skewness	0.3973	–0.1881	1.3528	–1.6483	–3.1185	–1.7445	–1.3330
Kurtosis	3.3156	27.785	11.942	5.6100	22.056	17.112	13.709
Jarque-Bera	3.7168	3123***	443.68***	89.876***	2043***	1074***	619.10***
(p-value)	(0.1559)	(0)	(0)	(0)	(0)	(0)	(0)
ADF (p-value)	0.6947	0.0000***	0.0000***	0.0133**	0.0000***	0.0014***	0.0033***
#obs	122	122	122	122	122	122	122

(*Continued*)

TABLE 4. (Continued)

D. Correlations of volatility demands for individual options category

	ΔVRP_t	$\lvert\Delta VRP_t\rvert$	$RNifty_t$	$\log(Vol_{Nifty})_t$	$VDOTM_{CE_t}$	$VDATM_{CE_t}$	$VDITM_{CE_t}$	$VDOTM_{PE_t}$	$VDATM_{PE_t}$	$VDITM_{PE_t}$
ΔVRP_t	1.0000									
$\lvert\Delta VRP_t\rvert$	0.4680***	1.0000								
$RNifty_t$	–0.5394***	–0.4449***	1.0000							
$\log(Vol_{Nifty})_t$	0.2956***	0.4212***	–0.1883**	1.0000						
$VDOTM_{CE_t}$	0.0863	0.0544	–0.0775	0.1021	1.0000					
$VDATM_{CE_t}$	0.2020**	0.2175***	–0.2043**	0.2788***	0.2393***	1.0000				
$VDITM_{CE_t}$	–0.0712	–0.1061	0.1747*	–0.0314	–0.0286	0.1021	1.0000			
$VDOTM_{PE_t}$	–0.0429	0.0378	0.0374	–0.0046	0.1509*	–0.0930	–0.0975	1.0000		
$VDATM_{PE_t}$	0.0173	0.0183	0.2107**	0.0208	0.1244	–0.0907	–0.3690***	0.2868***	1.0000	
$VDITM_{PE_t}$	–0.0455	–0.2550***	–0.0658	0.0132	0.1293	0.1881**	0.0456	0.1371	0.1650*	1.0000

(*Continued*)

TABLE 4. (Continued)

E. Descriptive statistics of volatility demands for individual options category

Statistics	$VDOTM_{CE}$	$VDATM_{CE}$	$VDITM_{CE}$	$VDOTM_{PE}$	$VDATM_{PE}$	$VDITM_{PE}$
Mean	21.231***	14.413***	3.3776	6.0582*	22.585***	10.802***
(t-stat)	(4.76)	(4.06)	(1.09)	(1.73)	(4.60)	(4.39)
Median	14.861	12.065	2.7762	4.5038	18.174	7.5438
Maximum	135.62	135.06	229.56	108.40	140.57	56.287
Minimum	–202.00	–88.351	–275.20	–323.00	–307.92	–41.517
Std. Dev.	33.173	30.341	35.219	45.604	41.224	15.136
Skewness	–1.7463	0.5307	–1.9916	–3.7122	–3.7589	–0.1411
Kurtosis	20.012	6.1504	47.023	26.938	35.851	5.0560
Jarque-Bera (p-value)	1533***	56.181***	9932***	3193***	5773***	21.894***
	(0)	(0)	(0)	(0)	(0)	(0.000018)
ADF (p-value)	0.0001***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
#obs	122	122	122	122	122	122

Note: We report in parentheses the t-statistics on the significance of mean adjusted for serial dependence by Newey-West method with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% level respectively.

respectively. We observe that volatility demand of *ITM* put $(VDITM_{PEt})$ maintains negative correlations with $\Delta VRP_t, |\Delta VRP_t|$, and $RNifty_t$. Further, the negative correlation is statistically significant for $|\Delta VRP_t|$. On the other hand, $VDOTM_{CEt}$ shows positive correlation with $|\Delta VRP_t|$, and it is not statistically significant and lower in terms of absolute value. So, we assume that increase in volatility demand of $VDITM_{PEt}$ decreases the absolute change of variance risk premium; in turn, category 04 options negatively impacts $|\Delta VRP_t|$. Both $VDATM_{CEt}$ and $VDATM_{PEt}$ maintain positive correlation with $|\Delta VRP_t|$, therefore, we assume *ATM* options (category 03) impacts $|\Delta VRP_t|$ positively, i.e., increase in volatility demand of *ATM* options increases $|\Delta VRP_t|$. Category 02 options ($VDOTM_{PEt}$, $VDITM_{CEt}$) show opposite correlations with $|\Delta VRP_t|$ and none of them is statistically significant.

Panel B shows autocorrelation function of the main variables. We observe $\log(Vol_{Nifty})_t$ has significant autocorrelations up to seven lags. We do not report the coefficients up to ten lags due to brevity. Therefore, we choose Newey-West t-statistics with seven lags.

Panel C and Panel E shows summary statistics of the variables. Mean of all the aggregated volatility demand components, $AVOI_t^{02}, AVOI_t^{03}$, and $AVOI_t^{04}$ are significantly positive. In case of individual options, the volatility demand of the mean of all the put option is significantly positive, whereas mean of volatility demand at *OTM* and *ATM* call options is significantly positive. All these variables (aggregated and individual volatility demand) are stationary.[7] Next, we discuss the pattern of the implied volatility skew for the period of study.

Implied volatility skew

We compute the Black-Scholes implied volatility skew of the options for the period 1 July, 2015 to 31 December, 2015. We observe that volatility skew of Nifty options form a forward skew.

The volatility skew pattern shows that *OTM* call options and *ITM* put options are expensive. Further, we observe that *ITM* put options are even more expensive than the *OTM* call options.

7. Note that trading volume is not stationary. We do not detrend volume following Lo and Wang (2000). They fail to detrend the volume without adequately removing serial correlation. Therefore, the paper advises to take shorter interval when analyzing trading volume (typically 5 years). Our study period interval is only 6 months.

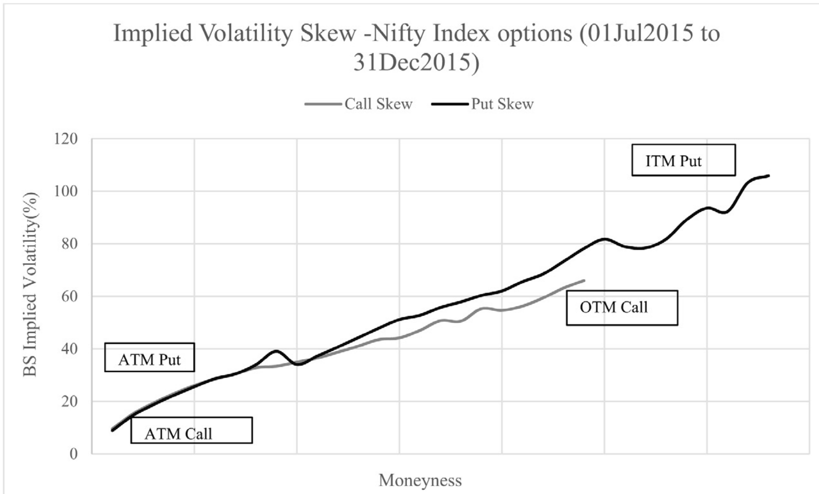

FIGURE 5.— Implied volatility skew of Nifty options

IV. Empirical results

In the empirical test section, we start with equation (2), where we regress change of variance risk premium with the set of independent variables and control variables, as mentioned in the equation specification.

A. Empirical results (change of variance risk premium)

Table 5 reports the result of equation (2). Results show that aggregate delta order imbalances $\left(ADOI_t^{02}, ADOI_t^{03}, ADOI_t^{04}\right)$ do not have any statistical significance on the changes of variance risk premium for Models (2) and (3). Further, aggregate volatility demands $\left(AVOI_t^{02}, AVOI_t^{03}, AVOI_t^{04}\right)$ do not show any statistical significance in Model (4) except in Model (2), where $AVOI_t^{02}$ impacts change of variance risk premium negatively. Adj R^2 of the models show that Model (1) best explains the relationship, followed by Model (4). For all the models, coefficients of aggregate delta order imbalance and aggregate vega order imbalance maintain consistency in their signs. We observe that coefficient of $ADOI_t^{04}$ have negative signs for all the models. Similarly, coefficients of $ADOI_t^{03}$ have positive signs and

TABLE 5. Results of equation (2)

Variable	(1)	(2)	(3)	(4)
Intercept	–0.00719*	–0.0063*	–0.00718*	–0.00644*
	(–1.96)	(–1.84)	(–1.90)	(–1.91)
$RNifty_t$	–0.00031***	–0.00033***	–0.00032***	–0.00031**
	(–2.91)	(–2.66)	(–2.88)	(–2.61)
$\log(Vol_{Nifty})_t$	0.00037*	0.00032*	0.000377*	0.00033*
	(1.95)	(1.82)	(1.89)	(1.90)
$ADOI_t^{02}$		0.00093	0.00043	
		(1.49)	(0.85)	
$ADOI_t^{03}$		–0.00135	–0.00133	
		(–1.66)	(–1.38)	
$ADOI_t^{04}$		–0.00018	–0.00019	
		(–0.48)	(–0.53)	
$AVOI_t^{02}(\times 10^{-6})$		–0.861*		–0.345
		(–1.70)		(–0.51)
$AVOI_t^{03}$ $(\times 10^{-6})$		1.347		1.166
		(0.96)		(0.99)
$AVOI_t^{04}(\times 10^{-6})$		–0.489		–0.580
		(–0.30)		(–0.36)
ΔVRP_{t-1}	0.2026**	0.2228**	0.2179**	0.1941**
	(2.30)	(2.62)	(2.59)	(2.16)
Adj R^2	0.3549	0.3465	0.3451	0.3506
#Obs	120	120	120	120

Note: $\Delta VRP_t = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + \gamma_1^{02} ADOI_t^{02} + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 \Delta VRP_t + \varepsilon$. Models (1), (2), (3), and (4) are the GMM estimates of the variables shown in the table. t-statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively.

coefficients of $ADOI_t^{02}$ have negative signs. Coefficients of ΔVRP_{t-1} have positive signs for all the models. We test whether equation (3) with magnitude of absolute change of variance risk premium as dependent variable can provide us better insights about the relationship. The results of equation (3) are reported in table 6.

B. Empirical results (magnitude of variance risk premium change)

Table 6 shows the result of equation (3). The magnitude regression improves Adj R^2 for all the models. In the magnitude regression, Model (4) best explains the relationship among all the other models.

We observe that *Intercept*, $RNifty_t$, and $\log(Vol_{Nifty})_t$ do not change their signs with absolute value change of variance risk premium. In

TABLE 6. Results of equation (3)

Variable	(1)	(2)	(3)	(4)
Intercept	–0.00766**	–0.00751**	–0.00787**	–0.00729**
	(–2.11)	(–2.11)	(–2.11)	(–2.09)
$RNifty_t$	–0.00021**	–0.00024**	–0.00022**	–0.00022**
	(–2.27)	(–2.32)	(–2.15)	(–2.41)
$\log(Vol_{Nifty})_t$	0.00041**	0.00040**	0.00042**	0.00039**
	(2.15)	(2.15)	(2.15)	(2.13)
$ADOI_t^{02}$		0.00027	0.00016	
		(0.78)	(0.46)	
$ADOI_t^{03}$		–0.00079	–0.0010	
		(–0.81)	(–0.96)	
$ADOI_t^{04}$		0.00021	0.00018	
		(0.68)	(0.57)	
$AVOI_t^{02}(\times 10^{-6})$		0.142		0.261
		(0.32)		(0.50)
$AVOI_t^{03}(\times 10^{-6})$		1.184*		1.131*
		(1.76)		(1.85)
$AVOI_t^{04}(\times 10^{-6})$		–1.93		–1.99
		(–1.53)		(–1.54)
$\lvert\Delta VRP_{t-1}\rvert$	0.3710***	0.3599***	0.3749***	0.3598***
	(2.83)	(2.95)	(2.83)	
Adj R^2	0.4241	0.4290	0.4154	0.4391
#Obs	120	120	120	120

Note: $|\Delta VRP_t| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + \gamma_1^{02} ADOI_t^{02} + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 |\Delta VRP_{t-1}| + \varepsilon$. Models (1), (2), (3), and (4) are the GMM estimates of the variables shown in the table. t-statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively.

equation (10), $ADOI_t^{04}$ and $AVOI_t^{02}$ reverse their signs. Everything else maintains consistency in terms of their signs. For Model (2) and Model (4), volatility demand of *ATM* options remains statistically significant. Further, this volatility demand positively impacts the magnitude change of variance risk premium. The reason could be that *ATM* options are most sensitive to volatility change. Therefore, market participants with volatility information would prefer to trade in *ATM* options. Moreover, in table 1, we see that *ATM* options are the most traded options in the list of all the categories. For all the categories of options, it is seen that delta order imbalances do not have any impact on change of variance risk premium, which is as per our expectation.

Coefficients of nifty returns ($RNifty_t$) by both equations (2) and (3), for all the models, are consistently negative. That is as per our expectation and consistent with the previous studies of Giot (2005), Whaley (2009), Badshah (2013), and Chakrabarti and Kumar (2017), which state that negative returns increase the implied volatility and that high volatility is a representative of high risk (Hibbert, Daigler and Dupoyet (2008); Badshah 2013). Increase in implied volatility, in turn, increases variance risk premium; thus, Nifty returns have negative impact on change as well as on the magnitude change of variance risk premium.

Coefficients of logarithm volume are positive for equations (2) and (3), for all the models as per expectation. This is because higher trading volume implies lower volatility (Bessembinder and Seguin, 1992) and lower volatility, in turn, lowers the magnitude of variance risk premium.

Table 6 shows that volatility demand of *ATM* options has significant positive impact on the magnitude of variance risk premium change. Comparison between table 5 and table 6 reveal that volatility demand information of *ATM* options does indeed contain information of absolute change; however, it but does not contain any significant information about the signed change of variance risk premium. From the analysis of table 5 and table 6, it is evident that equation (3) better describes the relationship between magnitude of variance risk premium and volatility demand of options. It is apparent that the sign of the variance risk premium change introduces additional noise, which makes the explanation difficult. With the magnitude of variance risk premium change as dependent variable, the statistical clarity of the data increases. We further regress magnitude of variance risk premium change with the volatility demand of individual call and put options.

TABLE 7. Results of equation (4)

Variable	(1)
Intercept	0.000052*
	(1.74)
ΔRV_t	0.000029*
	(1.82)
Adj R^2	0.0161
#Obs	120

Note: $\Delta RV_t = \alpha_0 + \alpha_1\, sign(\Delta VRP_t) + \varepsilon$. Model (1) is the GMM estimates of the variables s`hown in table. t-statistics are computed according to Newey and West (1987) with 30 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively.

C. Empirical results (Sign test)

We test hypothesis 2 by equation (4) and report the result in table 7. According to the hypothesis, sign of variance risk premium change should indicate expectation about the change of realized volatility. We expect a positive coefficient of $sign(\Delta VRP_t)$, because if the hypothesis holds true, a positive (negative) sign should indicate increase (decrease) in realized volatility. Results of table 8 shows that coefficient of $sign(\Delta VRP_t)$ is positive and statistically significant at the 10% level. This result confirms hypothesis 2 and is consistent with the evidence of Fan, Imerman and Dai (2016).

D. Further investigations

Further investigation is conducted to understand how the volatility demand of call and put options of various moneyness (*OTM*, *ATM*, and *ITM*) is affecting the magnitude of the change of the variance risk premium. The following empirical equation (5) is specified to estimate the impact.

$$\begin{aligned} |\Delta VRP_t| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log\left(Vol_{Nifty}\right)_t + C_{OTM} VDOTM_{CE_t} \\ + C_{ATM} VDATM_{CE_t} + C_{ITM} VDITM_{CE_t} \\ + P_{OTM} VDOTM_{PE_t} + P_{ATM} VDATM_{PE_t} \\ + P_{ITM} VDITM_{PE_t} + \theta_1 |\Delta VRP_{t-1}| + \varepsilon \end{aligned} \tag{5}$$

TABLE 8. Results of equation (5)

Variable	(1)
Intercept	–0.00762**
	(–2.22)
$RNifty_t$	–0.00024**
	(–2.41)
$\log(Vol_{Nifty})_t$	0.00041**
	(2.15)
$VDOTM_{CE_t}(\times 10^{-6})$	–0.869
	(–0.85)
$VDATM_{CE_t}(\times 10^{-6})$	0.834
	(0.94)
$VDITM_{CE_t}(\times 10^{-6})$	0.791
	(0.75)
$VDOTM_{PE_t}(\times 10^{-6})$	0.274
	(0.79)
$VDATM_{PE_t}(\times 10^{-6})$	1.81*
	(1.81)
$VDITM_{PE_t}(\times 10^{-6})$	–6.74***
	(–2.92)
$\lvert\Delta VRP_{t-1}\rvert$	0.3034***
	(2.66)
Adj R^2	0.4489
#Obs	120

Note: $|\Delta VRP_t| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + C_{OTM}\, VDOTM_{CE_t} + C_{ATM}\, VDATM_{CE_t} + C_{ITM}\, VDITM_{CE_t} + P_{OTM}\, VDOTM_{PE_t} + P_{ATM}\, VDATM_{PE_t} + P_{ITM} VDITM_{PE_t} + \theta_1 |\Delta VRP_{t-1}| + \varepsilon$. Model (1) is the GMM estimates of the variables shown in the Table. t-statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively.

$VDOTM_{CEt}$, $VDATM_{CEt}$, and $VDITM_{CEt}$ represent the volatility demand of *OTM*, *ATM*, and *ITM* call options, respectively. Similarly, $VDOTM_{PEt}$, $VDATM_{PEt}$, and $VDITM_{PEt}$ represent the volatility demand of *OTM*, *ATM*, and *ITM* put options, respectively. We report the results of the regression in table 8. Results show that Adj R^2 of the model increases with volatility demand components of call and put options. Further, we observe that while volatility demand at *ATM* and *ITM* put options is statistically significant it is insignificant for call options. Volatility demand of *ATM* put options has a positive impact whereas, *ITM* put options have negative impact on the magnitude of variance risk premium change. The sign of the impact is evident from the correlation analysis in table 4, where volatility demand at *ITM* put options maintains negative correlation while *ATM* put options maintain a positive correlation with magnitude of variance risk premium change. Another support for the evidence is the volatility skew pattern for the period of study. *ATM* and *ITM* put options are expensive relative to other put options. So volatility trading activity at *ATM* and *ITM* put options may have an impact on the magnitude of variance risk premium.

V. Robustness tests

We conduct series of robustness tests of the results. In the first robustness test, we compute the order imbalance as value of the orders, i.e., quantity is multiplied by the price. In equations (3) and (4), the order imbalance is simply computed as the difference between the numbers of buy and sell orders of the first hundred best orders standing in the order-book for execution. In the robustness test, the order imbalance is computed as the value of the buy and sell orders of the first hundred best orders standing in the order-book for execution. We estimate equation (4) in the robustness test considering order imbalance in terms of value (i.e. price*quantity). The result is reported in table 9.

Further, in the second robustness test, empirical investigation considers daily change of volatility risk premium (*vrp*) instead of daily change of variance risk premium (*VRP*), as the dependent variable. Volatility is the nonlinear monotone transform of variance. For the robustness of results, we specify daily signed change and daily absolute change of volatility risk premium as the dependent variables. We define volatility risk premium as, $vrp_t = IVIX_t - RV_{t,t+30}$, where realized volatility is calculated by the square root of sum of five-minute squared returns over thirty calendar days. Risk-neutral volatility is calculated by the India *VIX* value and appropriately transforming the model-free implied volatility into thirty calendar day volatility, since India *VIX* is disseminated in annualized terms.

The regression equations specified for the tests are given below.

$$\begin{aligned}\Delta vrp_t = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log\left(Vol_{Nifty}\right)_t + \gamma_1^{02} ADOI_t^{02} \\ + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} \\ + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 \Delta vrp_t + \varepsilon\end{aligned} \qquad (6)$$

TABLE 9. Table shows the results of equation (3) where order imbalance is computed by value (price*quantity)

Variable	(1)	(2)	(3)	(4)
Intercept	–0.0076**	–0.00746**	–0.00731**	–0.00777**
	(–2.11)	(–2.15)	(–2.11)	(–2.09)
$RNifty_t$	–0.00021**	–0.00022**	–0.00022**	–0.00022**
	(–2.27)	(–2.36)	(–2.33)	(–2.37)
$\log(Vol_{Nifty})_t$	0.00041**	0.00040**	0.00039**	0.00042**
	(2.15)	(2.20)	(2.15)	(2.14)
$ADOI_t^{02}$		0.000007	0.000075	
		(0.03)	(0.38)	
$ADOI_t^{03}$		–0.00059	–0.0009	
		(–0.97)	(–1.46)	
$ADOI_t^{04}$		0.000019	0.000032	
		(0.20)	(0.29)	
$AVOI_t^{02}(\times 10^{-6})$		0.584		0.581
		(0.95)		(1.25)
$AVOI_t^{03}$ $(\times 10^{-6})$		0.809		0.925**
		(1.53)		(2.44)
$AVOI_t^{04}$ $(\times 10^{-6})$		–1.97*		–2.11**
		(–2.21)		(–2.05)
$\Delta VRP_{(t-1)}$	0.3710***	0.3333**	0.3720***	0.3292***
	(2.83)	(2.62)	(2.83)	(2.65)
Adj R^2	0.4241	0.4242	0.4186	0.4357
#Obs	120	120	120	120

Note: $|\Delta VRP_t| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + \gamma_1^{02} ADOI_t^{02} + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 |\Delta VRP_{(t-1)}| + \varepsilon$. Models (1), (2), (3), and (4) are the GMM estimates of the variables shown in the table. t–statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively. Here we calculate order imbalance by value (price*quantity).

Equation (5) examines the impact of volatility demand on the daily signed change of the volatility risk premium (Δvrp_t). In order to understand whether absolute change of volatility risk premium ($|\Delta vrp_t|$) contains information different than the signed change of volatility risk premium (Δvrp_t), we estimate equation (6). These specifications are the same as equations (2) and (4), where the dependent variable is (absolute) change of variance risk premium instead of volatility risk premium.

TABLE 10. Table shows the results of equation (6)

Variable	(1)	(2)	(3)	(4)
Intercept	–0.04996	–0.03114	–0.04255	–0.04063
	(–1.55)	(–1.11)	(–1.35)	(–1.32)
$RNifty_t$	–0.00201***	–0.00216***	–0.0021***	–0.00201**
	(–3.00)	(–2.93)	(–3.21)	(–2.53)
$\log(Vol_{Nifty})_t$	0.00263	0.00161	0.00223	0.00213
	(1.54)	(1.08)	(1.33)	(1.31)
$ADOI_t^{02}$		–0.0018	–0.00156	
		(–0.49)	(–0.52)	
$ADOI_t^{03}$		–0.00642	–0.00667	
		(–1.06)	(–1.34)	
$ADOI_t^{04}$		–0.00131	–0.00081	
		(–0.99)	(–0.59)	
$AVOI_t^{02}(\times 10^{-6})$		1.44		–2.14
		(0.15)		(–0.35)
$AVOI_t^{03}\ (\times 10^{-6})$		–2.5		0.0956
		(–0.42)		(0.03)
$AVOI_t^{04}(\times 10^{-6})$		–20		–20
		(–1.38)		(–1.06)
$\Delta VolatilityRP_{t-1}$	0.2381***	0.2034**	0.2335***	0.21386**
	(2.85)	(2.42)	(2.76)	(2.60)
Adj R^2	0.2851	0.2843	0.2857	0.2819
#Obs	120	120	120	120

Note: $\Delta vrp_t = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + \gamma_1^{02} ADOI_t^{02} + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 \Delta vrp_t + \varepsilon$. Models (1), (2), (3), and (4) are the GMM estimates of the variables shown in the table. t-statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively. We calculate order imbalance by value (price*quantity).

$$|\Delta vrp_t| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log\left(Vol_{Nifty}\right)_t + \gamma_1^{02} ADOI_t^{02} + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 |\Delta vrp_t| + \varepsilon \tag{7}$$

Equations (6) and (7) are estimated considering the order imbalance in terms of value (i.e. price*quantity). The results are reported in the tables 10 and 11.

In the third robustness test, we estimate equation (7) i.e. impact of volatility demand of call and put options of various moneyness on the

TABLE 11. Table shows the results of equation (7)

Variable	(1)	(2)	(3)	(4)
Intercept	–0.058*	–0.05507*	–0.05834	–0.05363*
	(–1.72)	(–1.82)	(–1.76)	(–1.73)
$RNifty_t$	–0.00129**	–0.00137**	–0.00136**	–0.00136**
	(–2.19)	(–2.16)	(–2.24)	(–2.22)
$\log(Vol_{Nifty})_t$	0.00315*	0.00303*	0.00318*	0.00294*
	(1.77)	(1.88)	(1.81)	(1.79)
$ADOI_t^{02}$		0.00116	0.00119	
		(0.47)	(0.67)	
$ADOI_t^{03}$		–0.00431	–0.00727	
		(–0.93)	(–1.46)	
$ADOI_t^{04}$		0.00077	0.00101	
		(0.70)	(0.78)	
$AVOI_t^{02}(\times10^{-6})$		2.51		4.34
		(0.41)		(0.84)
$AVOI_t^{03}$ $(\times10^{-6})$		6.435		6.675**
		(1.54)		(2.29)
$AVOI_t^{04}(\times10^{-6})$		–20		–20*
		(–1.62)		(–1.67)
$\lvert\Delta VolatilityRP_{t-1}\rvert$	0.2447*	0.1852	0.2357	0.1894
	(1.69)	(1.40)	(1.62)	(1.52)
Adj R^2	0.2510	0.2637	0.2499	0.2742
#Obs	120	120	120	120

Note: $\lvert\Delta vrp_t\rvert = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + \gamma_1^{02} ADOI_t^{02} + \gamma_1^{03} ADOI_t^{03} + \gamma_1^{04} ADOI_t^{04} + \delta_1^{02} AVOI_t^{02} + \delta_1^{03} AVOI_t^{03} + \delta_1^{04} AVOI_t^{04} + \theta_1 \lvert\Delta vrp_t\rvert + \varepsilon$. Models (1), (2), (3), and (4) are the GMM estimates of the variables shown in the table. t-statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively. We calculate order imbalance by value (price*quantity).

volatility risk premium by considering the order imbalance in terms of value (i.e. price*quantity). The result is reported in table 12.

In table 9, it is observed that estimates are consistent, with no meaningful change in the result. The interpretation of tables 6 and 9 remains the same. Therefore, the computational procedure of order imbalance does not change the interpretation of the result. When change (absolute change) of volatility risk premium is estimated by equations (6) and (7), it is observed that results are mostly consistent with the change (absolute) in variance risk premium. Tables 10 and 11 show that volatility demand impacts both the variance and volatility risk premium. Even the results are consistent with the change of computational procedure of order imbalance. Thus, the results of the magnitude of the volatility risk premium change are consistent with those of magnitude

TABLE 12. Table shows the result of the impact of volatility demand on volatility risk premium where order imbalance is computed by value (price*quantity)

Variable	(1)
Intercept	–0.05128*
	(–1.84)
$RNifty_t$	–0.0014*
	(–1.96)
$\log(Vol_{Nifty})_t$	0.002819*
	(1.90)
$VDOTM_{CE'}(\times 10^{-6})$	–0.00002
	(–0.68)
$VDATM_{CE'}(\times 10^{-6})$	0.2033
	(0.02)
$VDITM_{CE'}(\times 10^{-6})$	2.848
	(0.48)
$VDOTM_{PE'}(\times 10^{-6})$	9.85*
	(1.68)
$VDATM_{PE'}(\times 10^{-6})$	8.103*
	(1.79)
$VDITM_{PE'}(\times 10^{-6})$	–30**
	(–2.72)
$\lvert \Delta VolatilityRP_{t-1} \rvert$	0.176946
	(1.43)
Adj R^2	0.2651
#Obs	120

Note: Table shows the results of equation $|\Delta vrp_t| = \alpha_0 + \beta_1 RNifty_t + \beta_2 \log(Vol_{Nifty})_t + C_{OTM} VDOTM_{CE'} + C_{ATM}\, VDATM_{CE'} + C_{ITM}\, VDITM_{CE'} + P_{OTM}\, VDOTM_{PE'} + P_{ATM}\, VDATM_{PE'} + P_{ITM}\, VDITM_{PE'} + \theta_1 |\Delta vrp_{t-1}| + \varepsilon$. Model (1) is the GMM estimates of the variables shown in the table. t-statistics are computed according to Newey and West (1987) with 7 lags. *,**,*** denote the statistical significance at 1%, 5%, and 10% levels respectively. We calculate order imbalance by value (price*quantity).

of variance risk premium change throughout. Again, with change of order, imbalance does not affect the meaning of the impact of volatility demand of the call and put options of various moneyness on the volatility risk premium.

Volatility is non-linear monotone transformation of variance. Thus, we also estimate the coefficients with change (absolute change) of volatility risk premium. Results are reported in tables 10, 11 and 12. We observe that the results are mostly consistent when we estimate coefficients by taking change of volatility risk premium. No meaningful change is observed. When we estimate coefficients with the magnitude of the volatility risk premium change, results are consistent with those of magnitude of variance risk premium change throughout, other than magnitude of the estimated coefficients.

These robustness tests confirm Hypothesis H1, i.e., change in net volatility demand influences the change in variance risk premium.

VI. Conclusion

In this paper, we investigate whether volatility demand of options impacts the magnitude of variance risk premium change. We further investigate whether the sign of variance risk premium change conveys information about realized volatility innovations. We calculate aggregated volatility demand by vega-weighted order imbalance. Further, we classify aggregated volatility demand of options into different moneyness categories.

Analysis shows that aggregated volatility demand of options significantly impacts the magnitude of variance risk premium change. We explore the nature of impact for different moneyness categories. Results show that aggregated volatility demand at *ATM* options positively impacts variance risk premium. Further, we analyse the impact of volatility demand of call and put options on magnitude of variance risk premium change. We find that volatility demand of *ATM* and *ITM* put options significantly impacts the variance risk premium change. Volatility skew pattern (for the period of study) supports this finding, as *ATM* and *ITM* put options remain expensive for the period of study. We conduct several robustness tests of our results. These test results show that findings of the study are also consistent with volatility risk premium.

We find that the sign of variance risk premium change conveys information about realized volatility innovations. Positive (negative) sign of variance risk premium change indicates positive (negative) realized volatility innovation.

Thus, the study concludes that the volatility demand information in options order flow impacts the volatility/variance risk premium, while nature and degree of the impact depend on the market structure.

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