Options Order Flow, Volatility Demand and Variance Risk Premium

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Abstract: This study investigates whether volatility demand of options impacts the magnitude of variance risk premium change. It further investigates whether the sign of variance risk premium change conveys information about realized volatility innovations. We calculate volatility demand of options by vega-weighted order imbalance. Further, we classify volatility demand of options into different moneyness categories. Analysis shows that volatility demand of options significantly impacts the variance risk premium change. Among the moneyness categories, we find that volatility demand of the most expensive options significantly impacts variance risk premium change. Further, we find 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

JEL Classifications: G12; G13; G14

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1. Introduction

It is consistently observed that systematic selling of volatility in options market results in economic gains. Options strategies that engage in selling volatility practice are gaining popularity among practitioners. Such strategies prompt practitioners to diversify investment opportunities distinct from the traditional asset classes. Theories of finance suggest that economic gains by selling volatility can be attributed to variance risk premium. Variance risk premium is defined as the difference between risk neutral and physical expectation of variance. Expected risk neutral variance consists of information about expected physical variance and market price of the variance risk i.e., variance risk premium. Thus, existence of variance risk premium makes expected risk neutral variance a biased estimator of expected physical variance, and the variance risk is systematically priced. Thus, variance risk premium is an insurance to hedge variance risk.

Many studies investigate the presence of volatility or variance risk premium. For example, Bakshi and Kapadia, 2003; Carr and Wu, 2009; Bollerslev et al. 2009; Garg and Vipul, 2015; document the presence of volatility/variance risk premium. These studies indicate that volatility risk is priced by variance risk premium and document stylized facts about variance risk premium. For example, Bollerslev et al., 2009, 2011; Bekaert and Hoerova, 2014; relate variance risk premium with market wide risk aversion. Carr and Wu, 2009 argue that variance risk is priced as an independent source of risk. But very few studies attempt to understand the determinants of variance risk premium and thus determinants of variance risk premium are much less understood. We take this up in this study and strive to understand the magnitude of variance risk premium in a demand and supply framework of options. Previous studies of Bollen and Whaley,2004; Garleanu et al., 2009, document 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 et al. (2009) document that market participants are net buyer of index options and demand of options influences prices. Based on these key ideas, we argue that volatility demand of options impacts the variance risk premium. Ni et al. (2008) argue that volatility demand of options contains the information of future realized volatility of the underlying asset. The present study uses vega-weighted order imbalance as volatility demand to forecast future volatility. We propose that changes in the expected volatility would change the net demand of volatility in the market place, 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 et al., (2014) decompose the volatility risk premium 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 changes 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 in variance risk premium reflects the expectation of realized volatility.

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.

We contribute to the literature in the following way. Studies on the structural determinants of volatility risk premium change are very rare. To the best of our knowledge, this would be the first of its kind of study to investigate the structural determinants of variance risk premium change.

The rest of the paper is organized as follows. Section 2 briefly reviews the literature and explains the motivation of the study. Section 3 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 4 describes the data used for the study and presents the summary. Section 5 reports the results of the empirical tests. Section 6 concludes the paper.

2. Background and motivation

We calculate variance risk premium in a model free manner. Model-free implied volatility framework is proposed by Demeterfiet al., 1999; Britten-Jones and Neuberger, 2000. Model-free implied volatility (MFIV) offers a framework to calculate risk neutral expectation of future volatility. Based on the MFIV framework, CBOE introduced volatility index (VIX), which measures the short term expectation of future volatility, in 2003. National Stock Exchange of India (NSE) introduced India VIX in March, 2008 based on the model-free implied volatility 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 et al., 2009; Drechsler and Yaron, 2011 use five-minute sum of squared returns to calculate realized variance. We 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 subtract ex-post realized variance of thirty calendar days from the current India VIX level (transforming India VIX into its 30 calendar days variance term), and denote it as variance risk premium. 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 discuss details of the calculations in the methodology section.

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 options owing to several reasons. Informed investors may prefer options over the underlying asset because of the high leverage provided by options (Black 1975; Grossman and Sanford 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 (Carr and Wu, 2009). These incentives prompt investors to participate in options trading. Previous studies investigate the informational role of options market and discuss whether informed traders trade on options market (Chakravarty et al., 2004). Informed players may use options to trade directional movement information of the underlying asset, expected future volatility information of the underlying asset, or any other information by taking long, short positions on call or put options, or different combinations of call and put options. A single underlying asset has a wide range of strike prices and multiple maturities. All these make information extraction from options trading difficult. In a recent study, Holowczak et al. (2014) show how to extract a particular type of information by aggregate option transactions. For our study, we are interested to extract information about volatility demand. We discuss how we follow Holowczak et al. (2014) to extract information about volatility demand. According to the study of Holowczak et al. (2014), a call option is a positive exposure to the underlying stock price and a 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 call options order imbalance and negative delta to put options order imbalance for the same strike price and same maturity. Thus, at aggregate level, order imbalance of call and put options should take opposite signs and the net aggregated order imbalance of 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 where they capture net buying pressure of options. Bollen and Whaley (2004) use 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 known as volatility smile or smirk or skew. Coming to the calculation of net volatility demand, Holowczak et al. (2014) argue that vega, which is the sensitivity of the option price to the underlying volatility movement, is 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 other 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 of the options 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). The extant literature documents the presence of volatility/variance risk premium across different financial markets. Many studies conclude that volatility risk is priced through variance risk premium (Bakshi and Kapadia, 2003; Carr and Wu, 2009; 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 (2009) 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 et al. (2008). Bollen and Whaley (2004) explain the shape of implied volatility function (IVF) by the net demand of options. In Black-Scholes framework, the supply curve of the options is horizontal regardless of the demand for the options. Bollen and Whaley (2004) argue that 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 makes them mispriced from their Black Scholes intrinsic values. Thus 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 motivated contracts traded and the number of seller motivated contracts traded multiplied by the absolute delta of that option contract. The paper concludes that absolute delta-weighted options order flow impact the implied volatility function. Similarly, Ni et al. (2008) measure volatility demand by the vega-weighted order imbalance. According to Ni et al. (2008), net volatility demand contents information about future realized volatility of the underlying asset. They use volatility demand to forecast future realized volatility.

Our study is related to Fan et al. (2014). This study investigates determinants of volatility risk premium in demand and supply framework. The 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 option open interest and captures supply effect by credit spread and TED spread. Our study differs from this approach in several ways. 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 et al (2014) investigate the level effect of

[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.

volatility risk premium, whereas we are interested to capture the magnitude change of variance risk premium in a volatility demand framework. We propose the following testable hypotheses:

H1: Change in net volatility demand influences the magnitude change in variance risk premium.

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

In the next section, we discuss details of the methodology.

3. Methodology

This section explains the calculation of variance risk premium. Following that, the section explains calculation details of volatility demand from the option order flows. Next we explain the empirical testing methods.

3.1 Volatility 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., $VRP_{t=}\ E_t^Q\left(Var_{t,t+1}\right) - E_t^P(Var_{t,t+1})$. Literature employs different proxies for measuring variance risk premium. Moreover, literature uses variance risk premium and volatility risk premium interchangeably. For example, Drechsler and Yaron (2011) measure variance risk premium as $VRP_t = VIX_t^2 - E(RV)_{t+30}^2$, where they use CBOE volatility index[2] squared, VIX_t^2 , as the proxy for risk neutral expectation of total return variance and forecast one month realized variance as the proxy for objective expectation of total return variance. Similarly, Bollerslev et al. (2009) use $VRP_t = VIX_{t,t+1}^2 - RV_{t-1,t}^2$ where $VIX_{t,t+1}^2$ is a proxy for risk neutral variance measure and $RV_{t-1,t}^2$ is the proxy for objective variance measure. They use the ex-post realized variance $RV_{t-1,t}^2$ as objective measure of variance to avoid forecasting bias of realized variance so that variance risk premium is observable at time t. Both the above studies use the sum of five-minute squared return over

[2] "VIX" is the trademarked ticker symbol CBOE volatility index.

a month as a proxy for realized variance. Moreover, both the studies treat overnight or weekend returns as one five-minute interval. According to Drechsler and Yaron (2011), this treatment does not bias the realized variance measure. Chen et al. (2016) use $VRP_t = RV^2_{t,t+30} - VIX^2_t$, where they use realized variance as the annualized 30- day (calendar days) return variance. Garg and Vipul (2015) define volatility risk premium as the difference between model-free implied volatility (MIFV) and realized volatility. They use India VIX[3] (IVIX) as the proxy for model-free implied volatility and forecast of two scaled return volatility (TSRV) as the proxy for realized volatility.

We define variance risk premium as,

$$VRP_t = IVIX^2_t - RV^2_{t,t+30} \tag{1}$$

where we proxy risk neutral measure by squared India VIX (after transforming into its 30-calendar days risk neutral variance) and realized variance, taking 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 (2011) and Bollerslev et al. (2009). We use ex-post realized variance to avoid forecasting bias. Thus the above measure gives the thirty calendar-day variance risk premium.

3.2 Moneyness of options and volatility order imbalance

We define moneyness of an option as $y = \log(K/F)$, following Carr and Wu (2009), 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.

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)	$-0.03 < y \leq +0.03$

[3] India VIX is the volatility index computed by National Stock Exchange of India based on Nifty options order book. For more details refer: https://www1.nseindia.com/content/indices/white_paper_IndiaVIX.pdf

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)	$y > +0.30$

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.

We employed tick test to calculate the number of traded Nifty options for the period of study. We obtained proprietary Nifty options trades data from National Stock Exchange (NSE) of India. 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 current trade price, the last state of classification is kept for the current state of trade price. By tick test, we calculated the number of options bought and number of options sold for each moneyness defined above in the period of study. The results are reported in Table 1.

We calculated the order imbalance of Nifty call and put options for each strike and for same expiry period. We took rolling over period two days prior to expiry of the near month options. We calculated the order imbalance on daily basis by the proprietary snapshot data obtained from NSE. This snapshot data is given for five timestamps in a trading day (we discuss data details in the data section). We created the order book for each timestamp from the snapshot data and we calculated vega-weighted (as well as delta-weighted) order imbalance for each of the timestamp and averaged 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.

Nifty options are European in style and their maturity is identical to those of Nifty Futures. Thus, we used Nifty futures prices following modified Black (1976) model to avoid dividend ratio calculation of Nifty index. The same procedure is followed by Garg and Vipul (2015). We calculate delta of call option as:

$$\Delta_c = N(d_1) \text{ where } d_1 = \frac{\ln(F/K) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{2}$$

Similarly, put delta is defined as $\Delta_p = N(d_1) - 1$. (3)

Here F=Nifty futures price, K=Strike price of the options, r =risk free interest rate, σ= volatility of the underlying and T= time to maturity. We obtained risk free interest data from the EPW time series[4] database. We used the daily 91 days Treasury bills YTM in the secondary Government Security fixed income market as our proxy for risk free rate of interest. Following Bollen and Whaley (2004), we used 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 in Black Scholes equation to calculate d_1.

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. (4)

In Equations (2), (3) and (4), $N(d_1)$ and $N'(d_1)$ represent the cumulative density and probability density function of the standard normal variable.

We calculated volatility demand by the vega-weighted order imbalance at each strike for the same maturity. It is given by:

$$VOI_{K,T}^{ts} = [CVI(K,T) + PVI(K,T)] \quad (5)$$

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

BO_t^j and SO_t^j represent the number of buy contracts and number of sell contracts outstanding for execution in the order book. We identified buy orders and sell orders that were standing for execution by the buy-sell indicator in the snapshot data. We took the first hundred best bid and ask orders, ignoring the rest orders. We scaled the difference down by the volume of total buy and sell contracts. Thus, volume represents the number of buy and sell orders for the first hundred orders. As discussed earlier, $VOI_{K,T}^{ts}$ represents volatility order imbalance at any timestamp ts: for each day we calculated average of $VOI_{K,T}^{ts}$ to get daily order imbalance for each strike.

$VOI_{K,T} = average(VOI_{K,T}^{ts})$ where ts= 11:00:00, 12:00:00, 13:00:00, 14:00:00,15:00:00 for each trading day. We divided each strike by moneyness. So accordingly, all the $VOI_{K,T}$, that belong to a single moneyness category were aggregated as follows:

$AVOI_t^{cat} = \sum_{cat,k=k_1}^{k_n} VOI_{K,T}$, where cat= 1, 2,3,4,5 as defined in Table1. (6)

Here k_1 to k_n represent the strike prices belonging to the category.

[4] Refer http://www.epwrfits.in/ for more details about EPW time series database.

Apart from calculating the vega order imbalance for each moneyness category, we also calculated the delta order imbalance (directional order imbalance) as a control for our empirical test. Delta order imbalance is given by,

$$DOI_{K,T}^{ts} = COI(K,T) + POI(K,T) \quad (7)$$

where $COI(K,T) = \left(BO_t^j - ST_t^j\right).\frac{\Delta_c}{Volume_t}$ and $POI(K,T) = \left(BO_t^j - SO_t^j\right).\frac{\Delta_p}{Volume_t}$

We averaged $DOI_{K,T}^{ts}$ to calculate daily delta order imbalance or directional order imbalance for a strike on the same maturity,

$DOI_{K,T} = average(DOI_{K,T}^{ts})$ where ts= 11:00:00, 12:00:00, 13:00:00, 14:00:00,15:00:00

Then we aggregated the directional imbalance for each moneyness as:

$ADOI_t^{cat} = \sum_{cat,k=k_1}^{k_n} DOI_{K,T}$, where cat= 1, 2,3,4,5 as defined in Table1. (8)

k_1 to k_n represent the strike prices belonging to the category.

For robustness check we changed the order imbalance definition from the number of contracts of best hundred orders to the value of the best hundred orders. We define value as number of contracts multiplied by the price (for best hundred orders) for both buy and sell contracts for each strike price.

3.3 Empirical testing method

3.3.1 Preliminary regression and magnitude regression equations

We employ the following empirical general equation.

$$\Delta VRP_t = \alpha_0 + \mu Control_t + \sum_{cat} \gamma_t^{cat} AVOI_t^{cat} + \delta_t\, \Delta VRP_{t-1+}\varepsilon \quad (9)$$

In the above equation, we regressed daily change of variance risk premium with the contemporaneous volatility demand over the moneyness categories of options as mentioned in Table 1. In the above equation, $AVOI_t^{cat}$ denotes the volatility demand of options of a particular category.

Now we test Hypothesis 1, where we regress absolute values of daily changes of variance risk premium with contemporaneous volatility demand.

$$|\Delta VRP_t| = \alpha_0 + \mu Control_t + \sum_{cat} \alpha_t^{cat} AVOI_t^{cat} + \beta_t |\Delta VRP_{t-1}| + \varepsilon \qquad (10)$$

Equation (10) specification contains the magnitude change of variance risk premium as a dependent variable. Equation (10) is employed to understand whether it provides us more insight about Hypothesis 1. Equation (9) and Equation (10) consider daily change (absolute change) of variance risk premium.

Further, the next empirical test considers daily change of volatility risk premium (instead of daily change of variance risk premium) as the dependent variable. Volatility is nonlinear monotone transforms of variance. For the robustness of results we specified daily change (absolute change) of volatility risk premium as the dependent variable. We defined volatility risk premium as, $VolatilityRP_t = IVIX_t - RV_{t,t+30}$, where realized volatility is calculated by the square root of sum of five-minute squared returns over thirty calendar days. The regression equations specified for the tests are given below.

$$\Delta VolatilityRP_t = \alpha_0 + \mu Control_t + \sum_{cat} \theta_t^{cat} AVOI_t^{cat} + \vartheta_t \, \Delta VolatilityRP_{t-1} + \varepsilon \quad (11)$$

$$|\Delta VolatilityRP_t| = \alpha_0 + \mu Control_t + \sum_{cat} \mu_t^{cat} AVOI_t^{cat} + \pi_t \, |\Delta VolatilityRP_t| + \varepsilon \; (12)$$

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. We estimated all 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 control variables chosen.

3.3.2 Model building and control variables

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 increases implied volatility. Previous studies (Giot 2005; Whaley 2009; Badshah 2013; Chakrabarti 2015) 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 et al. 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.

Next control variable chosen was Nifty traded volume. We included 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 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. We applied natural logarithm to scale down the Nifty volume.

The next set of control variable consisted of $ADOI_t^{cat}$ i.e., delta order imbalance. We controlled for delta order imbalance following Bollen and Whaley (2004). Bollen and Whaley (2004) show that absolute delta weighted order imbalances impact implied volatility. The way we calculated the delta-weighted order imbalance was different from Bollen and Whaley (2004). Our delta-weighted order imbalance contained information about the directional movement of Nifty, so we expect that delta-weighted order imbalance should not impact the magnitude of variance risk premium change.

The explanatory variable consisted of volatility demand $AVOI_t^{cat}$ for different categories of options. We ignored category 01 and category 05 options due to their thin traded volumes. Category 02 consisted 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 would depend on whether net demand of in-the-money call (ITM_CE) or out-of-the-money put (OTM_PE) got dominating impact on the magnitude change of variance risk premium. Similarly, Category 03 options consisted 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 was due to at-the-money options being most sensitive to volatility changes. So, increase in demand of ATM options would have positive impact on implied volatility and in turn on magnitude of variance risk premium change. Category 04 option consisted of in-the-money put (ITM_PE) and out-of-the-money (OTM_CE). Relationship between volatility demand at Category 04 options and absolute change in variance risk premium would depend on whether net demand of in-the-money put (ITM_PE) or out-of-the-money call (OTM_CE) got dominating impact on magnitude change of variance risk premium. Later on, to understand the effect of volatility demand on individual category of call and put options, we ran separate regression with magnitude change of variance risk premium as dependent variable. We kept lagged term of dependent variables as a control variable in the regression equations.

3.3.3 Empirical test with sign of change of variance risk premium

We discussed earlier that magnitude and sign of the change of variance risk premium have different information. Here we tested whether sign of the change of variance risk premium contented information about the expectation of realized volatility innovations. Fan et al. (2014) discuss that when volatility risk premium is positive (negative), market participants believe that future realized volatility would be higher (lower). This is the expectation hypothesis given by Ait-Sahalia et al. (2013). Following a similar line of argument, we tested whether sign of variance risk premium change conveyed any information regarding the realized volatility innovations. Based on that we tested Hypothesis 2 is,

$$\Delta RV_t = \alpha_0 + \alpha_1 sign(\Delta VRP_t) + \varepsilon \tag{13}$$

We expect α_1 to be positive, because when there is a positive (negative) change in variance risk premium, market expectation is realized volatility change would be higher (lower). Equation 13 was estimated by generalized methods of moments (GMM), and report Newey and West (1987) corrected t-statistics with 30 lags due to overlapping data. The next section describes data and sample of the study.

4. Data and Sample Description

This section gives an overview about the Indian equity market. Then we explain data sources. Lastly we present the summary statistics of variables.

4.1 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. National Stock Exchange of India (NSE) has 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 NSE 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 figured 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 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 our 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). India VIX 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.

4.2 Data Sources

Sample period of the study ranged from 1 July, 2015 to 31 December, 2015. We obtained proprietary Nifty options trade data from NSE. NSE trade 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 used NSE trade data to calculate the number of buy trades and number of 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, Date for GTD. We used regular book as book type section. These were order book snapshots at 11 am, 12 noon, 1 pm, 2 pm and 3 pm on a trading day. We obtained minute data of Nifty from Thomson Reuters DataStream. We used the minute data to calculate five-minute squared return to find realized variance of the Nifty index. We obtained daily Nifty adjusted closing prices, Nifty traded volume and Nifty Futures prices from NSE database. We obtained risk free interest data from the EPW time series database, as mentioned in the methodology section.

4.3 Statistics of variables

4.3.1 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.

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

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.

Category	Buy Call	Sell Call	Buy Put	Sell Put	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)	337550	334400	19500	23475	671950	0.000039	42975	0.000002	3150	-3975
Category 02 (ITM_CE and OTM_PE)	46436025	46523975	1499116125	1543271775	92960000	0.005394	3042387900	0.176538	-87950	-44155650
Category 03 (ATM_CE and ATM_PE)	2919770975	3001981825	2544880225	2630805125	5921752800	0.343617	5175685350	0.300325	-82210850	-85924900
Category 04 (OTM_CE and ITM_PE)	1417336475	1457551150	61255950	63846525	2874887625	0.166819	125102475	0.007259	-40214675	-2590575
Category 05 (DOTM_CE and DITM_PE)	18000	22725	44100	36425	40725	0.000002	80525	0.000005	-4725	7675
Total	**4383899025**	**4506414075**	**4105315900**	**4237983325**	**8890313100**	**0.5159**	**8343299225**	**0.4841**	**-122515050**	**-132667425**

Trading activity of the Nifty options reveals some important aspects. First, total trading activity on call options (51.59%) is greater than on put options (48.41%). Unlike the developed markets, where trading activity in put index options is greater than 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 largest compared to 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 16.68% and OTM put contributes 17.65%). ITM call and ITM put come next as contributors to 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, trading activity proportion in Category01 and Category05 are negligible. Therefore we ignore Category01 and Category05 for all empirical tests.

4.3.2 Variance risk premium

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

Table 3: 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 ($|\Delta VRP_t|$), 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.

Panel A:

	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

Panel B: Correlations

	VRP_t	ΔVRP_t	$\lvert\Delta VRP_t\rvert$	$MFIV_t$	RV_t	$RNifty_t$
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

Panel C: Autocorrelation functions

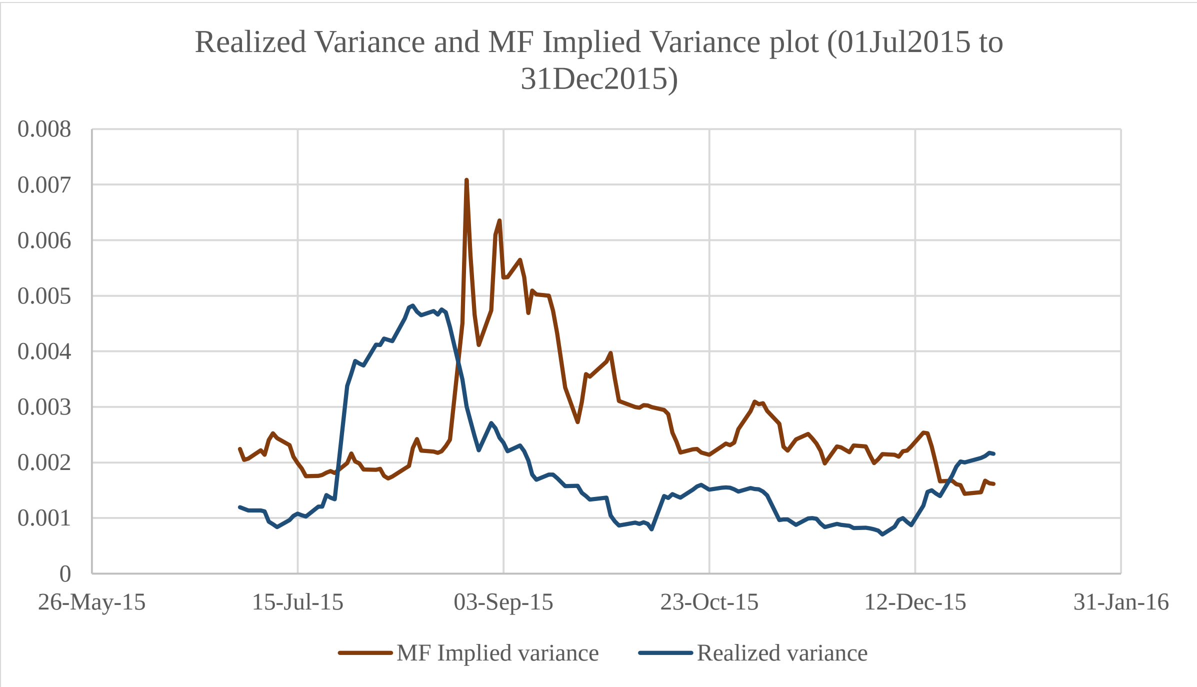
Lag	VRP_t	ΔVRP_t	$\lvert\Delta VRP_t\rvert$	$MFIV_t$	RV_t	$RNifty_t$
1	0.944**	0.297**	0.477**	0.923**	0.975**	0.343 **
2	0.857**	-0.156	0.235**	0.806**	0.941**	0.019
3	0.786**	-0.126	0.056	0.739**	0.902**	-0.055
4	0.727**	-0.052	0.013	0.710**	0.859**	-0.105
5	0.674**	0.093	0.124	0.688**	0.809**	-0.087

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.

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_tshow 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_tseries here for brevity. ΔVRP_t does not show autocorrelation more than one lag. Similarly, $|\Delta VRP_t|$ does not show autocorrelation more than two lags.

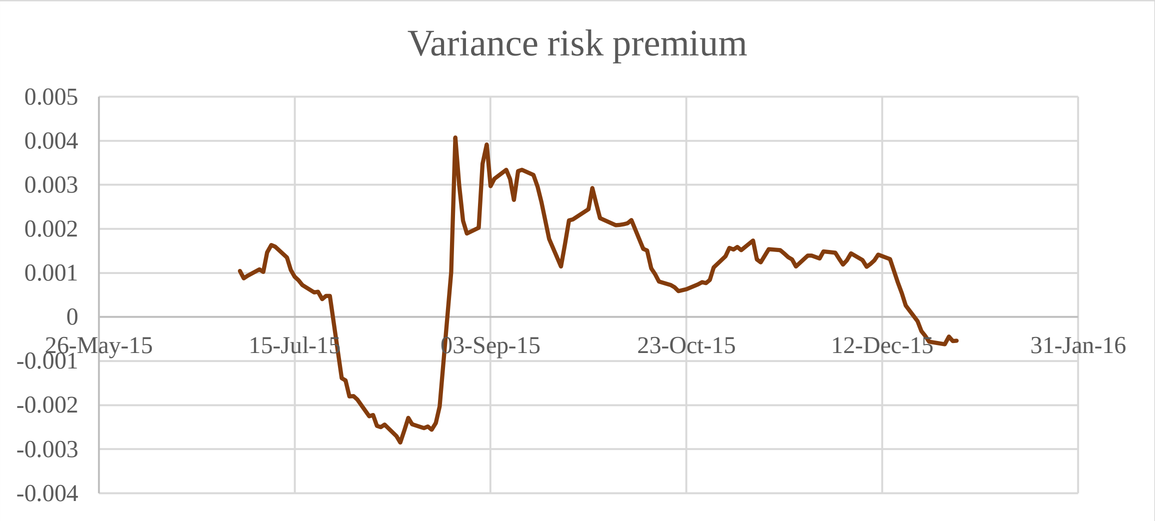
Figure 1 shows the realized variance and model free implied variance (MFIV) plot for the period 1 July, 2015 to 31 December, 2015. It is observed that MFIV is consistently higher up to mid-July, and after the month of August i.e., from the starting of September, 2015.

Figure 1: Realized variance and MFIV plot (01Jul2015 to 31Dec2015)



One reason of MFIV being less than RV, especially during the month of August 2015, may be because of distress in the market due to the China slowdown that affected 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 Bollerslev et al., 2009, 2011; 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 et al.(2014) argue that the sign of negative volatility risk premium can be related to the delta-hedged gains or losses of volatility short portfolios.

Figure 2: VRP dynamics plot (01Jul2015 to 31Dec2015)



We plot the change of variance risk premium and magnitude change of variance risk premium in Figure 3 and Figure 4.

Figure 3: Change of variance risk premium (01Jul2015 to 31Dec2015)

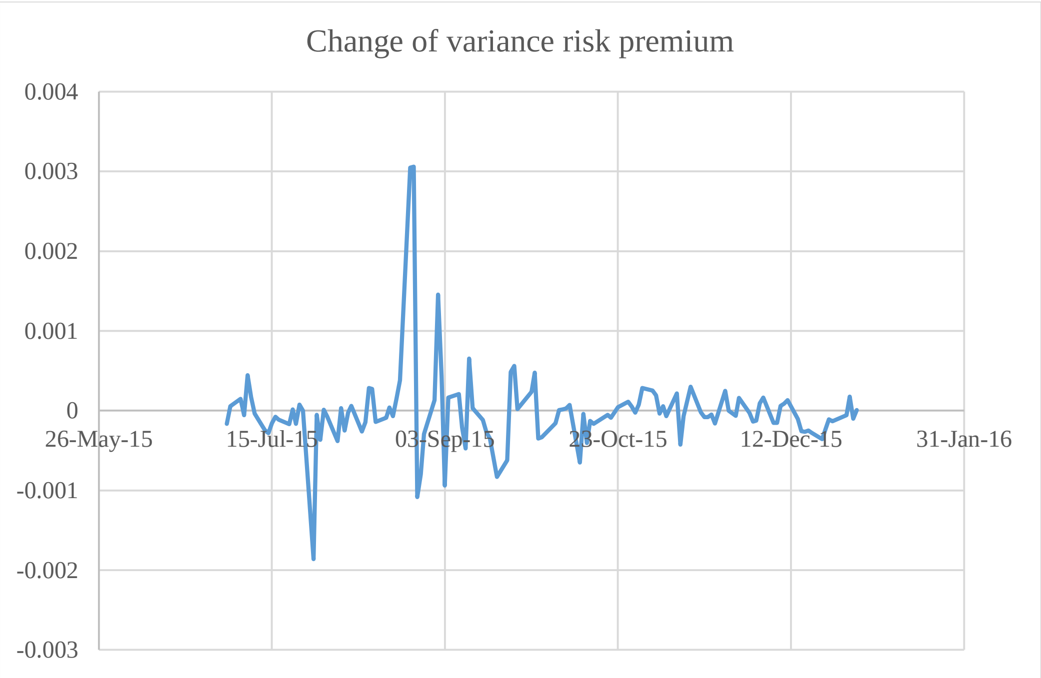
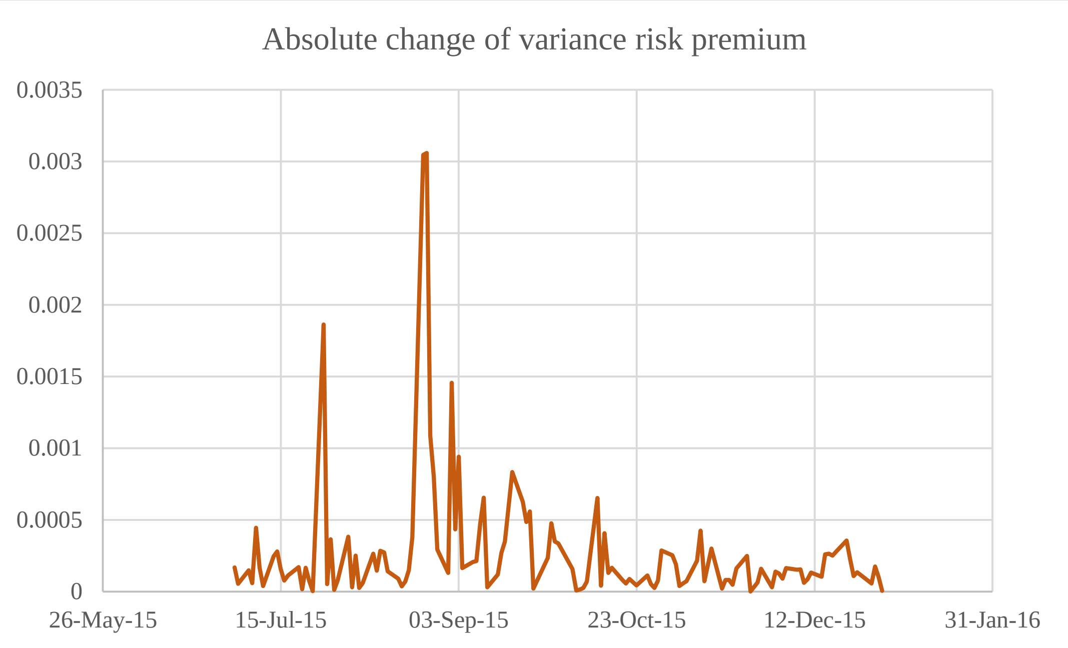


Figure 4: Change of absolute variance risk premium (01Jul2015 to 31Dec2015)



4.3.3 Statistics of the variables

Table 4, Panel A represents the correlations among main variables. Here $ADOI_t^{02}$, $ADOI_t^{03}$, $ADOI_t^{04}$ represent aggregate delta order imbalance and $AVOI_t^{02}$, $AVOI_t^{03}$, $AVOI_t^{04}$ represent aggregate vega order imbalance (volatility demand) for category 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 $VDOTM\_CE_t$, $VDATM\_CE_t$, $VDITM\_CE_t$ represent volatility demand for OTM call, ATM call, and ITM call options and $VDOTM\_PE_t$, $VDATM\_PE_t$, $VDITM\_PE_t$ represent volatility demand for OTM put, ATM put, and ITM put options respectively. We observe that volatility demand of ITM put ($VDITM\_PE_t$) maintains negative correlations with

Table 4: Correlations, Autocorrelation function and summary statistics of the variables (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)

Panel 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

Panel 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

Panel 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 (p-value)	3.7168 (0.1559)	3123*** (0)	443.68*** (0)	89.876*** (0)	2043*** (0)	1074*** (0)	619.10*** (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

Panel 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									
$\lvert\Delta VRP\rvert_t$	0.4680***	1.0000								
$RNifty_t$	-0.5394***	-0.4449***	1.0000							
$\log(Vol_{Nifty})_t$	0.2956***	0.4212***	-0.1883**	1.0000						
$VDOTM\_CE_t$	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

Panel E: Descriptive statistics of volatility demands for individual options category

Statistics	$VDOTM\_CE_t$	$VDATM\_CE_t$	$VDITM\_CE_t$	$VDOTM\_PE_t$	$VDATM\_PE_t$	$VDITM\_PE_t$
Mean (t-stat)	21.231*** (4.76)	14.413*** (4.06)	3.3776 (1.09)	6.0582* (1.73)	22.585*** (4.60)	10.802*** (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*** (0)	56.181*** (0)	9932*** (0)	3193*** (0)	5773*** (0)	21.894*** (0.000018)
ADF (p-value)	0.0001***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
#obs	122	122	122	122	122	122

ΔVRP_t, $|\Delta VRP_t|$, and $RNifty_t$. Further, the negative correlation is statistically significant for $|\Delta VRP_t|$. On the other hand, $VDOTM\_CE_t$ 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 $VDITM\_PE_t$ decreases absolute change of variance risk premium; in turn Category 04 options negatively impacts $|\Delta VRP_t|$. Both $VDATM\_CE_t$ and $VDATM\_PE_t$ maintain positive correlation with $|\Delta VRP_t|$, therefore we assume ATM options (Category 03) impacts $|\Delta VRP_t|$ positively. That is increase in volatility demand of ATM options increases$|\Delta VRP_t|$. Category 02 options ($VDOTM\_PE_t$,$VDITM\_CE_t$) 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.

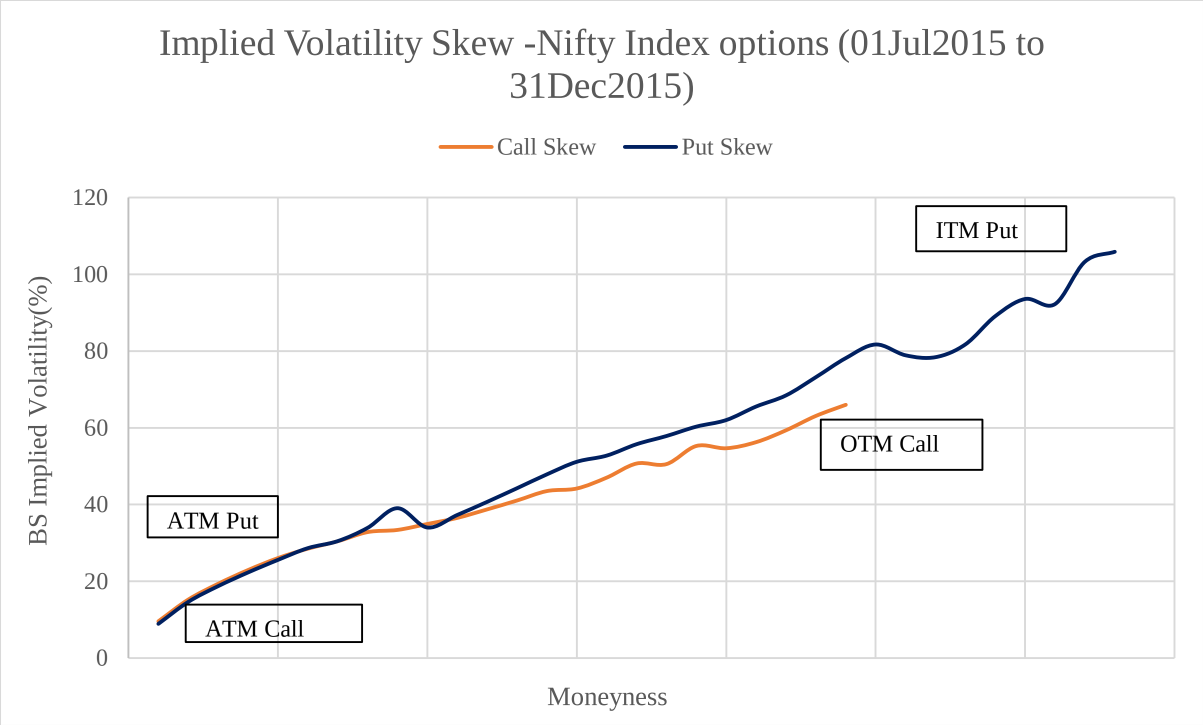
Panel C and Panel E shows summary statistics of the variables. Mean of all the aggregated volatility demand components $AVOI_t^{02}$,$AVOI_t^{03}$, $AVOI_t^{04}$ are significantly positive. In case of individual options, mean of all the put option's volatility demand are significantly positive, whereas mean of volatility demand at OTM and ATM call options are significantly positive. All these variables (aggregated and individual volatility demand) are stationary.[5] Next we discuss the pattern of the implied volatility skew for the period of study.

4.3.4 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 forward skew.

Figure 5: Implied volatility skew of Nifty options

[5] 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.



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 OTM call options.

5. Empirical results

In the empirical test section, we start with Equation 9, where we regress change of variance risk premium with the set of independent variables and control variables as mentioned in the equation specification.

5.1 Empirical results (change of variance risk premium)

Table 5 reports the result of Equation 9. Results show that aggregate delta order imbalances ($ADOI_t^{02}$,$ADOI_t^{03}$, $ADOI_t^{04}$) do not have any statistical significance on the changes of variance risk premium for Models (2) and (3). Further, aggregate volatility demands ($AVOI_t^{02}$,$AVOI_t^{03}$, $AVOI_t^{04}$) 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

Table 5: Results of Equation (9)

$\Delta VRP_t = \alpha_0 + \mu Control_t + \sum_{cat} \gamma_t^{cat} AVOI_t^{cat} + \delta_t \, \Delta VRP_{t-1+} \varepsilon$. 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.

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

for all the models. Similarly, coefficients of $ADOI_t^{03}$ have positive signs and coefficients of $ADOI_t^{02}$ have negative signs. Coefficients of ΔVRP_{t-1} have positive signs for all the models. Continuing with Hypothesis 1, we test whether Equation (10) with magnitude of absolute change of variance risk premium as dependent variable can provide us better insights about the relationship. The results of Equation (1) can be found in Table 6.

5.2 Empirical results (magnitude of variance risk premium change)

Table 6 shows the result of Equation (10). The magnitude regression improves $Adj\ R^2$ for all the models. In the magnitude regression, Model (4) best explains the relationship among all other models.

Table 6: Results of Equation (10)

$|\Delta VRP_t| = \alpha_0 + \mu Control_t + \sum_{cat} \alpha_t^{cat} AVOI_t^{cat} + \beta_t |\Delta VRP_{t-1}| + \varepsilon$. 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.

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

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 the Equation (10), $ADOI_t^{04}$ and $AVOI_t^{02}$ reverse their signs. Everything else maintain consistency in terms of their signs. For Model (2) and Model (4) volatility demand of ATM options remain statistically significant. Further, volatility demand of ATM options 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 (9) and (10), 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; Chakrabarti 2015, that state negative returns increases the implied volatility and high volatility is a representative of high risk (Hibbert et al. 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 magnitude change of variance risk premium.

Coefficients of logarithm volume are positive for Equations (9) and (10), 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 have significant positive impact on the magnitude of variance risk premium change. We further regress magnitude of variance risk premium change with the volatility demand of individual call and put options.

5.3 Empirical results (magnitude of variance risk premium change with volatility demand of call and put options)

We report the results of the regression in Table 7. Results show that $Adj\ R^2$ of the model increases with volatility demand components of call and put options. Further, we see that volatility demand at ATM and ITM put options are statistically significant. Volatility demand of call options is insignificant. Volatility demand of ATM put options has positive impact on the magnitude of variance risk premium change, whereas, ITM put options have negative impact on magnitude of variance risk premium change. The sign of the impact is evident from the correlation analysis in Table 4, where we have seen that volatility demand at ITM put options maintain negative correlation with magnitude of variance risk premium change, and ATM put options have positive correlation with magnitude of variance risk premium change. Another support for the evidence is the volatility skew pattern for the period of study. We see that ATM and ITM put options are expensive, relative to other put options. So volatility trading activity at ATM and ITM put options may have impact on the magnitude of variance risk premium.

Table 7: Results of equation

$|\Delta VRP_t| = \alpha_0 + \mu Control_t + \sum_{call,put} \alpha_t^{Call,put} VD^i + \beta_t |\Delta VRP_{t-1}| + \varepsilon$. 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.

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)
$\|\Delta VRP_{t-1}\|$	0.3034 ***
	(2.66)
$Adj\ R^2$	0.4489
#Obs	120

From the analysis of Table 5 and Table 6 it is evident that Equation (10) 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.

5.4 Empirical results (robustness checks)

We conduct robustness tests of our models. We have done first robustness test by taking order imbalance in terms of value (quantity*price) in magnitude regression. Table 9 reports the results. We see that estimates are consistent, with no meaningful change in the result other than magnitude of the estimated coefficients.

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 Table 10, Table 11 and Table 12. We observe that results are mostly consistent when we estimate coefficients 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 the results of magnitude of variance risk premium change throughout, other than magnitude of the estimated coefficients. Table 9, Table 10, Table 11, and Table 12 are included in Appendix.

These empirical tests confirm Hypothesis 1 i.e., change in net volatility demand influences the change in variance risk premium.

5.5 Empirical results (Sign test)

We test Hypothesis 2 by Equation (13). The results can be found in Table 8. According to our 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 Equation (8) shows that coefficient of $sign(\Delta VRP_t)$ is positive and statistically significant at 10% level. This result confirms Hypothesis 2, although the $Adj\ R^2$ is less.

Table 8: Results of Equation 13

$\Delta RV_t = \alpha_0 + \alpha_1 sign(\Delta VRP_t) + \varepsilon$. Model (1) is the GMM estimates of the variables shown 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.

Variable	**(1)**
$Intercept$	0.000052 * (1.74)

ΔRV_t	0.000029 *
	(1.82)
$Adj\ R^2$	0.0161
#Obs	120

Fan et al. (2014) discuss that the sign of volatility risk premium contents the information of delta-hedged gains or losses of option portfolios. Further analysis in this regard can be taken up in the course of future studies.

6. 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, volatility demand of ATM and ITM put options significantly impact 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 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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Appendix

Table 9: Table shows the results of Equation (10) $|\Delta VRP_t| = \alpha_0 + \mu Control_t + \sum_{cat} \alpha_t^{cat} AVOI_t^{cat} + \beta_t |\Delta VRP_{t-1}| + \varepsilon$. 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).

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)
ΔVRP_{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

Table 10: Table shows the results of Equation (11) $\Delta VolatilityRP_t = \alpha_0 + \mu Control_t + \sum_{cat} \theta_t^{cat} AVOI_t^{cat} + \vartheta_t \, \Delta VolatilityRP_{t-1} + \varepsilon$ .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. We calculate order imbalance by value (price*quantity).

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

Table 11: Table shows the results of Equation (12) $|\Delta VolatilityRP_t| = \alpha_0 + \mu Control_t + \sum_{cat} \mu_t^{cat} AVOI_t^{cat} + \pi_t\, |\Delta VolatilityRP_t| + \varepsilon$. 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).

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$Intercept$	-0.058* (-1.72)	-0.05507* (-1.82)	-0.05834 (-1.76)	-0.05363* (-1.73)
$RNifty_t$	-0.00129** (-2.19)	-0.00137** (-2.16)	-0.00136** (-2.24)	-0.00136** (-2.22)
$\log(Vol_{Nifty})_t$	0.00315* (1.77)	0.00303* (1.88)	0.00318* (1.81)	0.00294* (1.79)
$ADOI_t^{02}$		0.00116 (0.47)	0.00119 (0.67)	
$ADOI_t^{03}$		-0.00431 (-0.93)	-0.00727 (-1.46)	
$ADOI_t^{04}$		0.00077 (0.70)	0.00101 (0.78)	
$AVOI_t^{02}(\times 10^{-6})$		2.51 (0.41)		4.34 (0.84)
$AVOI_t^{03}\ (\times 10^{-6})$		6.435 (1.54)		6.675** (2.29)
$AVOI_t^{04}(\times 10^{-6})$		-20 (-1.62)		-20* (-1.67)
$\|\Delta VolatilityRP_{t-1}\|$	0.2447* (1.69)	0.1852 (1.40)	0.2357 (1.62)	0.1894 (1.52)
$Adj\ R^2$	0.2510	0.2637	0.2499	0.2742
#Obs	120	120	120	120

Table 12: Table shows the results of equation $|\Delta VolatilityRP_t| = \alpha_0 + \mu Control_t + \sum_{call,put} \alpha_t^{Call,put} VD^i + \beta_t |\Delta VRP_{t-1}| + \varepsilon$. 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).

Variable	(1)
$Intercept$	-0.05128* (-1.84)
$RNifty_t$	-0.0014* (-1.96)
$\log(Vol_{Nifty})_t$	0.002819* (1.90)
$VDOTM\_CE_t(\times 10^{-6})$	-0.00002 (-0.68)
$VDATM\_CE_t(\times 10^{-6})$	0.2033 (0.02)
$VDITM\_CE_t(\times 10^{-6})$	2.848 (0.48)
$VDOTM\_PE_t(\times 10^{-6})$	9.85* (1.68)
$VDATM\_PE_t\ (\times 10^{-6})$	8.103* (1.79)
$VDITM\_PE_t(\times 10^{-6})$	-30** (-2.72)
$\|\Delta VolatilityRP_{t-1}\|$	0.176946 (1.43)
$Adj\ R^2$	0.2651
#Obs	120