Algorithmic Traders and Volatility Information Trading

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Abstract

Are algorithmic traders informed about future realized volatility? We construct demand for volatility through the trading volume in stock options and relate this to future realized volatility in the spot market. Using six months (Jan - Jun 2015) of trading data in both stock and stock options market for 160 stocks, we find that non-algorithmic traders and not algorithmic traders are informed about future volatility. Both propitiatory and agency algorithmic traders behave similarly in this regard. We also find that the predictability for future realized volatility in the spot market does not last beyond two trading days. We use both scheduled earnings announcements and unscheduled corporate announcements as exogenous information events. We also find that the volatility demand of non-algorithmic traders is positively related to changes in options prices.

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1 Introduction

Do algorithmic traders have information on future volatility? The informational role of algorithmic traders has been discussed extensively in the literature. Most of the studies suggest that algorithmic traders do not have directional information, but react much faster to publicly available information (Frino, Viljoen, Wang, Westerholm, & Zheng, 2015). Unlike directional information, which is primarily utilized in the spot (cash) or futures market, the options market is uniquely suited for traders with volatility-related information. In this paper, we examine whether algorithmic trades in the Indian stock options market have predictive ability for future realized volatility in the spot market.

The benefit of leverage and lower margin requirements suggest that derivative markets are better suited for informed traders. The nature of the information that traders use could be either directional or volatility-related. In the case of directional information, the trader is supposed to know if the price of particular security was to go up or down. In the case of volatility information, the direction of future price movement is not known to the trader. However, the trader is better informed to predict if the price level is supposed to move from its current level (in either direction).

The last decade has witnessed significant growth in algorithmic trading activities, not just in developed markets, but also in developing markets. A significant proportion of the order messages received by the exchanges is generated automatically through computers without any real time manual intervention. A subset of these algorithmic traders is known as high-frequency traders (HFT) who use the advantage of speed to bring the round-trip trade execution time down to microseconds. Academic research shows that these HFTs have taken on the role of 'modern market makers' (Menkveld, 2013). This significant change in dynamics calls for a better understanding of the role of algorithmic traders, especially in derivative markets, where they are more active.

We use the framework provided by Ni, Pan, and Poteshman (2008) to estimate if any particular trader group has volatility-related information while trading in the options market. We use a unique dataset obtained from the National Stock Exchange of India, which provides identifiers for algorithmic trades. NSE is a completely order-driven market with no designated market maker. Due to their non-linear payoff structures, stock options are usually perceived riskier by the less sophisticated (retail) traders. Considering that NSE also has a liquid stock futures market, the stock options market is usually more attractive for algorithmic and other sophisticated traders.

We estimate the volatility demand of algorithmic and non-algorithmic traders and check if this demand has the predictive ability for future realized volatility in the spot market. We use six months (Jan-Jun 2015) of intraday data for all 159 stocks, which are permitted to be traded in the derivatives market during this period. We use data for both spot and options markets to estimate the volatility demand and realized volatility measures. We also further split algorithmic traders into proprietary and agency algorithmic traders and check if they behave differently with respect to trading on volatility-related information.

Our primary findings suggest that non-algorithmic traders are informed regarding future volatility while algorithmic traders are not. The options market volatility demand for non-algorithmic traders has the predictive ability for future realized volatility in the spot market, even after controlling for options implied volatility and other relevant controls. However, the predictive ability of options market volatility demand rarely lasts more than two days into the future. We also find that neither proprietary (who trade in their own account) nor agency (who execute trades on behalf of others) algorithmic traders have volatility-related information. We consider both scheduled and unscheduled corporate announcements for periods with higher information asymmetry. Our findings are robust for both these announcement types. We also document the variation in results with respect to different estimates of realized spot market volatility. We also test for the impact of this informativeness on options price changes. We find similar results stating the positive relationship between volatility informativeness of non-algorithmic traders and price changes.

2 Relevant Literature

The traditional financial theory had initially conceptualized derivative products as a medium for risk-sharing (Arrow, 1964; Ross, 1976). But later on, these securities turned out to be important vehicles for informed investors (Black, 1975; Grossman, 1977). The body of literature inspecting whether informed traders use directional information market in the options market is quite extensive (Stephan & Whaley, 1990; Amin & Lee, 1997; Easley, Hara, & Srinivas, 1998; Chan, Chung, & Fong, 2002; Chakravarty, Gulen, & Mayhew, 2004; Cao, Chen, & Griffin, 2005; Pan & Poteshman, 2006). The evidence clearly suggests that informed traders choose the options market as their preferred choice of venue. Comparatively, the literature on whether the options market is preferred for volatility information trading (Ni et al., 2008) is comparatively scarce. Ni et al. (2008) show that Vega-adjusted net trading volume can be used to measure volatility demand for a particular trader group. They also show that non-market maker's demand for volatility is positively related to future realized volatility in the spot market. Considering implied volatility has strong predictive ability regarding future realized volatility (Latane & Rendleman, 1976; Chiras & Manaster, 1978; Beckers, 1981; Canina & Figlewski, 1993; Lamoureux & Lastrapes, 1993; Jorion, 1995; Ederington & Lee, 1996; Christensen & Prabhala, 1998), the Ni et al. (2008) model controls for it.

The literature on algorithmic trading is comparatively new. Research seems to suggest that an increase in algorithmic trading activity is related to a decrease in arbitrage opportunity and an increase in informational efficiency, primarily by speeding up price discovery (J. A. Brogaard, 2010; Chaboud, Chiquoine, Hjalmarsson, & Vega, 2014). Algorithmic or machine trading also increases the adverse selection cost for slower traders. The direction of trading of the HFTs is correlated with public information (J. Brogaard, Hendershott, & Riordan, 2014). Algorithmic traders react faster to events (Hendershott & Riordan, 2013). Return volatilities have increased since the introduction of algorithmic trading (Kelejian & Mukerji, 2016), raising concerns whether algorithmic and, more specifically, HFT increases the systemic risk (Jain, Jain, & McInish, 2016).

3 Volatility Information Trading

Investors with access to private information regarding future volatility are likely to take positions in options contracts that are positively related to future realized volatility. Ni et al. (2008) extends the literature on the relation of options volume and future volatility and show that non-market maker's demand for volatility is positively related to future realized volatility, indicating that non-market makers trade on private information related to future volatility. Order-driven markets do not have any designated market-makers. Limit orders from various market participants are matched to each other by the exchange matching engine. However, in recent times algorithmic traders, and more specifically, HFTs have assumed the role of modern market makers. Unlike traditional market makers, they are not obliged to provide quotes at all times. As such, it might be expected that the behavior of algorithmic traders should resemble that of traditional market makers, while non-algorithmic traders behave like non-market makers. Our testable hypothesis with respect to the information content of non-algorithmic traders' demand for volatility can be framed as -

Hypothesis 1 *In an order-driven market, non-algorithmic traders' demand for volatility in the stock options market is positively related to future realized volatility in the spot market.*

Corporate announcements create increase information asymmetry in the market, with market participants with access to private information able to leverage that information earlier compared to others. The situations result in volatility spikes. Ni et al. (2008) use the earnings announcement as exogenous shocks to exploit the time-varying nature of information asymmetry. In periods leading to the corporate announcements, informed investors are likely to use volatility information in the options market. We argue that similar to pre-scheduled earnings announcements, un-scheduled corporate announcements create similar situations of information asymmetry. As such, the trading volume of informed investors prior to any corporate announcement should convey additional information.

Hypothesis 2 *Investors trading on volatility-related information in the stock options market behave similarly in periods leading up to both scheduled and unscheduled corporate announcements.*

Algorithmic traders are not expected to homogeneous in their behavior. The motivation for proprietary and agency algorithmic traders are very different. The proprietary algorithmic traders, who primarily engage in high-frequency trading, try to use their advantage of speed to exploit any arbitrage opportunity existing in the market. They are day-traders, who rarely carry over inventory. On the other hand, agency algorithmic traders execute trades on someone else's behalf. Their primary role is to split orders in such a way that the price impact is minimum. They also prevent investors trading on information from the risk of being front-run. As such, the information content of institutional trades may not be present when the trade is executed through algorithms. As such we frame our final testable hypothesis as-

Hypothesis 3 *Trades executed by both proprietary and agency algorithmic traders in the stock options market do not convey private information regarding future realized volatility in the spot market.*

The demand for volatility of a particular trader-group (Ni et al., 2008) can be estimated through the net trading volume of that trader group in call and put options contracts. Unlike other financial contracts, both and put options prices are positively affected by increasing volatility. As such, investors with information of increasing (decreasing) volatility are likely to buy (sell) call and put options contracts. Options contracts are available for different expiry dates and strike prices. As such, in order to construct the aggregate measure of volatility demand, the net trading volume in individual contracts need to weighted by the contract Vegas [1]. The volatility demand $D\_TG^{\sigma}_{i,t}$ of a particular trader group TG for i-th stock on t-th day can be expressed as-

$$\begin{aligned} D\_TG^{\sigma}_{i,t} = & \sum_{K}\sum_{T}\frac{\partial lnC^{K,T}_{i,t}}{\partial\sigma_{i,t}}(BuyCall\_TG^{K,T}_{i,t} - SellCall\_TG^{K,T}_{i,t}) \\ & + \sum_{K}\sum_{T}\frac{\partial lnP^{K,T}_{i,t}}{\partial\sigma_{i,t}}(BuyPut\_TG^{K,T}_{i,t} - SellPut\_TG^{K,T}_{i,t}) \end{aligned} \tag{1}$$

Where $C^{K,T}_{i,t}$ is the price of the call on underlying stock i at time t with strike price K and maturity T; $P^{K,T}_{i,t}$ is the price for similar put options; $\sigma_{i,t}$ is the volatility of underlying stock i at time t; $BuyCall\_TG^{K,T}_{i,t}$ is the number of call contracts purchased by the trader group TG on day t on underlying stock i with strike price K and maturity T; and $SellCall\_TG^{K,T}_{i,t}$, $BuyPut\_TG^{K,T}_{i,t}$ and $SellPut\_TG^{K,T}_{i,t}$ are the analogous quantities for, respectively, the sale of calls and the purchase and sale of puts by the trader group TG. For empirical calculations, the partial derivatives are difficult to compute and hence, $(\partial lnC^{K,T}_{i,t}/\partial\sigma_{i,t})$ is approximated by $(1/C^{K,T}_{i,t}).BlackScholesCallVega^{K,T}_{i,t}$ and $(\partial lnP^{K,T}_{i,t}/\partial\sigma_{i,t})$ is approximated by $(1/P^{K,T}_{i,t}).BlackScholesPutVega^{K,T}_{i,t}$. We estimate the Vega using 20-day rolling realized volatility measure based on the Andersen, Bollerslev, Diebold, and Ebens (2001) measure of realized volatility [2].

We relate this volatility demand to future realized volatility in the spot market. Due to the GARCH type clustering of realized volatility, we control for lagged realized volatility up to 5 trading days. We also control for lagged implied volatility, as it is known to have predictive ability about realized volatility. Other control variables being trading volume in the stock and trading volume in the options market. To eliminate the problem of scaling, we use the natural logarithm of the volume measures. We also specifically control for the absolute value of the delta-weighted traded volume of the particular traded group TG. This term is analogous to the equivalent traded quantity in the spot market.

[1]Vega for a options contract is defined as the rate of change of options price with respect to change in volatility

[2]We also run a robustness test using the sample volatility of sixty trading days leading up to t for computation of the Black Scholes Vega similar to the one used in Ni et al. (2008). The results are qualitatively similar. (Results not reported here)

Information asymmetry is supposed to increase prior to corporate announcements. Ni et al. (2008) control for the volatility spike due to pre-scheduled earnings announcements. In order to accommodate this, Ni et al. (2008) use dummies for earnings announcements as well as interaction terms. The actual empirical specification for estimating the informativeness of different trader groups for future volatility is as follows-

$$\begin{aligned}
OneDayRV_{i,t} =& \alpha + \beta_1.D_TG^{\sigma}_{i,t-j} + \beta_2.D_TG^{\sigma}_{i,t-j}.EAD_{i,t} \\
&+ \beta_3.OneDayRV_{i,t-1} + \beta_4.OneDayRV_{i,t-1}.EAD_{i,t} \\
&+ \beta_5.OneDayRV_{i,t-2} + \beta_6.OneDayRV_{i,t-2}.EAD_{i,t} \\
&+ \beta_7.OneDayRV_{i,t-3} + \beta_8.OneDayRV_{i,t-3}.EAD_{i,t} \\
&+ \beta_9.OneDayRV_{i,t-4} + \beta_{10}.OneDayRV_{i,t-4}.EAD_{i,t} \\
&+ \beta_{11}.OneDayRV_{i,t-5} + \beta_{12}.OneDayRV_{i,t-5}.EAD_{i,t} \\
&+ \beta_{13}.EAD_{i,t} + \beta_{14}.IV_{i,t-1} + \beta_{15}.IV_{i,t-1}.EAD_{i,t} + \beta_{16}.abs(D_TG^{\Delta}_{i,t-j}) \\
&+ \beta_{17}.abs(D_TG^{\Delta}_{i,t-j}).EAD_{i,t} + \beta_{18}.ln(optVolume_{i,t-j}) \\
&+ \beta_{19}.ln(optVolume_{i,t-j}).EAD_{i,t} + \beta_{20}.ln(stkVolume_{i,t-j}) \\
&+ \beta_{21}.ln(stkVolume_{i,t-j}).EAD_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{2}$$

where $OneDayRV_{i,t}$ is the volatility of the underlying security i on day t. $EAD_{i,t}$ is a proxy that takes up the value of 1 if date t is a corporate announcement date for security i, 0 otherwise. $IV_{i,t}$ is the average implied volatility of the ATM [3] Call and Put options contract for the security i with the shortest maturity on date t. $abs(D\_TG^{\Delta}_{i,t})$ is the absolute value of the delta adjusted options market net traded volume across all expiry dates and strike prices for the trader group TG for security i on date t. We scale down the values of the variables $abs(D\_TG^{\Delta}_{i,t})$ by a factor of one million. $ln(stkVolume_{i,t})$ and and $ln(optVolume_{i,t})$ are the natural logarithm of the spot and options market traded volume respectively for security i on day t. We estimate the equation for different values

[3] ATM: At the Money contract

of $j = 1, 2, 3, 4, 5$ to interpret about the predictive ability of volatility demand for j days ahead realized volatility.

We argue that the same model may be used in case of unscheduled corporate announcements also. We use a modified model that uses dummy UAD for unscheduled corporate announcements instead of earnings announcement dummies. Similar to the earlier specification for earnings announcement dummy, the $UAD_{i,t}$ is a proxy that takes up the value of 1 if date t is an unscheduled corporate announcement date for security i, 0 otherwise.

$$\begin{aligned}
OneDayRV_{i,t} =& \alpha + \beta_1.D_TG^{\sigma}_{i,t-j} + \beta_2.D_TG^{\sigma}_{i,t-j}.UAD_{i,t} \\
& + \beta_3.OneDayRV_{i,t-1} + \beta_4.OneDayRV_{i,t-1}.UAD_{i,t} \\
& + \beta_5.OneDayRV_{i,t-2} + \beta_6.OneDayRV_{i,t-2}.UAD_{i,t} \\
& + \beta_7.OneDayRV_{i,t-3} + \beta_8.OneDayRV_{i,t-3}.UAD_{i,t} \\
& + \beta_9.OneDayRV_{i,t-4} + \beta_{10}.OneDayRV_{i,t-4}.UAD_{i,t} \\
& + \beta_{11}.OneDayRV_{i,t-5} + \beta_{12}.OneDayRV_{i,t-5}.UAD_{i,t} \\
& + \beta_{13}.UAD_{i,t} + \beta_{14}.IV_{i,t-1} + \beta_{15}.IV_{i,t-1}.UAD_{i,t} + \beta_{16}.abs(D_TG^{\Delta}_{i,t-j}) \\
& + \beta_{17}.abs(D_TG^{\Delta}_{i,t-j}).UAD_{i,t} + \beta_{18}.ln(optVolume_{i,t-j}) \\
& + \beta_{19}.ln(optVolume_{i,t-j}).UAD_{i,t} + \beta_{20}.ln(stkVolume_{i,t-j}) \\
& + \beta_{21}.ln(stkVolume_{i,t-j}).UAD_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{3}$$

4 Data

For our analysis, we use six months (01 Jan 2015 to 30 Jun 2015) of options market trading data obtained from the NSE for 159 stocks [4]. Our dataset contains information

[4] Actual number of stocks permitted in the derivatives market during the period was 160. Out of these, one stock did not have sufficient number of observations at daily level to be included in our analysis.

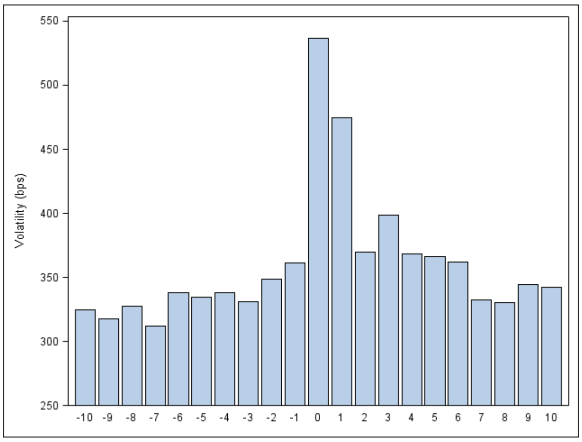
regarding 37 million transactions in the options market during the period of 120 trading days. We summarize this dataset to create daily demand for volatility measures and other control variables. For our analysis, we club algorithmic trades executed by Custodian and NCNP groups into a single class of agency algorithmic traders. Prop algorithmic traders are our best available proxy for HFTs. Our dataset does not provide estimates for implied volatility. As such, we run optimization exercises to estimate the implied volatility using the options traded price and the Black-Scholes options pricing model.

Table 1: Summary statistics of the variables used in the analysis. Volatility figures are expressed in basis points (bps), where 100 bps = 1%

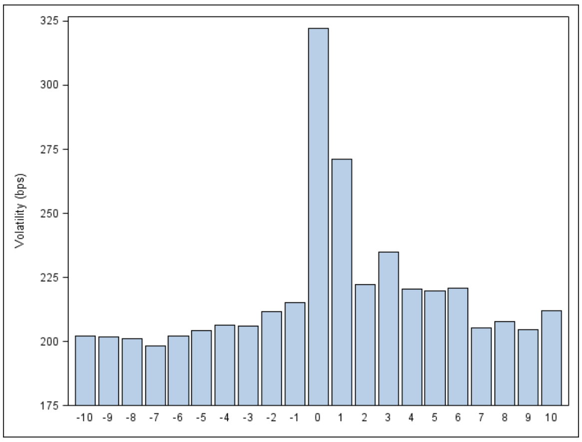
Variable	Obs	Mean	Median	Std Dev	Min.	Max.
OneDayRV [Anderson]	17772	208.26	189.94	99.15	55.68	5839.29
OneDayRV [Alizadeh]	17772	343.01	297.94	370.62	70.60	42546.70
Implied Vol. (Annualized)	17769	3863.51	3705.92	1156.84	1010.09	16476.62
Volatility Demand (D_Algo^{σ})	17772	-0.70	-0.13	7.32	-145.39	122.00
Volatility Demand (D_NA^{σ})	17772	0.70	0.13	7.32	-122.00	145.39
Volatility Demand (D_PA^{σ})	17772	-0.52	-0.07	5.38	-126.46	84.79
Volatility Demand (D_AA^{σ})	17772	-0.17	-0.04	4.20	-107.75	73.51
$abs(D\_Algo^{\Delta})$	17772	0.06	0.02	0.12	0.00	3.16
$abs(D\_NA^{\Delta})$	17772	0.06	0.02	0.12	0.00	3.16
$abs(D\_PA^{\Delta})$	17772	0.05	0.01	0.10	0.00	2.78
$abs(D\_AA^{\Delta})$	17772	0.02	0.01	0.04	0.00	0.88
ln(Options_Vol)	17772	13.50	13.84	2.11	4.83	19.51
ln(Spot_Vol)	17772	14.22	14.33	1.32	8.34	20.12

For the estimation of realized volatility, we use two alternative definitions. For the first definition is based on the method followed by Andersen et al. (2001). In this method, realized volatility is calculated from intra-day returns of every five minutes as $\sigma_{i,t,Anderson} = \sqrt{\sum_{k=1}^{n_t} (r_{k,t})^2}$ where $r_{k,t}$ is the intra-day return of the k-th five-minute sub-period for the i-th security on t-th day.

The second definition is based on the method followed by Alizadeh, Brandt, and Diebold (2002). The same measure was used by Ni et al. (2008). In this method, realized volatility is calculated from daily high, low and closing prices and estimated as $\sigma_{i,t,Range} = \frac{High_{i,t} - Low_{i,t}}{Close_{i,t}}$ where $High_{i,t}$, $Low_{i,t}$ and $Close_{i,t}$ are the daily high, low and closing prices for the i-th security on t-th day.



(a) Volatility Estimate (Anderson et. al. 2001)

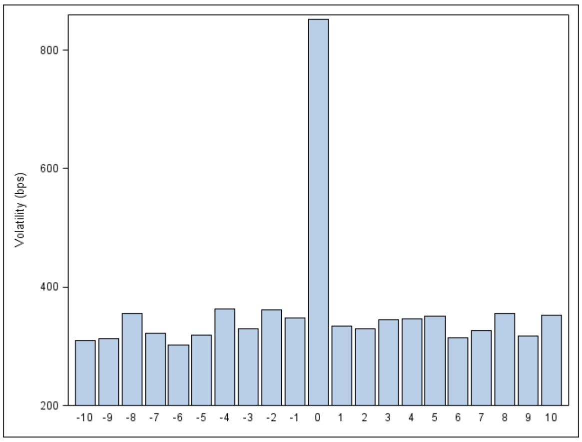


(b) Volatility Estimate (Alizadeh et. al. 2002)

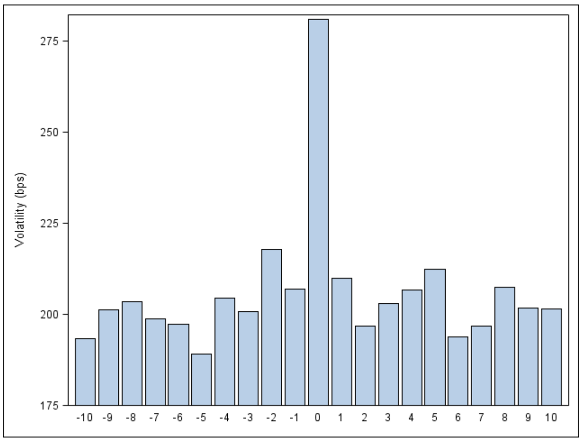
Figure 1: The figure plots average realized volatility around earnings announcement. The x-axis represents the time line around the pre-scheduled earnings announcement. 0 represents the earnings announcement date. negative values indicate trading days prior to announcement and positive values indicate trading days post announcement.

The earnings announcement data is obtained from Prowess database by CMIE (Centre for Monitoring Indian Economy). We consider both quarterly as well as annual earnings announcements. During our sample period, we have 269 observations of earnings announcements for our selected list of companies.

For unscheduled corporate announcements, we consider the following corporate actions - M&A announcement, share buyback, stock split, bonus issue (stock dividend), joint venture announcements, special dividend (cash), reverse-split (consolidation), demerger, bankruptcy & delisting. We obtain data for the same from the Thomson Eikon database. Our dataset consists of 88 such events of unscheduled corporate announce-



(a) Volatility Estimate (Anderson et. al. 2001)



(b) Volatility Estimate (Alizadeh et. al. 2002)

Figure 2: figure plots average realized volatility around unscheduled corporate announcement. The x-axis represents the time line around the corporate announcement. 0 represents the announcement date. negative values indicate trading days prior to announcement and positive values indicate trading days post announcement.

ments.

The plots for average volatility around the announcement dates depict a clear pattern. In the case of earnings announcement (Fig. 1), the volatility has spikes on Day 0 (announcement date) and Day 1 (one day after announcement date). This empirical observation may be explained due to the nature of the announcement. Most of these earnings announcement information come post-market hours, which explains the high volatility on the next trading day. In case of an unscheduled announcement (Fig. 2), however, the information usually comes within market hours, resulting in a prominent volatility spike only on Day 0 [5]. Also, we can notice how the volatility definition affects the shape of the plot.

5 Results

For our first set of models, we run fixed effect panel models, regressing the one-day realized volatility on volatility-demand measures for algorithmic as well as non-algorithmic traders. Econometric tests suggest that fixed-effect models fit the data better than the pooled model used by Ni et al. (2008). We use both definitions of realized volatility - volatility computed using intraday returns (Andersen et al., 2001) (Table 2 & 3) and volatility computed by range-based estimators (Alizadeh et al., 2002) (Table 4 & 5). For each definition of realized volatility, we run separate models using dummies for pre-scheduled earnings announcements (Tables 2 & 4) and unscheduled corporate announcements (Tables 3 & 5).

Each table consists of two panels, where we differentiate our trader group (TG) as algorithmic and non-algorithmic traders. By definition, the volatility-demand measures (D_TG^{σ}) for algorithmic and non-algorithmic traders are equal in magnitude and opposite in sign. The absolute value of delta-adjusted traded volume ($abs(D\_TG^{\Delta})$) of these two trader groups will also be the same by construction. As such, the two panels exhibit exactly the same results except for the coefficients corresponding to the volatility demand of these two groups, which have the same magnitude but opposite sign. Apart from the trader-group (TG) specific terms, we also report the coefficients corresponding to lagged realized volatility measures, dummies for the announcement, and the interaction terms. Due to space constraints, we do not report coefficients corresponding to the additional control variables. While positive values for the coefficients corresponding to volatility demand represent the informativeness of the trader group, the negative sign indicates that the counter-party is informed.

[5]For a sub-sample of out dataset, where the time stamp of the news related to the announcement was available, around 70% of the news item were timed before market closing hours.

Table 2: Results of fixed effect panel regression model to test volatility information trading by algorithmic and non-algorithmic traders in the NSE options market controlling for scheduled earnings announcements.
Measure of volatility (RV): Anderson (2001), estimate of realized volatility using intra-day five-minute return of the security.

j	Const.	D_TG^{σ} (t-j)	D_TG^{σ} (t-j) *EAD	OneDayRV (t-1)	(t-1) *EAD	(t-2)	(t-2) *EAD	(t-3)	(t-3) *EAD	(t-4)	(t-4) *EAD	(t-5)	(t-5) *EAD	EAD	$abs(D\_TG^{\Delta})$ (t-j)	$abs(D\_TG^{\Delta})$ (t-j) *EAD	$Model R^2$
Trader Group: Algorithmic Trader																	
1	-86.54***	-0.35***	-1.7***	0.19***	0.04	0.06***	0.28***	0.07***	0.01	0.04***	0.32***	0.01	-0.5***	191.92***	28.88***	63.72**	0.3608
	(-4.4)	(-4.03)	(-3.95)	(22.66)	(0.45)	(7.68)	(2.71)	(9.71)	(0.09)	(5.62)	(3.11)	(1.61)	(-5.72)	(2.7)	(4.43)	(2.08)	
2	37.64*	-0.21**	1.02	0.22***	0.02	0.06***	0.31***	0.07***	0.02	0.04***	0.31***	0.01	-0.52***	251.15***	-2.51	159.78*	0.3551
	(1.91)	(-2.49)	(1.21)	(28.81)	(0.21)	(6.93)	(3.14)	(9.41)	(0.23)	(5.58)	(3.04)	(1.59)	(-5.95)	(3.43)	(-0.39)	(1.74)	
3	34.9*	-0.02	-1.53*	0.22***	0.04	0.06***	0.23**	0.07***	0.03	0.04***	0.31***	0.01	-0.51***	160.87**	-12.46*	97.34*	0.3549
	(1.78)	(-0.25)	(-1.69)	(29.02)	(0.43)	(8.14)	(2.31)	(8.38)	(0.39)	(5.39)	(3.01)	(1.44)	(-5.79)	(2.09)	(-1.92)	(1.65)	
4	32.43*	-0.04	-2.33***	0.22***	0.04	0.06***	0.23**	0.07***	0	0.03***	0.31***	0.01	-0.5***	144.94*	18.41***	88.62	0.3557
	(1.65)	(-0.44)	(-3.2)	(29.07)	(0.49)	(8.1)	(2.28)	(8.92)	(-0.02)	(3.92)	(3.02)	(1.48)	(-5.66)	(1.95)	(2.84)	(1.64)	
5	90.19***	-0.03	-0.27	0.22***	0.03	0.06***	0.28***	0.07***	-0.02	0.04***	0.33***	0.02*	-0.56***	74.9	3.74	29.04	0.3542
	(4.61)	(-0.41)	(-0.39)	(28.89)	(0.29)	(8.13)	(2.83)	(9.21)	(-0.21)	(5.71)	(3.17)	(1.95)	(-6.11)	(0.99)	(0.58)	(0.48)	
Trader Group: Non-Algorithmic Trader																	
1	-86.54***	0.35***	1.7***	0.19***	0.04	0.06***	0.28***	0.07***	0.01	0.04***	0.32***	0.01	-0.5***	191.92***	28.88***	63.72**	0.3608
	(-4.4)	(4.03)	(3.95)	(22.66)	(0.45)	(7.68)	(2.71)	(9.71)	(0.09)	(5.62)	(3.11)	(1.61)	(-5.72)	(2.7)	(4.43)	(2.08)	
2	37.64*	0.21**	-1.02	0.22***	0.02	0.06***	0.31***	0.07***	0.02	0.04***	0.31***	0.01	-0.52***	251.15***	-2.51	159.78*	0.3551
	(1.91)	(2.49)	(-1.21)	(28.81)	(0.21)	(6.93)	(3.14)	(9.41)	(0.23)	(5.58)	(3.04)	(1.59)	(-5.95)	(3.43)	(-0.39)	(1.74)	
3	34.9*	0.02	1.53*	0.22***	0.04	0.06***	0.23**	0.07***	0.03	0.04***	0.31***	0.01	-0.51***	160.87**	-12.46*	97.34*	0.3549
	(1.78)	(0.25)	(1.69)	(29.02)	(0.43)	(8.14)	(2.31)	(8.38)	(0.39)	(5.39)	(3.01)	(1.44)	(-5.79)	(2.09)	(-1.92)	(1.65)	
4	32.43*	0.04	2.33***	0.22***	0.04	0.06***	0.23**	0.07***	0	0.03***	0.31***	0.01	-0.5***	144.94*	18.41***	88.62	0.3557
	(1.65)	(0.44)	(3.2)	(29.07)	(0.49)	(8.1)	(2.28)	(8.92)	(-0.02)	(3.92)	(3.02)	(1.48)	(-5.66)	(1.95)	(2.84)	(1.64)	
5	90.19***	0.03	0.27	0.22***	0.03	0.06***	0.28***	0.07***	-0.02	0.04***	0.33***	0.02*	-0.56***	74.9	3.74	29.04	0.3542
	(4.61)	(0.41)	(0.39)	(28.89)	(0.29)	(8.13)	(2.83)	(9.21)	(-0.21)	(5.71)	(3.17)	(1.95)	(-6.11)	(0.99)	(0.58)	(0.48)	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Results of fixed effect panel regression model to test volatility information trading by algorithmic and non-algorithmic traders in the NSE options market controlling for unscheduled corporate announcements.
Measure of volatility (RV): Anderson (2001), estimate of realized volatility using intra-day five-minute return of the security.

		D_TG^{σ}		OneDayRV											$abs(D\_TG^{\Delta})$		
j	**Const.**	**(t-j)**	**(t-j) *UAD**	**(t-1)**	**(t-1) *UAD**	**(t-2)**	**(t-2) *UAD**	**(t-3)**	**(t-3) *UAD**	**(t-4)**	**(t-4) *UAD**	**(t-5)**	**(t-5) *UAD**	**UAD**	**(t-j)**	**(t-j) *UAD**	$Model R^2$
Trader Group: Algorithmic Trader																	
1	-66.55***	-0.39***	-4.73***	0.18***	0.42***	0.05***	1.95***	0.07***	1.36***	0.03***	3.35***	0.01**	-3.44***	451.68***	32.41***	182.3***	0.4283
	(-3.58)	(-4.84)	(-8.65)	(22.74)	(2.9)	(6.43)	(13.14)	(9.24)	(8.11)	(4.47)	(19.41)	(2.05)	(-19.48)	(3.54)	(5.34)	(2.67)	
2	62.89***	-0.12	-5.67***	0.21***	0.5***	0.05***	1.87***	0.07***	1.34***	0.03***	3.44***	0.01**	-3.5***	-494.68***	-3.07	-542.03***	0.4187
	(3.37)	(-1.45)	(-9.02)	(28.6)	(3.38)	(6.64)	(12.1)	(9)	(7.82)	(4.37)	(19.95)	(2)	(-19.48)	(-3.91)	(-0.5)	(-6.43)	
3	52.35***	-0.01	-5.45***	0.21***	0.6***	0.05***	1.99***	0.07***	0.89***	0.03***	3.72***	0.01*	-3.63***	-577.86***	-10.4*	-451.66***	0.4189
	(2.81)	(-0.16)	(-6.92)	(28.66)	(4.17)	(6.93)	(13.25)	(8.55)	(5.06)	(4.34)	(21.06)	(1.91)	(-19.99)	(-5.2)	(-1.69)	(-6.75)	
4	55.54***	-0.09	-0.8	0.21***	0.26*	0.05***	1.94***	0.06***	1.57***	0.03***	3.51***	0.01**	-3.73***	78.89	23.56***	-764.88***	0.4192
	(2.99)	(-1.1)	(-0.85)	(28.68)	(1.77)	(6.75)	(13.12)	(8.46)	(9.3)	(3.48)	(20.32)	(2.07)	(-20.86)	(0.62)	(3.83)	(-7.75)	
5	89.24***	0.01	-0.01	0.21***	0.38***	0.05***	1.94***	0.06***	1.43***	0.03***	3.55***	0.02**	-3.82***	-225.28*	5.44	-323.53***	0.4161
	(4.8)	(0.07)	(-0.01)	(28.43)	(2.59)	(6.86)	(13.06)	(8.6)	(8.4)	(4.61)	(20.64)	(2.56)	(-20.27)	(-1.72)	(0.88)	(-5)	
Trader Group: Non-Algorithmic Trader																	
1	-66.55***	0.39***	4.73***	0.18***	0.42***	0.05***	1.95***	0.07***	1.36***	0.03***	3.35***	0.01**	-3.44***	451.68***	32.41***	182.3***	0.4283
	(-3.58)	(4.84)	(8.65)	(22.74)	(2.9)	(6.43)	(13.14)	(9.24)	(8.11)	(4.47)	(19.41)	(2.05)	(-19.48)	(3.54)	(5.34)	(2.67)	
2	62.89***	0.12	5.67***	0.21***	0.5***	0.05***	1.87***	0.07***	1.34***	0.03***	3.44***	0.01**	-3.5***	-494.68***	-3.07	-542.03***	0.4187
	(3.37)	(1.45)	(9.02)	(28.6)	(3.38)	(6.64)	(12.1)	(9)	(7.82)	(4.37)	(19.95)	(2)	(-19.48)	(-3.91)	(-0.5)	(-6.43)	
3	52.35***	0.01	5.45***	0.21***	0.6***	0.05***	1.99***	0.07***	0.89***	0.03***	3.72***	0.01*	-3.63***	-577.86***	-10.4*	-451.66***	0.4189
	(2.81)	(0.16)	(6.92)	(28.66)	(4.17)	(6.93)	(13.25)	(8.55)	(5.06)	(4.34)	(21.06)	(1.91)	(-19.99)	(-5.2)	(-1.69)	(-6.75)	
4	55.54***	0.09	0.8	0.21***	0.26*	0.05***	1.94***	0.06***	1.57***	0.03***	3.51***	0.01**	-3.73***	78.89	23.56***	-764.88***	0.4192
	(2.99)	(1.1)	(0.85)	(28.68)	(1.77)	(6.75)	(13.12)	(8.46)	(9.3)	(3.48)	(20.32)	(2.07)	(-20.86)	(0.62)	(3.83)	(-7.75)	
5	89.24***	-0.01	0.01	0.21***	0.38***	0.05***	1.94***	0.06***	1.43***	0.03***	3.55***	0.02**	-3.82***	-225.28*	5.44	-323.53***	0.4161
	(4.8)	(-0.07)	(0.01)	(28.43)	(2.59)	(6.86)	(13.06)	(8.6)	(8.4)	(4.61)	(20.64)	(2.56)	(-20.27)	(-1.72)	(0.88)	(-5)	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results of fixed effect panel regression model to test volatility information trading by algorithmic and non-algorithmic traders in the NSE options market controlling for scheduled earnings announcements.
Measure of volatility (RV): Alizadeh (2002), estimate of realized volatility computed through difference between the stock's intraday high and low price divided by the closing stock price.

		D_TG^{σ}		OneDayRV											$abs(D\_TG^{\Delta})$		
j	**Const.**	**(t-j)**	**(t-j) *EAD**	**(t-1)**	**(t-1) *EAD**	**(t-2)**	**(t-2) *EAD**	**(t-3)**	**(t-3) *EAD**	**(t-4)**	**(t-4) *EAD**	**(t-5)**	**(t-5) *EAD**	**EAD**	**(t-j)**	**(t-j) *EAD**	$ModelR^2$
Trader Group: Algorithmic Trader																	
1	-538.61***	-1.54***	-3.31*	0.02**	0.16	0.03***	0.22	0.04***	-0.02	0.02**	0.18	-0.01	-0.25	222.62	43.88	75.19	0.0718
	(-6.29)	(-3.92)	(-1.71)	(2.56)	(1.01)	(3.54)	(1.29)	(5.46)	(-0.1)	(2.01)	(1.05)	(-1.62)	(-1.6)	(0.7)	(1.49)	(0.55)	
2	-217.8**	-1.3***	1.3	0.04***	0.25	0.02***	0.2	0.04***	-0.04	0.02**	0.18	-0.01	-0.28*	296.21	-22.99	236.81	0.067
	(-2.55)	(-3.37)	(0.34)	(5.03)	(1.62)	(3.02)	(1.19)	(4.97)	(-0.21)	(2.14)	(1.09)	(-1.55)	(-1.81)	(0.91)	(-0.79)	(0.57)	
3	-158.24*	-0.32	-5.56	0.04***	0.26*	0.03***	0.19	0.03***	-0.08	0.01*	0.17	-0.01	-0.27*	202.93	2.64	192.44	0.0661
	(-1.86)	(-0.82)	(-1.37)	(5.26)	(1.74)	(4.27)	(1.14)	(4.24)	(-0.47)	(1.73)	(1.01)	(-1.55)	(-1.68)	(0.59)	(0.09)	(0.71)	
4	-105.76	-0.39	-3.07	0.04***	0.24	0.03***	0.19	0.04***	-0.04	0.01	0.12	-0.01*	-0.27*	-25.4	45.56	35.61	0.0659
	(-1.25)	(-1)	(-0.93)	(5.26)	(1.59)	(4.44)	(1.1)	(5.24)	(-0.24)	(0.93)	(0.71)	(-1.84)	(-1.68)	(-0.08)	(1.55)	(0.14)	
5	146.99*	-0.49	-0.02	0.04***	0.25	0.03***	0.2	0.04***	-0.05	0.02**	0.2	-0.01	-0.3*	103.65	38.85	50.8	0.0648
	(1.74)	(-1.27)	(0)	(5.24)	(1.64)	(4.52)	(1.22)	(5.49)	(-0.31)	(2.15)	(1.17)	(-1.62)	(-1.88)	(0.31)	(1.33)	(0.18)	
Trader Group: Non-Algorithmic Trader																	
1	-538.61***	1.54***	3.31*	0.02**	0.16	0.03***	0.22	0.04***	-0.02	0.02**	0.18	-0.01	-0.25	222.62	43.88	75.19	0.0718
	(-6.29)	(3.92)	(1.71)	(2.56)	(1.01)	(3.54)	(1.29)	(5.46)	(-0.1)	(2.01)	(1.05)	(-1.62)	(-1.6)	(0.7)	(1.49)	(0.55)	
2	-217.8**	1.3***	-1.3	0.04***	0.25	0.02***	0.2	0.04***	-0.04	0.02**	0.18	-0.01	-0.28*	296.21	-22.99	236.81	0.067
	(-2.55)	(3.37)	(-0.34)	(5.03)	(1.62)	(3.02)	(1.19)	(4.97)	(-0.21)	(2.14)	(1.09)	(-1.55)	(-1.81)	(0.91)	(-0.79)	(0.57)	
3	-158.24*	0.32	5.56	0.04***	0.26*	0.03***	0.19	0.03***	-0.08	0.01*	0.17	-0.01	-0.27*	202.93	2.64	192.44	0.0661
	(-1.86)	(0.82)	(1.37)	(5.26)	(1.74)	(4.27)	(1.14)	(4.24)	(-0.47)	(1.73)	(1.01)	(-1.55)	(-1.68)	(0.59)	(0.09)	(0.71)	
4	-105.76	0.39	3.07	0.04***	0.24	0.03***	0.19	0.04***	-0.04	0.01	0.12	-0.01*	-0.27*	-25.4	45.56	35.61	0.0659
	(-1.25)	(1)	(0.93)	(5.26)	(1.59)	(4.44)	(1.1)	(5.24)	(-0.24)	(0.93)	(0.71)	(-1.84)	(-1.68)	(-0.08)	(1.55)	(0.14)	
5	146.99*	0.49	0.02	0.04***	0.25	0.03***	0.2	0.04***	-0.05	0.02**	0.2	-0.01	-0.3*	103.65	38.85	50.8	0.0648
	(1.74)	(1.27)	(0)	(5.24)	(1.64)	(4.52)	(1.22)	(5.49)	(-0.31)	(2.15)	(1.17)	(-1.62)	(-1.88)	(0.31)	(1.33)	(0.18)	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Results of fixed effect panel regression model to test volatility information trading by algorithmic and non-algorithmic traders in the NSE options market controlling for unscheduled corporate announcements.
Measure of volatility (RV): Alizadeh (2002), estimate of realized volatility computed through difference between the stock's intraday high and low price divided by the closing stock price.

		D_TG^{σ}		OneDayRV											$abs(D\_TG^{\Delta})$		
j	**Const.**	**(t-j)**	**(t-j) *UAD**	**(t-1)**	**(t-1) *UAD**	**(t-2)**	**(t-2) *UAD**	**(t-3)**	**(t-3) *UAD**	**(t-4)**	**(t-4) *UAD**	**(t-5)**	**(t-5) *UAD**	**UAD**	**(t-j)**	**(t-j) *UAD**	$Model R^2$
Trader Group: Algorithmic Trader																	
1	-340.48***	-0.91***	-47.85***	0.02***	-2.39***	0.01	10.85***	0.04***	2.13***	0.01	7.34***	-0.01	-4.05***	5261.84***	40.22*	1863.72***	0.4947
	(-5.4)	(-3.17)	(-25.26)	(4.2)	(-11)	(1.6)	(63.03)	(6.38)	(8.67)	(0.9)	(36.84)	(-0.97)	(-16.66)	(11.67)	(1.88)	(7.83)	
2	-3.48	-0.44	-19.63***	0.04***	-1.91***	0.01*	10.88***	0.04***	1.47***	0.01	7.67***	0	-3.25***	1484.45***	-26.55	-4047.59***	0.4609
	(-0.05)	(-1.49)	(-8.42)	(6.46)	(-8.39)	(1.95)	(58.76)	(6.07)	(5.73)	(1.05)	(37.46)	(-0.78)	(-12.4)	(3.16)	(-1.2)	(-13.51)	
3	-1.2	-0.04	-8.84***	0.04***	-1.76***	0.01**	10.91***	0.03***	1.71***	0	7.21***	0	-3.74***	-1910.04***	3.5	-1240.98***	0.4561
	(-0.02)	(-0.12)	(-3.06)	(6.45)	(-7.82)	(2.29)	(61.34)	(5.56)	(6.65)	(0.85)	(33.6)	(-0.81)	(-13.84)	(-4.74)	(0.16)	(-5.28)	
4	57.75	-0.36	0.43	0.04***	-2.4***	0.01**	10.77***	0.04***	2.08***	0	7.94***	-0.01	-3.29***	4471.13***	61.11***	-3604.67***	0.4639
	(0.9)	(-1.23)	(0.13)	(6.5)	(-10.79)	(2.39)	(61.15)	(6.15)	(8.19)	(0.44)	(37.64)	(-0.88)	(-12.77)	(9.56)	(2.76)	(-10.17)	
5	130.15**	-0.22	-8.75***	0.04***	-2.94***	0.01**	11.36***	0.04***	2.03***	0.01	7.93***	-0.01	-2.97***	7348.68***	37.56*	685.45***	0.4617
	(2.03)	(-0.76)	(-2.68)	(6.46)	(-12.92)	(2.43)	(63.85)	(6.24)	(7.97)	(1.06)	(38.69)	(-0.89)	(-11.08)	(15.5)	(1.7)	(2.94)	
Trader Group: Non-Algorithmic Trader																	
1	-340.48***	0.91***	47.85***	0.02***	-2.39***	0.01	10.85***	0.04***	2.13***	0.01	7.34***	-0.01	-4.05***	5261.84***	40.22*	1863.72***	0.4947
	(-5.4)	(3.17)	(25.26)	(4.2)	(-11)	(1.6)	(63.03)	(6.38)	(8.67)	(0.9)	(36.84)	(-0.97)	(-16.66)	(11.67)	(1.88)	(7.83)	
2	-3.48	0.44	19.63***	0.04***	-1.91***	0.01*	10.88***	0.04***	1.47***	0.01	7.67***	0	-3.25***	1484.45***	-26.55	-4047.59***	0.4609
	(-0.05)	(1.49)	(8.42)	(6.46)	(-8.39)	(1.95)	(58.76)	(6.07)	(5.73)	(1.05)	(37.46)	(-0.78)	(-12.4)	(3.16)	(-1.2)	(-13.51)	
3	-1.2	0.04	8.84***	0.04***	-1.76***	0.01**	10.91***	0.03***	1.71***	0	7.21***	0	-3.74***	-1910.04***	3.5	-1240.98***	0.4561
	(-0.02)	(0.12)	(3.06)	(6.45)	(-7.82)	(2.29)	(61.34)	(5.56)	(6.65)	(0.85)	(33.6)	(-0.81)	(-13.84)	(-4.74)	(0.16)	(-5.28)	
4	57.75	0.36	-0.43	0.04***	-2.4***	0.01**	10.77***	0.04***	2.08***	0	7.94***	-0.01	-3.29***	4471.13***	61.11***	-3604.67***	0.4639
	(0.9)	(1.23)	(-0.13)	(6.5)	(-10.79)	(2.39)	(61.15)	(6.15)	(8.19)	(0.44)	(37.64)	(-0.88)	(-12.77)	(9.56)	(2.76)	(-10.17)	
5	130.15**	0.22	8.75***	0.04***	-2.94***	0.01**	11.36***	0.04***	2.03***	0.01	7.93***	-0.01	-2.97***	7348.68***	37.56*	685.45***	0.4617
	(2.03)	(0.76)	(2.68)	(6.46)	(-12.92)	(2.43)	(63.85)	(6.24)	(7.97)	(1.06)	(38.69)	(-0.89)	(-11.08)	(15.5)	(1.7)	(2.94)	

t statistics in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

We vary the value of the parameter j in order to measure the predictive ability of the volatility demand. The interaction terms with the announcement dummies interpret additional information content prior to announcements. Consistent with our first hypothesis, we find that the volatility-demand for non-algorithmic traders has a positive relation with future realized volatility, indicating non-algorithmic traders are informed regarding future realized-volatility, whereas algorithmic traders are not. The results are consistent across both definitions of realized volatility and for both types of announcements- pre-scheduled earnings announcements (Table 2 & 4) and unscheduled corporate announcements (Table 3 & 5). The fact that the coefficients have a similar sign and significance level for the two types of announcements seems to support our second hypothesis that volatility information based trading has similar implications with regard to both scheduled and unscheduled announcements. Similar to Ni et al. (2008), we find that the interaction term for the volatility demand and the EAD dummy is positive (for non-algo traders), suggesting options trading volume prior to earnings announcement date has additional information regarding future realized volatility. But unlike Ni et al. (2008), we find that the predictive ability of options trading volume does not extend till five trading days, rather it is hardly significant beyond two trading days. We do observe a change in the level of significance for the lagged variables based on the definition of one day realized volatility. Prior to announcement dates, however, lagged terms do provide additional information [6].

For our next set of models, we split the algorithmic trader group into proprietary algorithmic traders and agency algorithmic traders as these two groups differ fundamentally in the way they employ algorithms. Proprietary algorithmic traders are primarily high-frequency traders who use their advantage of speed to execute a large number of relatively small-sized trades in a very short time. Agency algorithmic traders provide trade execution services for other investors. Results indicate that coefficients corresponding to

[6] A possible argument can be made that it is the surprise component of the earnings announcement that drives the volatility spikes, where surprise is defined as the difference in earnings levels from the levels foretasted by analysts. We also run robustness tests by sub-sampling the dataset for high and low earnings surprise (results not reported). However the results remain consistent in both cases.

volatility demand for both these trader groups are negative, indicating none of them have prior information regarding future volatility. Similar to our first set of models, we use both definitions of volatility for both scheduled (Table 6 & 8) and unscheduled announcements (Table 7 & 9). Institutional investors are usually known to trade on information. However, when institutional investors use algorithms to execute trades on their behalf, the agency algorithms split the orders to ensure minimal price impact. As such, trades executed by agency algorithmic traders on behalf of informed investors do not convey information.

Table 6: Results of fixed effect panel regression model to test volatility information trading by proprietary and agency algorithmic traders in the NSE options market controlling for scheduled earnings announcements.
Measure of volatility (RV): Anderson (2001), estimate of realized volatility using intra-day five-minute return of the security.

		D_TG^{σ}		OneDayRV											$abs(D\_TG^{\Delta})$		
j	Const.	(t-j)	(t-j) *EAD	(t-1)	(t-1) *EAD	(t-2)	(t-2) *EAD	(t-3)	(t-3) *EAD	(t-4)	(t-4) *EAD	(t-5)	(t-5) *EAD	EAD	(t-j)	(t-j) *EAD	$Model R^2$
Trader Group: Prop Algorithmic Trader																	
1	-89.33***	-0.29**	-2.46***	0.19***	0.05	0.06***	0.27***	0.07***	0.02	0.04***	0.31***	0.01	-0.5***	166.19**	30.34***	46.18	0.360
	(-4.55)	(-2.49)	(-3.36)	(22.7)	(0.62)	(7.72)	(2.67)	(9.7)	(0.24)	(5.62)	(3.07)	(1.58)	(-5.74)	(2.38)	(3.96)	(1.43)	
2	33.5*	-0.23**	-0.22	0.22***	0.03	0.06***	0.31***	0.07***	0.03	0.04***	0.32***	0.01	-0.53***	230.45***	-11.16	75.77	0.355
	(1.7)	(-1.97)	(-0.2)	(28.91)	(0.33)	(7)	(3.07)	(9.42)	(0.31)	(5.54)	(3.11)	(1.55)	(-6.02)	(3.19)	(-1.48)	(0.72)	
3	31.22	-0.15	-1.16	0.22***	0.04	0.06***	0.23**	0.07***	0.04	0.04***	0.31***	0.01	-0.52***	150.95**	-23.4***	90.35	0.3551
	(1.59)	(-1.29)	(-1.13)	(28.99)	(0.47)	(8.17)	(2.33)	(8.44)	(0.43)	(5.41)	(3.03)	(1.43)	(-5.88)	(1.96)	(-3.1)	(1.43)	
4	26.72	-0.04	-1	0.22***	0.04	0.06***	0.25**	0.07***	0.02	0.03***	0.29***	0.01	-0.52***	138.19*	9.77	147.14**	0.3551
	(1.36)	(-0.34)	(-0.97)	(29.05)	(0.5)	(8.11)	(2.47)	(8.98)	(0.27)	(4.01)	(2.82)	(1.46)	(-5.85)	(1.87)	(1.29)	(2.11)	
5	89.12***	-0.07	0.57	0.22***	0.03	0.06***	0.28***	0.07***	-0.02	0.04***	0.32***	0.02*	-0.55***	89.66	2.4	75.05	0.3542
	(4.57)	(-0.65)	(0.51)	(28.91)	(0.3)	(8.12)	(2.83)	(9.21)	(-0.21)	(5.72)	(3.13)	(1.96)	(-6.04)	(1.19)	(0.32)	(0.95)	
Trader Group: Agency Algorithmic Trader																	
1	-98.14***	-0.54***	-1.85***	0.19***	0.02	0.06***	0.23**	0.07***	0.04	0.04***	0.32***	0.01	-0.51***	123.47*	39.12**	-61.52	0.3596
	(-5.02)	(-3.56)	(-2.68)	(22.91)	(0.21)	(7.55)	(2.28)	(9.58)	(0.43)	(5.55)	(3.09)	(1.48)	(-5.82)	(1.71)	(2.13)	(-0.42)	
2	37.77*	-0.27*	3.47**	0.22***	0	0.06***	0.32***	0.07***	0.01	0.04***	0.31***	0.01	-0.51***	265.24***	-3.83	407.59*	0.3552
	(1.93)	(-1.83)	(2.4)	(28.86)	(0.03)	(6.98)	(3.21)	(9.35)	(0.11)	(5.55)	(3)	(1.59)	(-5.79)	(3.62)	(-0.21)	(1.92)	
3	40.15**	0.16	-1.38	0.22***	0.04	0.06***	0.25**	0.07***	-0.04	0.04***	0.34***	0.01	-0.51***	185.49**	-8.85	741.82***	0.355
	(2.05)	(1.1)	(-0.79)	(29.05)	(0.41)	(8.13)	(2.49)	(8.32)	(-0.43)	(5.44)	(3.31)	(1.48)	(-5.85)	(2.45)	(-0.48)	(3.03)	
4	30.59	-0.03	-5.03***	0.22***	0.03	0.06***	0.18*	0.07***	0	0.03***	0.35***	0.01	-0.52***	135.14*	50.82***	116.59	0.3559
	(1.57)	(-0.2)	(-4.25)	(29.06)	(0.39)	(8.11)	(1.85)	(9)	(0.03)	(3.97)	(3.29)	(1.47)	(-5.87)	(1.79)	(2.73)	(0.71)	
5	90.54***	0.02	-0.96	0.22***	0.02	0.06***	0.27***	0.07***	-0.02	0.04***	0.33***	0.02*	-0.56***	48.67	16.91	-80.55	0.3543
	(4.66)	(0.13)	(-0.92)	(28.89)	(0.24)	(8.13)	(2.77)	(9.22)	(-0.19)	(5.74)	(3.2)	(1.95)	(-6.14)	(0.67)	(0.91)	(-0.47)	

t statistics in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 7: Results of fixed effect panel regression model to test volatility information trading by proprietary and agency algorithmic traders in the NSE options market controlling for unscheduled corporate announcements.
Measure of volatility (RV): Anderson (2001), estimate of realized volatility using intra-day five-minute return of the security.

		D_TG^{σ}		OneDayRV										$abs(D\_TG^{\Delta})$		
j	Const.	(t-j)	(t-j) *UAD	(t-1)	(t-1) *UAD	(t-2)	(t-2) *UAD	(t-3)	(t-3) *UAD	(t-4)	(t-4) *UAD	(t-5)	(t-5) *UAD	UAD	(t-j)	(t-j) *UAD	$ModelR^2$
Trader Group: Prop Algorithmic Trader																	
1	-70.43***	-0.45***	-2.87***	0.18***	0.45***	0.05***	1.71***	0.07***	1.49***	0.03***	3.53***	0.01**	-3.37***	556.18***	31.71***	492.87***	0.4265
	(-3.79)	(-4.1)	(-3.87)	(22.76)	(3.07)	(6.5)	(11.38)	(9.24)	(8.82)	(4.47)	(20.72)	(2.01)	(-19.05)	(4.45)	(4.46)	(5.79)	
2	59.18***	-0.21*	-3.52***	0.21***	0.46***	0.05***	1.97***	0.07***	1.27***	0.03***	3.48***	0.01**	-3.69***	-539.85***	-9.95	-707.83***	0.4174
	(3.17)	(-1.83)	(-5.48)	(28.62)	(3.1)	(6.65)	(12.68)	(9.01)	(7.38)	(4.35)	(20.27)	(1.97)	(-20.58)	(-4.26)	(-1.39)	(-6.83)	
3	49.27***	-0.11	-9.7***	0.21***	0.58***	0.05***	1.94***	0.07***	0.92***	0.03***	3.8***	0.01*	-3.64***	-706.88***	-20.93***	-747.86***	0.4212
	(2.65)	(-1.02)	(-8.91)	(28.69)	(4.07)	(6.98)	(13.11)	(8.65)	(5.3)	(4.37)	(21.55)	(1.89)	(-20.04)	(-6.29)	(-2.93)	(-9.28)	
4	48.32***	-0.09	-3.26**	0.21***	0.29**	0.05***	1.93***	0.06***	1.42***	0.03***	3.66***	0.01**	-3.63***	186.76	14.16**	-651.16***	0.4181
	(2.6)	(-0.82)	(-2.43)	(28.63)	(2)	(6.75)	(13.04)	(8.53)	(8.39)	(3.56)	(21.17)	(2.03)	(-20.27)	(1.45)	(1.98)	(-6.02)	
5	88.08***	0.01	-1.75	0.21***	0.43***	0.05***	1.89***	0.06***	1.43***	0.03***	3.54***	0.02**	-3.75***	-150.85	4.29	-327.12***	0.4159
	(4.75)	(0.07)	(-1.47)	(28.44)	(2.89)	(6.85)	(12.7)	(8.59)	(8.43)	(4.61)	(20.6)	(2.56)	(-20.07)	(-1.17)	(0.6)	(-4.27)	
Trader Group: Agency Algorithmic Trader																	
1	-77.58***	-0.4***	-23.9***	0.18***	0.51***	0.05***	2.19***	0.07***	1.31***	0.03***	2.76***	0.01*	-3.18***	54	43.13**	-665.66***	0.4332
	(-4.22)	(-2.84)	(-16.38)	(23.22)	(3.53)	(6.32)	(14.99)	(9.12)	(7.87)	(4.38)	(15.77)	(1.87)	(-18.03)	(0.43)	(2.5)	(-5.17)	
2	62.69***	-0.05	-18.59***	0.21***	0.61***	0.05***	1.41***	0.07***	1.32***	0.03***	3.53***	0.01**	-3.58***	-249.9**	0	134.98	0.4191
	(3.38)	(-0.35)	(-10.95)	(28.64)	(4.14)	(6.61)	(9.19)	(8.98)	(7.81)	(4.35)	(20.51)	(2)	(-20.05)	(-1.98)	(0)	(0.56)	
3	57.78***	0.13	-5.26**	0.21***	0.68***	0.05***	1.73***	0.07***	1.06***	0.03***	3.75***	0.01*	-3.72***	-544.99***	-0.96	-718.63***	0.4166
	(3.11)	(0.92)	(-2.51)	(28.61)	(4.72)	(6.88)	(11.67)	(8.44)	(6.16)	(4.36)	(21.14)	(1.92)	(-20.61)	(-4.95)	(-0.05)	(-4.11)	
4	52.62***	-0.11	-4.46***	0.21***	0.13	0.05***	1.85***	0.06***	2.25***	0.03***	3.39***	0.01**	-3.89***	-74.73	72.34***	-4055.86***	0.4262
	(2.86)	(-0.76)	(-3.19)	(28.83)	(0.86)	(6.79)	(12.64)	(8.61)	(12.93)	(3.51)	(19.74)	(2.05)	(-21.97)	(-0.62)	(4.13)	(-16.49)	
5	90.44***	0.01	3.79	0.21***	0.49***	0.05***	1.85***	0.06***	1.43***	0.03***	3.57***	0.02**	-3.76***	-91.49	22.21	-565.43**	0.4155
	(4.9)	(0.05)	(1.54)	(28.39)	(3.3)	(6.84)	(12.3)	(8.58)	(8.43)	(4.61)	(20.65)	(2.55)	(-20.1)	(-0.72)	(1.26)	(-2.41)	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Results of fixed effect panel regression model to test volatility information trading by proprietary and agency algorithmic traders in the NSE options market controlling for scheduled earnings announcements.
Measure of volatility (RV): Alizadeh (2002), estimate of realized volatility computed through difference between the stock's intraday high and low price divided by the closing stock price.

		D_TG^{σ}		OneDayRV											$abs(D\_TG^{\Delta})$		
j	**Const.**	**(t-j)**	**(t-j) *EAD**	**(t-1)**	**(t-1) *EAD**	**(t-2)**	**(t-2) *EAD**	**(t-3)**	**(t-3) *EAD**	**(t-4)**	**(t-4) *EAD**	**(t-5)**	**(t-5) *EAD**	**EAD**	**(t-j)**	**(t-j) *EAD**	$Model R^2$
Trader Group: Prop Algorithmic Trader																	
1	-546.13***	-0.7	-6.81**	0.02***	0.17	0.03***	0.22	0.04***	-0.01	0.02**	0.19	-0.01	-0.25	180.83	48.33	43.59	0.0710
	(-6.39)	(-1.32)	(-2.08)	(2.61)	(1.08)	(3.63)	(1.3)	(5.41)	(-0.07)	(2)	(1.11)	(-1.62)	(-1.61)	(0.58)	(1.4)	(0.3)	
2	-233.69***	-1.1**	-0.01	0.04***	0.24	0.02***	0.2	0.04***	-0.03	0.02**	0.19	-0.01	-0.28*	261.55	-54.65	60.25	0.0667
	(-2.74)	(-2.09)	(0)	(5.13)	(1.61)	(3.12)	(1.18)	(5.04)	(-0.19)	(2.09)	(1.13)	(-1.55)	(-1.81)	(0.82)	(-1.61)	(0.13)	
3	-176.37**	-0.71	-6.09	0.04***	0.27*	0.03***	0.2	0.03***	-0.08	0.01*	0.18	-0.01	-0.27*	191.13	-33.89	201.45	0.0662
	(-2.08)	(-1.36)	(-1.32)	(5.25)	(1.79)	(4.29)	(1.16)	(4.29)	(-0.46)	(1.74)	(1.07)	(-1.56)	(-1.7)	(0.56)	(-1)	(0.69)	
4	-123.78	-0.49	-1.8	0.04***	0.25	0.03***	0.19	0.04***	-0.03	0.01	0.13	-0.01*	-0.28*	-45.07	18.83	15.1	0.0658
	(-1.46)	(-0.94)	(-0.39)	(5.26)	(1.63)	(4.44)	(1.13)	(5.28)	(-0.2)	(0.98)	(0.76)	(-1.82)	(-1.74)	(-0.13)	(0.55)	(0.05)	
5	141.46*	-0.83	2.32	0.04***	0.25*	0.03***	0.2	0.04***	-0.05	0.02**	0.2	-0.01	-0.3*	134.71	36.27	151.66	0.0648
	(1.68)	(-1.59)	(0.46)	(5.25)	(1.65)	(4.52)	(1.21)	(5.51)	(-0.31)	(2.17)	(1.17)	(-1.62)	(-1.88)	(0.4)	(1.07)	(0.42)	
Trader Group: Agency Algorithmic Trader																	
1	-563***	-3.43***	-1.85	0.02***	0.16	0.03***	0.19	0.04***	-0.01	0.01*	0.17	-0.01	-0.25	172.96	33.76	-0.4	0.0721
	(-6.62)	(-5.04)	(-0.59)	(2.68)	(1.07)	(3.44)	(1.14)	(5.42)	(-0.08)	(1.95)	(1)	(-1.63)	(-1.62)	(0.53)	(0.41)	(0)	
2	-211.65**	-2.18***	4.26	0.04***	0.24	0.02***	0.21	0.04***	-0.04	0.02**	0.18	-0.01	-0.28*	292.19	-25.33	444.72	0.0669
	(-2.5)	(-3.24)	(0.65)	(4.99)	(1.55)	(3.05)	(1.23)	(4.93)	(-0.22)	(2.11)	(1.03)	(-1.56)	(-1.81)	(0.89)	(-0.31)	(0.46)	
3	-153.44*	0.2	-1.11	0.04***	0.24	0.03***	0.21	0.03***	-0.11	0.01*	0.16	-0.01	-0.25	244.18	45.23	1300.11	0.0661
	(-1.81)	(0.3)	(-0.14)	(5.29)	(1.58)	(4.3)	(1.22)	(4.26)	(-0.62)	(1.77)	(0.97)	(-1.57)	(-1.57)	(0.72)	(0.54)	(1.18)	
4	-110.04	-0.32	-5.71	0.04***	0.24	0.03***	0.19	0.04***	-0.05	0.01	0.12	-0.01*	-0.27*	-7.1	134.98	162.26	0.0659
	(-1.3)	(-0.47)	(-1.08)	(5.26)	(1.6)	(4.44)	(1.09)	(5.27)	(-0.33)	(0.99)	(0.73)	(-1.83)	(-1.7)	(-0.02)	(1.61)	(0.22)	
5	135.64	-0.07	-2.04	0.04***	0.24	0.03***	0.2	0.04***	-0.04	0.02**	0.19	-0.01	-0.3*	73.86	84.52	-29.5	0.0646
	(1.62)	(-0.1)	(-0.43)	(5.25)	(1.61)	(4.53)	(1.19)	(5.52)	(-0.26)	(2.2)	(1.15)	(-1.54)	(-1.87)	(0.23)	(1.01)	(-0.04)	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Results of fixed effect panel regression model to test volatility information trading by proprietary and agency algorithmic traders in the NSE options market controlling for unscheduled corporate announcements.
Measure of volatility (RV): Alizadeh (2002), estimate of realized volatility computed through difference between the stock's intraday high and low price divided by the closing stock price.

		D_TG^{σ}		OneDayRV											$abs(D\_TG^{\Delta})$		
j	**Const.**	**(t-j)**	**(t-j) *UAD**	**(t-1)**	**(t-1) *UAD**	**(t-2)**	**(t-2) *UAD**	**(t-3)**	**(t-3) *UAD**	**(t-4)**	**(t-4) *UAD**	**(t-5)**	**(t-5) *UAD**	**UAD**	**(t-j)**	**(t-j) *UAD**	$Model R^2$
Trader Group: Prop Algorithmic Trader																	
1	-356.38***	-0.93**	-36.46***	0.02***	-2.43***	0.01	10.55***	0.04***	2***	0.01	7.87***	-0.01	-3.61***	5648.06***	23.04	3307.65***	0.4827
	(-5.59)	(-2.36)	(-13.89)	(4.2)	(-11.12)	(1.64)	(60.53)	(6.28)	(8.04)	(0.89)	(38.8)	(-0.98)	(-14.61)	(12.71)	(0.91)	(11.27)	
2	-10.87	-0.66	-9.7***	0.04***	-2.22***	0.01**	11.09***	0.04***	1.62***	0.01	7.48***	0	-3.64***	1406.75***	-42.81*	-5063.26***	0.4603
	(-0.17)	(-1.64)	(-4.15)	(6.49)	(-9.84)	(1.97)	(60.48)	(6.09)	(6.35)	(1.03)	(36.51)	(-0.78)	(-13.84)	(3)	(-1.66)	(-13.82)	
3	-15.33	-0.15	-24.76***	0.04***	-1.72***	0.01**	10.81***	0.03***	1.81***	0	7.25***	0	-3.51***	-2001.44***	-27.06	-1836.85***	0.4571
	(-0.24)	(-0.37)	(-6.18)	(6.45)	(-7.66)	(2.31)	(60.71)	(5.64)	(6.98)	(0.84)	(33.71)	(-0.83)	(-12.95)	(-4.91)	(-1.04)	(-6.3)	
4	37.93	-0.38	16.08***	0.04***	-2.6***	0.01**	10.89***	0.04***	2.1***	0	7.92***	-0.01	-3.24***	5106.99***	35.49	-2453.29***	0.4624
	(0.59)	(-0.96)	(3.33)	(6.5)	(-11.7)	(2.39)	(61.73)	(6.17)	(8.24)	(0.5)	(37.45)	(-0.87)	(-12.54)	(10.93)	(1.37)	(-6.3)	
5	127.61**	-0.3	-8.51**	0.04***	-2.92***	0.01**	11.41***	0.04***	2.02***	0.01	7.99***	-0.01	-3.07***	7803.14***	40.04	1573.25***	0.4625
	(2)	(-0.75)	(-2.01)	(6.48)	(-12.92)	(2.44)	(63.96)	(6.25)	(7.92)	(1.08)	(39.07)	(-0.89)	(-11.48)	(16.65)	(1.55)	(5.64)	
Trader Group: Agency Algorithmic Trader																	
1	-350.96***	-1.12**	-201.48***	0.03***	-2.11***	0.01	10.89***	0.04***	1.94***	0	6.85***	-0.01	-4.36***	3979.22***	41.27	921.99**	0.5197
	(-5.75)	(-2.33)	(-41.45)	(4.52)	(-9.99)	(1.64)	(63.98)	(6.47)	(8.12)	(0.88)	(35.33)	(-1.02)	(-18.38)	(9.02)	(0.69)	(2.06)	
2	2.34	-0.36	-85.5***	0.04***	-2.31***	0.01*	10.59***	0.04***	1.8***	0.01	7.43***	0	-2.98***	4580.6***	-25.04	3593.54***	0.4605
	(0.04)	(-0.71)	(-13.79)	(6.42)	(-9.9)	(1.88)	(56.99)	(6.04)	(7.06)	(1.01)	(36.63)	(-0.8)	(-11.54)	(9.8)	(-0.4)	(4.05)	
3	14.26	0.14	32.83***	0.04***	-2.12***	0.01**	11.3***	0.03***	1.72***	0.01	7.33***	0	-4.6***	-234.47	87.76	7467.19***	0.4596
	(0.22)	(0.27)	(4.32)	(6.47)	(-9.48)	(2.3)	(63.3)	(5.57)	(6.71)	(0.87)	(34.91)	(-0.82)	(-17.09)	(-0.59)	(1.38)	(11.57)	
4	49.42	-0.45	-45.66***	0.04***	-1.32***	0.01**	9.95***	0.04***	2.88***	0	8.28***	-0.01	-3.64***	2934.92***	207.7***	-21466.5***	0.4779
	(0.78)	(-0.89)	(-9.05)	(6.56)	(-5.83)	(2.4)	(56.05)	(6.24)	(11.42)	(0.49)	(39.98)	(-0.9)	(-14.27)	(6.63)	(3.31)	(-24.25)	
5	121.7*	-0.14	-29.14***	0.04***	-3.05***	0.01**	11.55***	0.04***	2.07***	0.01	7.86***	0	-2.97***	7841.74***	90.23	6205.76***	0.4629
	(1.92)	(-0.27)	(-3.2)	(6.48)	(-13.13)	(2.44)	(63.83)	(6.25)	(8.16)	(1.1)	(38.69)	(-0.82)	(-10.92)	(17.03)	(1.42)	(7.31)	

t statistics in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

6 Price Impact and Information Asymmetry

We further study the informativeness of algorithmic and non-algorithmic traders by inspecting how their demand for volatility is related to options price changes. If a certain group of traders has information regarding future volatility, it is likely that their positive(negative) demand for volatility will be positively related to increasing(decreasing) options prices. Following Ni et al. (2008), we estimate this change in options prices through changes in implied volatility.

To construct clean securities that have high sensitivity to realizations of equity volatility but low sensitivity to directional changes in the underlying stock, we identify options straddles. We identify the near-the-money call and put options by identifying options contracts with the strike-price closest to the day's equity closing price. We also ensure that the options contracts are of near-month maturity and have at least five trading days to maturity. The chosen call and put options have the same expiry date. Prices of both call and put options contracts increase(decrease) with increasing (decreasing) volatility, but the prices move in opposite directions with change in the underlying prices. As such, this combination has a high sensitivity to volatility but low sensitivity to directional movements.

For the implied volatility for the chosen call/put options contract, we consider the daily average of implied volatility corresponding to each trade on that day. Consistent with the earlier section, we compute the implied volatility by solving the Black-Scholes options pricing model corresponding to the options prices. For particular security i on the day t, the implied volatility is calculated as the average of the day's average implied volatility for call and put options contracts.

$$IV_{i,t} = \frac{1}{2} \times (IV^c_{i,t} + IV^p_{i,t}) \tag{4}$$

Following Ni et al. (2008), we use the following empirical model to estimate the impact of volatility demand on options price changes. Unlike Ni et al. (2008), we use a fixed effect panel regression model instead of a pooled regression model. The coefficient β_1 corresponding to the net demand for volatility for a particular trader-group TG, corresponds to the change in options prices (in terms of IV) to a unit change in volatility demand.

$$\begin{aligned}(IV_{i,t} - IV_{i,t-1})/IV_{i,t-1} =& \alpha + \beta_1 D\_TG^{\sigma}_{i,t} + D\_TG^{\sigma}_{i,t}(\beta^{AD}_{-5} Ind(AD-5)_{i,t} + ..\\ &+ \beta^{AD}_{0} Ind(AD)_{i,t} + .. + \beta^{AD}_{+5} Ind(AD+5)_{i,t})\\ &+ \gamma^{AD}_{-5} Ind(AD-5)_{i,t} + .. + \gamma^{AD}_{0} Ind(AD)_{i,t} + ..\\ &+ \gamma^{AD}_{+5} Ind(AD+5)_{i,t} + \delta_i + \epsilon_{i,t}\end{aligned} \tag{5}$$

As it can be seen from the model we use dummy indicator variables for days around scheduled/unscheduled corporate announcements - $Ind(AD \mp \theta)_{i,t}$ that take up the value of one if the said date t for the security i is θ days before(after) the corporate announcement (AD), zero otherwise. The price impact can be either driven by information asymmetry or by demand pressure. If information asymmetry is the primary source, then leading up to the corporate announcement, information asymmetry should rise, and hence we should expect an increasing value of the coefficient of the interaction term between the volatility demand and the indicator variable $D\_TG^{\sigma}_{i,t} \times Ind(AD-\theta)_{i,t}$.

To control for other stock characteristics that may influence price impact, we consider four stock-specific characteristics - the book to market ratio (BM), the relative trading volume of options contracts compared to spot (relOptVolume), the stock volatility (histStockVol) and size - (ln(size)).Considering our sample period is from Jan-Jun 2015, we compute the variables based on the previous calendar year's (2014) data. relOptVolume is the ratio of aggregate options traded volume for the stock to the aggregate spot traded volume for the year 2014. histStockVol is 100 times the standard deviation of stock returns (based on daily closing price) for the entire calendar year 2014. BM -book to market ratio is computed as the ratio of the book value of equity to the market value of equity as on 31 Dec 2014. Size is computed as the natural logarithm of total assets (in INR millions) reported for FY 2014. As we use only six months of data for our analysis, we don't use these controls independently in our model [7], rather we use only their interaction terms with the demand for volatility term.

We report our results based on the analysis of price impact leading up to both scheduled (Table 10) and unscheduled corporate announcements (Table 11). As we have used fixed-effect models, any stock-specific characteristics should be captured by the fixed effect. We report the results both without (Models 1 and 2) and with the (Models 3 and 4) interaction terms with the stock specific controls. To test if the impact of demand for volatility has a non-linear relationship with price impact, we substitute the demand parameter with its square term (Models 2 and 4).

As seen from the results (Tables 10 and 11), the demand for volatility for the non-algorithmic traders is positively related to change in options prices. However, we do not find information asymmetry as the primary reason behind these results. For both scheduled as well as unscheduled announcements, we do not find an incremental increase in information asymmetry. We do not find evidence in support of the non-linear relationship between the volatility demand and price changes. For unscheduled announcements, there is a significant spike on the announcement day. This may be explained by the fact that for earnings announcements, the market already starts incorporating the information prior to the actual announcements. However, due to the unanticipated nature of unscheduled announcements, there is price correction on the announcement date itself. Also, consistent with our earlier analysis, we infer that due to modern electronic markets, the information asymmetry related to earnings announcement has reduced over time.

We only report the results corresponding to the volatility demand of the non-algorithmic trader classes. By construction, the demand variable for the algorithmic trader class will be equal in magnitude and opposite in sign. As such, the results corresponding to the algorithmic traders will be the exact opposite in this case. As our earlier analysis does not

[7] as the observations across the time dimension will not have any variation, the panel model will drop the controls if use independently

Table 10: This table reports estimates from fixed effect panel regression for the sample period of Jan to Jun 2015. The dependent variable is 10,000 times the daily change in implied volatility divided by the level of the implied volatility for underlying stock i on trade date $(t-1)$. The D_NA variable is the non algorithmic trader's demand for volatility in the options market for underlying stock i on trade day t. This table reports the results corresponding to scheduled earnings announcements. Models 1 and 2 do not use the stock specific controls, whereas models 3 and 4 do. Models 2 and 4 use the squared demand for volatility to test for non-linear relationship.

Variable	(1)		(2)		(3)		(4)	
Intercept	49.26	(0.55)	8.92	(0.10)	44.72	(0.50)	34.74	(0.39)
D_NA	15.42***	(12.25)			98.02***	(8.80)		
$(D\_NA)^2$			0.04*	(1.71)			0.03	(1.26)
D_NA × Ind(EAD-5)	3.66	(0.42)	18.70**	(2.15)	4.96	(0.57)	6.02	(0.69)
D_NA × Ind(EAD-4)	−0.20	(-0.02)	14.56	(1.64)	0.56	(0.06)	1.82	(0.2)
D_NA × Ind(EAD-3)	2.24	(0.20)	16.71	(1.50)	−1.38	(-0.12)	3.06	(0.28)
D_NA × Ind(EAD-2)	10.39	(1.01)	24.75**	(2.41)	9.71	(0.95)	11.08	(1.08)
D_NA × Ind(EAD-1)	−6.12	(-1.17)	6.80	(1.30)	−3.22	(-0.60)	0.13	(0.02)
D_NA × Ind(EAD-0)	−3.41	(-0.89)	10.85***	(2.93)	1.48	(0.38)	−1.15	(-0.29)
D_NA × Ind(EAD+1)	−1.75	(-0.39)	14.58***	(3.34)	−4.17	(-0.94)	0.43	(0.10)
D_NA × Ind(EAD+2)	−4.93	(-0.53)	10.68	(1.16)	−7.84	(-0.85)	−4.77	(-0.51)
D_NA × Ind(EAD+3)	13.39	(1.48)	28.83***	(3.20)	11.53	(1.28)	15.28*	(1.69)
D_NA × Ind(EAD+4)	6.68	(0.65)	20.73**	(2.03)	4.90	(0.48)	7.18	(0.70)
D_NA × Ind(EAD+5)	−4.84	(-0.55)	10.22	(1.16)	−8.68	(-0.98)	−5.27	(-0.60)
Ind(EAD-5)	163.2**	(2.46)	152.78**	(2.29)	157.23**	(2.38)	159.08**	(2.40)
Ind(EAD-4)	151.74**	(2.22)	141.87**	(2.07)	155.55**	(2.29)	153.60**	(2.25)
Ind(EAD-3)	186.46***	(2.67)	178.07**	(2.54)	189.97***	(2.73)	186.99***	(2.68)
Ind(EAD-2)	94.90	(1.34)	86.74	(1.22)	93.79	(1.33)	89.44	(1.27)
Ind(EAD-1)	266.21***	(3.75)	262.09***	(3.67)	225.55***	(3.18)	229.9***	(3.23)
Ind(EAD-0)	166.47**	(2.41)	151.46**	(2.18)	89.96	(1.30)	127.36*	(1.84)
Ind(EAD+1)	−667.44***	(-10.30)	−682.39***	(-10.47)	−668.04***	(-10.34)	−670.15***	(-10.34)
Ind(EAD+2)	−308.89***	(-4.74)	−318.78***	(-4.87)	−308.7***	(-4.75)	−307.94***	(-4.73)
Ind(EAD+3)	24.54	(0.38)	14.27	(0.22)	22.5	(0.35)	22.75	(0.35)
Ind(EAD+4)	−91.58	(-1.39)	−100.84	(-1.52)	−83.21	(-1.27)	−92.94	(-1.41)
Ind(EAD+5)	−106.96	(-1.61)	−117.47*	(-1.75)	−104.48	(-1.57)	−110.41*	(-1.66)
D_NA × BM					5.73**	(2.35)	3.19	(1.31)
D_NA × relOptVolume					−10.17***	(-5.72)	−12.54***	(-7.12)
D_NA × histStockVol					3.06***	(3.83)	1.20	(1.54)
D_NA × ln(Size)					−5.69***	(-6.39)	1.88***	(8.33)
R Square		0.0321		0.0224		0.039		0.034

t statistics in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

exhibit any difference in behavior between proprietary and agency algorithmic traders, we do not run the model in this section separately for proprietary and agency algorithmic traders.

7 Conclusion

The exponential growth of algorithmic traders in the financial markets demands a better understanding of the role played by these machine traders. A lot of recent literature has been devoted to their role in the spot market, especially in issues related to the provisioning of liquidity. However, the extent of literature focused on the role of algorithmic traders in the derivative markets is considerably lesser. Existing research seems to suggest that

Table 11: This table reports estimates from fixed effect panel regression for the sample period of Jan to Jun 2015. The dependent variable is 10,000 times the daily change in implied volatility divided by the level of the implied volatility for underlying stock i on trade date $(t-1)$. The D_NA variable is the non algorithmic trader's demand for volatility in the options market for underlying stock i on trade day t. This table reports the results corresponding to non-scheduled corporate announcements. Models 1 and 2 do not use the stock specific controls, whereas models 3 and 4 do. Models 2 and 4 use the squared demand for volatility to test for non-linear relationship.

Variable	(1)		(2)		(3)		(4)	
Intercept	45.73	(0.51)	8.48	(0.09)	41.07	(0.46)	35.13	(0.4)
D_NA	15.96***	(14.15)			98.89***	(8.98)		
$(D\_NA)^2$			0.04*	(1.84)			0.02	(0.68)
D_NA × Ind(UAD-5)	−5.96	(-0.48)	8.54	(0.68)	−6.5	(-0.52)	−8.43	(-0.67)
D_NA × Ind(UAD-4)	−10.31	(-0.88)	4.18	(0.35)	−7.85	(-0.67)	−7.38	(-0.63)
D_NA × Ind(UAD-3)	4.2	(0.39)	19.66*	(1.85)	11.15	(1.05)	8.69	(0.81)
D_NA × Ind(UAD-2)	−4.69	(-0.58)	8.95	(1.09)	4.81	(0.59)	−1.28	(-0.15)
D_NA × Ind(UAD-1)	−12.57*	(-1.8)	5.04	(0.72)	−3.82	(-0.54)	−6.21	(-0.87)
D_NA × Ind(UAD-0)	74.35***	(7.26)	89.99***	(8.78)	79.47***	(7.76)	80.86***	(7.87)
D_NA × Ind(UAD+1)	−20.7*	(-1.89)	−5.11	(-0.47)	−16.72	(-1.53)	−16.75	(-1.53)
D_NA × Ind(UAD+2)	12.09	(1.17)	27.22***	(2.62)	14.79	(1.43)	15.17	(1.46)
D_NA × Ind(UAD+3)	2.25	(0.18)	19.09	(1.53)	4.9	(0.39)	9.56	(0.77)
D_NA × Ind(UAD+4)	2.34	(0.2)	18.47	(1.61)	2.74	(0.24)	3.68	(0.32)
D_NA × Ind(UAD+5)	−5.9	(-0.73)	10.56	(1.3)	−1.32	(-0.16)	−1.92	(-0.23)
Ind(UAD-5)	−14.93	(-0.12)	−27.13	(-0.22)	−15.67	(-0.13)	−22.99	(-0.19)
Ind(UAD-4)	144.97	(1.15)	134.91	(1.07)	154.84	(1.24)	149.31	(1.19)
Ind(UAD-3)	−102.72	(-0.84)	−117.03	(-0.95)	−107.69	(-0.88)	−110.5	(-0.9)
Ind(UAD-2)	−42.46	(-0.35)	−56.4	(-0.47)	−41.61	(-0.35)	−30.01	(-0.25)
Ind(UAD-1)	150.12	(1.28)	124.31	(1.05)	98.44	(0.84)	128.16	(1.09)
Ind(UAD-0)	1101.11***	(9.65)	1084.99***	(9.44)	1094.55***	(9.63)	1085.9***	(9.52)
Ind(UAD+1)	−53.34	(-0.46)	−68.35	(-0.59)	−69.1	(-0.6)	−51.36	(-0.44)
Ind(UAD+2)	−103.01	(-0.89)	−116.94	(-1)	−106.63	(-0.92)	−116.69	(-1.01)
Ind(UAD+3)	−9.87	(-0.08)	−24.94	(-0.21)	−8.99	(-0.08)	−14.57	(-0.12)
Ind(UAD+4)	−123.97	(-0.97)	−139.61	(-1.09)	−129	(-1.02)	−150.39	(-1.18)
Ind(UAD+5)	39.76	(0.32)	19.76	(0.16)	5.25	(0.04)	14.1	(0.11)
D_NA × BM					5.4**	(2.19)	2.56	(1.05)
D_NA × relOptVolume					−11.47***	(-6.51)	−13.84***	(-7.93)
D_NA × histStockVol					3.02***	(3.71)	1.07	(1.35)
D_NA × ln(Size)					−5.6***	(-6.31)	2.11***	(9.56)
R Square		0.0327		0.0197		0.0404		0.0352

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

algorithmic traders react much faster to public information. We do not find any literature exploring whether algorithmic traders have information regarding future volatility. The benefit of leverage suggests that informed investors are better off using that information in the derivatives market compared to the spot market. The non-linear payoff structure indicates that options are ideal securities for utilizing any volatility-related information. Using the framework provided by Ni et al. (2008) we inspect if algorithmic traders have information regarding future realized volatility.

We use a large dataset obtained from the National Stock Exchange of India, which provides exact identifiers for trades executed by algorithmic traders. We use six months of intraday data (Jan-Jun 2015) for both stock and options market [8] for 159 stocks to create

[8] Number of trades executed in the NSE stock options market during this period is more than 37 mn

daily demand for volatility for various trader groups and relate that to future realized volatility in the spot market. We find that non-algorithmic traders are informed about future realized volatility while algorithmic traders are not. We use scheduled earnings announcements as well as unscheduled corporate announcements as an exogenous shock. We find that different trader groups behave similarly to both these types of events. We also find that the predictive ability of volatility demand for non-algorithmic traders for future realized volatility rarely lasts beyond one trading day.

We further split the class of algorithmic traders into proprietary and agency algorithmic traders. Due to the inherent difference in the motivation of these two groups, we study if their trades convey different information. However, we find that none of these two groups have information regarding future volatility. Proprietary algorithms are primarily used for high-frequency trading (HFT), which is not supposed to based on information. While institutional investors are known to trade in information, we argue that, when they employ algorithms to execute trades on their behalf, the information contained in their trading volume may be lost.

We further inspect the relationship of this volatility with the change in options prices. Instead of using options prices directly, we use the change in implied volatility as a proxy. We find that the volatility demand of non-algorithmic traders is positively related to change in options prices. By the construct of the volatility demand measure, the conjecture about the algorithmic traders would be just the opposite. However, it seems that the price impact is driven more by demand pressure rather than information asymmetry. However, we find slightly different results relative to scheduled and unscheduled corporate announcements. We find that information asymmetry is a significant factor in explaining price changes on the unscheduled announcement date. Presently there is more market-wide information dissipation using the electronic platforms, which might reduce the overall information asymmetry between various trader groups in general. As such, it might be possible that the market already incorporates the estimated information regards to scheduled corporate announcements such as earnings announcements. However, the same may not be true in the case of unscheduled announcements. These findings further strengthen our argument about the volatility informativeness of non-algorithmic traders.

8 Robustness Test

We run robustness tests by using pooled regression models [9] (similar to Ni et al. (2008)) instead of fixed effect panel models, but the primary results are consistent.

In this essay we use two alternate definitions of realized volatility - the realized volatility based on the Andersen et al. (2001) model and the same based on (Alizadeh et al., 2002). To test for the robustness, we use three more volatility estimates based on Garman and Klass (1980), Rogers and Satchell (2007) and Parkinson (1980). All three of these realized volatility estimates are range-based. While Parkinson (1980) estimate use just daily high and low prices; Garman and Klass (1980) and Rogers and Satchell (2007) use daily open and close prices along with daily high and low prices. As evident (Table 12), the correlation coefficient between the three new volatility measures and the realized volatility measure as per Andersen et al. (2001) is high (more than 0.80). As such, we argue that using these alternate definitions of realized volatility in our models wouldn't significantly change the results.

Table 12: Pearson correlation coefficient for the five measures of realized volatility.

	Anderson	Garman Klass	Rogers Satchell	Parkinson
Alizadeh	0.747	0.781	0.597	0.900
Anderson		0.870	0.807	0.852
Garman Klass			0.957	0.951
Rogers Satchell				0.827

[9]Results not reported.

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