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 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. The primary results are robust for various measures of realized volatility.

1 Introduction

Do algorithmic traders have information on future volatility? 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

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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 chapter, 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 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 a particular security was to go up or down. In 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 a 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 are 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 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 market 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 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.

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). Evidence clearly suggests that informed traders choose the options market as their preferred choice of venue. Comparatively the literature on whether 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 systemic risk (Jain, Jain, & McInish, 2016).

3 Volatility Information Trading

Ni et al. (2008) show that the demand for volatility for non-market makers 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 maker. 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 the 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 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 announcements, un-scheduled announcements create similar situations of information asymmetry. As such 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. Options contracts are available in different expiries 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-

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

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

[1] rate of change of options price with respect to change in volatility

and hence, $(\partial ln C_{i,t}^{K,T}/\partial\sigma_{i,t})$ is approximated by $(1/C_{i,t}^{K,T}).BlackScholesCallVega_{i,t}^{K,T}$ and $(\partial ln P_{i,t}^{K,T}/\partial\sigma_{i,t})$ is approximated by $(1/P_{i,t}^{K,T}).BlackScholesPutVega_{i,t}^{K,T}$. We use sample volatility of sixty trading days leading up to t for computation of the Black Scholes Vega.

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 traded volume in the stock and traded volume in the options market. We also specifically control for 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.

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-

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

where $OneDayRV_{i,t}$ is the volatility of the underlying security i n day t. $EAD_{i,t}$ is a proxy which takes up the value of 1 if date t is an corporate announcement date for security i, 0 otherwise. $IV_{i,t}$ is the average implied volatility of the ATM [2] Call and Put option contract for the security i with 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. $optVolume_{i,t}$ is the volume of options market trading activity on day t for security i. We scale down the values of the variables $abs(D\_TG^{\Delta}_{i,t})$ and $optVolume_{i,t}$ by a factor of one million. $ln(stkVolume_{i,t})$ is the natural logarithm of the spot market traded volume for security i on day t. We estimate the equation for different values 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 which takes up the value of 1 if date t is an unscheduled corporate announcement date for security i, 0 otherwise.

[2]ATM: At the Money contract

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

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 [3]. Our dataset contains information 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. The dataset has the unique feature of classifying the trader as algorithmic and non-algorithmic. It also provides information if the trader was proprietary (Prop) in nature, custodian (Cust) or others (NCNP). For our analysis, we club algorithmic trades executed by Custodian and NCNP group 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

[3] 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.

to estimate the implied volatility using the options traded price and the Black-Scholes options pricing model.

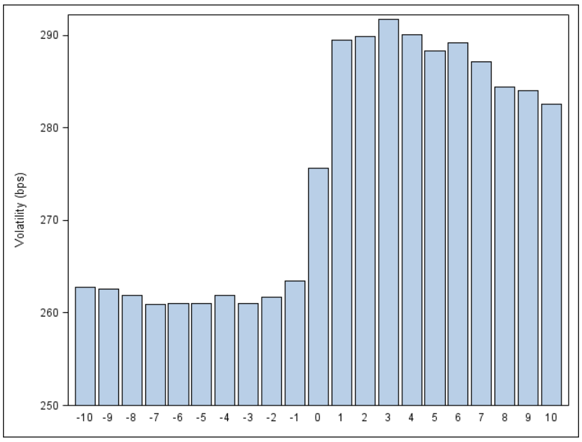
Table 1: Summary statistics of the variables used in analysis. Volatility figures are expressed in basis points (bps), where 100 bps = 1%

Variable	Obs	Mean	Median	Std Dev	Min.	Max.
OneDayRV [NSE Reported]	17772	267.66	252.54	87.02	103.91	1346.05
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
Options_Vol (Million)	17772	3.33	1.03	8.78	0.00	296.22
ln(Spot_Vol)	17772	14.22	14.33	1.32	8.34	20.12

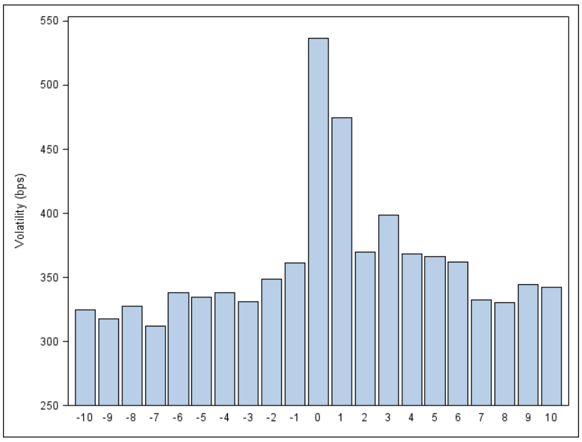
For the estimation of realized volatility, we use 3 alternative definitions. For the first definition, we use the daily volatility reported by NSE. The exchange computes the volatility as $\sigma_{i,t,NSE} = \sqrt{0.96 * \sigma^2_{i,t-1,NSE} + 0.04 * (ln\frac{Close_{i,t}}{Open_{i,t}})^2}$ or GARCH (1;1) model for the volatility index INDIAVIX. Where $\sigma_{i,t,NSE}$ is the volatility reported by NSE for i-th security on t-th day, while $Open_{i,t}$ and $Close_{i,t}$ are the the daily opening and closing prices for the i-th security on t-th day.

The second definition is based on the method followed by Andersen, Bollerslev, Diebold, and Ebens (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.

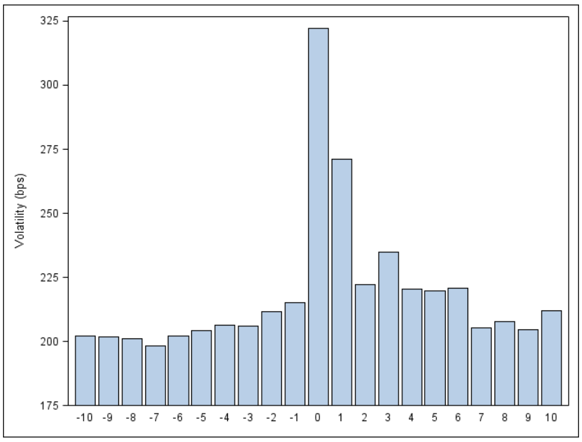
The third and final definition is based on the method followed by (Alizadeh, Brandt, & Diebold, 2002). The same measure was used by Ni et al. (2008). In this method, realized volatility is calculated from daily high, low and closing prices and estimated as $\sigma_{i,t,Range} = \frac{High_{i,t}-Low_{i,t}}{Close_{i,t}}$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



(a) Volatility Estimate (NSE Reported)

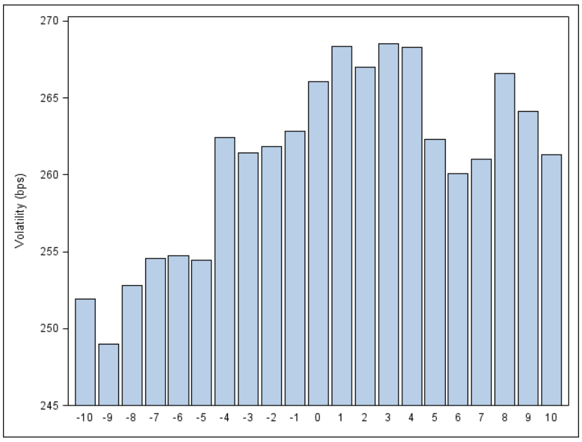


(b) Volatility Estimate (Anderson et. al. 2001)

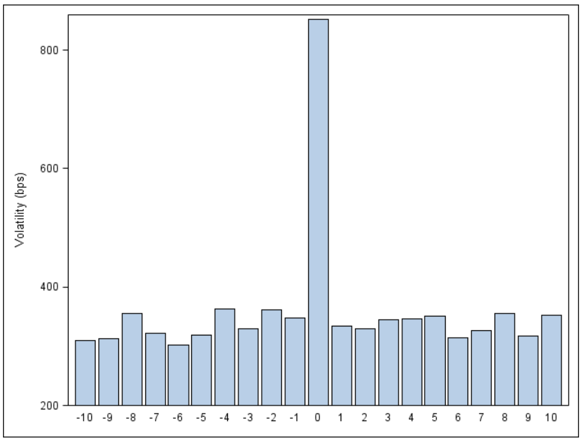


(c) Volatility Estimate (Alizadeh et. al. 2002)

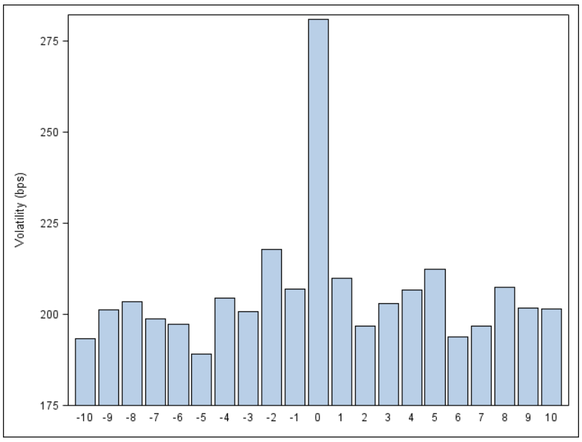
Figure 1: The figure plots average realized volatility around earnings announcement. The x-axis represents the time line around the pre-scheduled earnings announcement. 0 represents the earnings announcement date. negative values indicate trading days prior to announcement and positive values indicate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



(a) Volatility Estimate (NSE Reported)



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



(c) 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.

The earnings announcement data is obtained form 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 announcements.

The plots for average volatility around the announcement dates depict a clear pattern. In 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 prominent volatility spike only on Day 0 [4]. Also, we can notice how the volatility definition affects the shape of the plot. In case of exchange (NSE) reported volatility, it seems that the high level of volatility post announcement is persistent for several trading days. It is primarily due to the high weight given to the one-day lagged volatility for computation of present-day volatility.

[4] 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.

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 pooled model used by Ni et al. (2008). We use all three definitions of realized volatility - NSE reported volatility (Table 2 & 3), volatility computed using intraday returns (Andersen et al., 2001) (Table 4 & 5) and volatility computed by range estimator (Alizadeh et al., 2002) (Table 6 & 7). For each definition of realized volatility, we run separate models using dummies for pre-scheduled earnings announcements (Table 2, 4 & 6) and unscheduled corporate announcements (Table 3, 5 & 7).

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 same by construction. As such the two panels exhibit exactly same results except for the coefficients corresponding to volatility demand of these two groups, which have 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 announcement and the interaction terms. Due to space constraint, we do not report coefficients corresponding to the additional control variables. While positive values for the coefficients corresponding to volatility demand represent informativeness of the trader group, the negative sign indicates that the counterparty is informed.

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 positive relation with

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): Stock volatility reported by NSE [Sqrt $(0.94 * Prev\_Day\_Volatility^2 + 0.06 * Same\_Day\_Return^2)$ or GARCH (1;1) model for INDIAVIX]

		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: Algorithmic Trader																	
1	-7.16	-0.06***	-0.56***	0.95***	0.18**	-0.01	0.06	-0.01	0.12	0.02*	-0.26**	-0.03***	-0.14*	-13.83	-0.63	1.9	0.9576
	(-1.61)	(-3.27)	(-5.77)	(110.36)	(2.06)	(-1.08)	(0.49)	(-0.61)	(0.87)	(1.8)	(-1.98)	(-3.65)	(-1.74)	(-0.9)	(-0.39)	(0.23)	
2	5.59	-0.03	-0.47**	0.96***	0.14*	-0.01	0.11	-0.02	0.25*	0.02*	-0.4***	-0.03***	-0.14*	11.74	-2.19	12.36	0.9572
	(1.26)	(-1.64)	(-2.48)	(123.86)	(1.68)	(-1.03)	(0.88)	(-1.41)	(1.76)	(1.75)	(-3.08)	(-3.81)	(-1.72)	(0.75)	(-1.36)	(0.56)	
3	3.82	-0.01	-0.43**	0.96***	0.14*	-0.02*	0.08	-0.01	0.19	0.02*	-0.32**	-0.03***	-0.13*	7.13	1.08	2.49	0.9572
	(0.87)	(-0.72)	(-2.12)	(124.32)	(1.66)	(-1.74)	(0.61)	(-1.06)	(1.27)	(1.77)	(-2.36)	(-3.6)	(-1.65)	(0.45)	(0.67)	(0.17)	
4	7.65*	-0.03	-0.34**	0.96***	0.13	-0.02*	0.09	-0.01	0.19	0.02	-0.34**	-0.02***	-0.11	-25.12	6.04***	16.95	0.9573
	(1.76)	(-1.64)	(-2.2)	(124.25)	(1.5)	(-1.72)	(0.69)	(-0.99)	(1.32)	(1.35)	(-2.56)	(-2.97)	(-1.39)	(-1.57)	(3.73)	(1.08)	
5	12.77***	-0.01	-0.27*	0.96***	0.15*	-0.02*	0.12	-0.01	0.19	0.02*	-0.37***	-0.03***	-0.14*	-0.38	1.38	-20.46	0.9572
	(3)	(-0.63)	(-1.74)	(124.08)	(1.77)	(-1.67)	(0.91)	(-0.99)	(1.33)	(1.84)	(-2.8)	(-3.68)	(-1.74)	(-0.02)	(0.87)	(-1.18)	
Trader Group: Non-Algorithmic Trader																	
1	-7.16	0.06***	0.56***	0.95***	0.18**	-0.01	0.06	-0.01	0.12	0.02*	-0.26**	-0.03***	-0.14*	-13.83	-0.63	1.9	0.9576
	(-1.61)	(3.27)	(5.77)	(110.36)	(2.06)	(-1.08)	(0.49)	(-0.61)	(0.87)	(1.8)	(-1.98)	(-3.65)	(-1.74)	(-0.9)	(-0.39)	(0.23)	
2	5.59	0.03	0.47**	0.96***	0.14*	-0.01	0.11	-0.02	0.25*	0.02*	-0.4***	-0.03***	-0.14*	11.74	-2.19	12.36	0.9572
	(1.26)	(1.64)	(2.48)	(123.86)	(1.68)	(-1.03)	(0.88)	(-1.41)	(1.76)	(1.75)	(-3.08)	(-3.81)	(-1.72)	(0.75)	(-1.36)	(0.56)	
3	3.82	0.01	0.43**	0.96***	0.14*	-0.02*	0.08	-0.01	0.19	0.02*	-0.32**	-0.03***	-0.13*	7.13	1.08	2.49	0.9572
	(0.87)	(0.72)	(2.12)	(124.32)	(1.66)	(-1.74)	(0.61)	(-1.06)	(1.27)	(1.77)	(-2.36)	(-3.6)	(-1.65)	(0.45)	(0.67)	(0.17)	
4	7.65*	0.03	0.34**	0.96***	0.13	-0.02*	0.09	-0.01	0.19	0.02	-0.34**	-0.02***	-0.11	-25.12	6.04***	16.95	0.9573
	(1.76)	(1.64)	(2.2)	(124.25)	(1.5)	(-1.72)	(0.69)	(-0.99)	(1.32)	(1.35)	(-2.56)	(-2.97)	(-1.39)	(-1.57)	(3.73)	(1.08)	
5	12.77***	0.01	0.27*	0.96***	0.15*	-0.02*	0.12	-0.01	0.19	0.02*	-0.37***	-0.03***	-0.14*	-0.38	1.38	-20.46	0.9572
	(3)	(0.63)	(1.74)	(124.08)	(1.77)	(-1.67)	(0.91)	(-0.99)	(1.33)	(1.84)	(-2.8)	(-3.68)	(-1.74)	(-0.02)	(0.87)	(-1.18)	

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): Stock volatility reported by NSE [Sqrt $(0.94 * Prev\_Day\_Volatility^2 + 0.06 * Same\_Day\_Return^2)$ or GARCH (1;1) model for INDIAVIX]

		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: Algorithmic Trader																	
1	-7.28	-0.09***	-0.25*	0.95***	0.47***	-0.01	-0.44	-0.01	0.26	0.02**	-0.21	-0.03***	-0.06	53.37**	0.5	-54.68***	0.9576
	(-1.64)	(-4.7)	(-1.84)	(110.19)	(3.02)	(-0.69)	(-1.59)	(-0.85)	(0.99)	(2.03)	(-1.14)	(-3.94)	(-0.46)	(2.22)	(0.32)	(-3.14)	
2	6.12	-0.03*	-0.23	0.96***	0.94***	0	-1.21***	-0.02*	0.68**	0.02*	-0.27	-0.03***	-0.08	40.85	-1.98	-40.65*	0.9572
	(1.38)	(-1.67)	(-1.45)	(123.26)	(7.46)	(-0.37)	(-4.57)	(-1.67)	(2.46)	(1.91)	(-1.41)	(-4.12)	(-0.64)	(1.6)	(-1.24)	(-1.87)	
3	4.12	-0.02	-0.29	0.96***	1.02***	-0.01	-1.33***	-0.01	0.81***	0.02**	-0.4**	-0.03***	-0.05	28.35	1.28	-34.92*	0.9572
	(0.93)	(-0.91)	(-1.53)	(123.69)	(8.35)	(-1.23)	(-5.45)	(-1.13)	(3.07)	(1.98)	(-2.03)	(-3.94)	(-0.36)	(1.11)	(0.79)	(-1.94)	
4	8.12*	-0.04**	0.28	0.96***	1.02***	-0.01	-1.21***	-0.01	0.64**	0.02*	-0.4**	-0.03***	0	24.81	6.63***	-1.19	0.9572
	(1.86)	(-2.1)	(1.24)	(123.57)	(8.3)	(-1.21)	(-4.82)	(-1.17)	(2.55)	(1.71)	(-2.06)	(-3.35)	(-0.04)	(0.99)	(4.1)	(-0.05)	
5	12.18***	-0.01	0.25	0.96***	1.04***	-0.01	-1.22***	-0.01	0.67***	0.02**	-0.37*	-0.03***	-0.06	36.38	1.57	-34.36*	0.9572
	(2.86)	(-0.76)	(1.12)	(123.44)	(8.47)	(-1.17)	(-5.08)	(-1.15)	(2.67)	(2.07)	(-1.94)	(-3.97)	(-0.45)	(1.47)	(0.98)	(-1.82)	
Trader Group: Non-Algorithmic Trader																	
1	-7.28	0.09***	0.25*	0.95***	0.47***	-0.01	-0.44	-0.01	0.26	0.02**	-0.21	-0.03***	-0.06	53.37**	0.5	-54.68***	0.9576
	(-1.64)	(4.7)	(1.84)	(110.19)	(3.02)	(-0.69)	(-1.59)	(-0.85)	(0.99)	(2.03)	(-1.14)	(-3.94)	(-0.46)	(2.22)	(0.32)	(-3.14)	
2	6.12	0.03*	0.23	0.96***	0.94***	0	-1.21***	-0.02*	0.68**	0.02*	-0.27	-0.03***	-0.08	40.85	-1.98	-40.65*	0.9572
	(1.38)	(1.67)	(1.45)	(123.26)	(7.46)	(-0.37)	(-4.57)	(-1.67)	(2.46)	(1.91)	(-1.41)	(-4.12)	(-0.64)	(1.6)	(-1.24)	(-1.87)	
3	4.12	0.02	0.29	0.96***	1.02***	-0.01	-1.33***	-0.01	0.81***	0.02**	-0.4**	-0.03***	-0.05	28.35	1.28	-34.92*	0.9572
	(0.93)	(0.91)	(1.53)	(123.69)	(8.35)	(-1.23)	(-5.45)	(-1.13)	(3.07)	(1.98)	(-2.03)	(-3.94)	(-0.36)	(1.11)	(0.79)	(-1.94)	
4	8.12*	0.04**	-0.28	0.96***	1.02***	-0.01	-1.21***	-0.01	0.64**	0.02*	-0.4**	-0.03***	0	24.81	6.63***	-1.19	0.9572
	(1.86)	(2.1)	(-1.24)	(123.57)	(8.3)	(-1.21)	(-4.82)	(-1.17)	(2.55)	(1.71)	(-2.06)	(-3.35)	(-0.04)	(0.99)	(4.1)	(-0.05)	
5	12.18***	0.01	-0.25	0.96***	1.04***	-0.01	-1.22***	-0.01	0.67***	0.02**	-0.37*	-0.03***	-0.06	36.38	1.57	-34.36*	0.9572
	(2.86)	(0.76)	(-1.12)	(123.44)	(8.47)	(-1.17)	(-5.08)	(-1.15)	(2.67)	(2.07)	(-1.94)	(-3.97)	(-0.45)	(1.47)	(0.98)	(-1.82)	

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): 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)	OneDayRV (t-1) *EAD	OneDayRV (t-2)	OneDayRV (t-2) *EAD	OneDayRV (t-3)	OneDayRV (t-3) *EAD	OneDayRV (t-4)	OneDayRV (t-4) *EAD	OneDayRV (t-5)	OneDayRV (t-5) *EAD	EAD	$abs(D\_TG^{\Delta})$ (t-j)	$abs(D\_TG^{\Delta})$ (t-j) *EAD	$ModelR^2$
Trader Group: Algorithmic Trader																	
1	-62.24***	-0.38***	-1.72***	0.18***	0.05	0.06***	0.26***	0.08***	0.01	0.04***	0.32***	0.01*	-0.5***	173.08**	8.13	88.61**	0.3628
	(-3.16)	(-4.46)	(-4.04)	(21.14)	(0.52)	(7.67)	(2.64)	(9.85)	(0.13)	(5.86)	(3.13)	(1.78)	(-5.76)	(2.54)	(1.15)	(2.47)	
2	30.5	-0.21**	0.76	0.22***	0.03	0.06***	0.27***	0.07***	0.02	0.04***	0.31***	0.01	-0.53***	219.97***	2.88	157.82	0.3552
	(1.55)	(-2.52)	(0.92)	(28.82)	(0.32)	(7.1)	(2.74)	(9.43)	(0.25)	(5.56)	(3.01)	(1.52)	(-5.98)	(3.18)	(0.41)	(1.63)	
3	18.95	-0.03	-1.38	0.22***	0.04	0.06***	0.22**	0.08***	0.02	0.04***	0.31***	0.01	-0.51***	136.48*	-1.35	70.83	0.3554
	(0.96)	(-0.31)	(-1.56)	(28.96)	(0.45)	(8.31)	(2.25)	(8.85)	(0.25)	(5.41)	(2.97)	(1.33)	(-5.82)	(1.93)	(-0.19)	(1.09)	
4	22.04	-0.03	-2.18***	0.22***	0.05	0.06***	0.21**	0.07***	0	0.04***	0.31***	0.01	-0.49***	102.84	28.25***	132.81**	0.3563
	(1.12)	(-0.31)	(-3.16)	(28.91)	(0.54)	(8.06)	(2.14)	(9.1)	(-0.06)	(4.47)	(3.02)	(1.49)	(-5.58)	(1.47)	(4.01)	(1.99)	
5	85.55***	-0.02	-0.15	0.22***	0.02	0.06***	0.27***	0.07***	-0.02	0.04***	0.32***	0.02**	-0.56***	25.38	6.9	23.51	0.3542
	(4.37)	(-0.25)	(-0.22)	(28.81)	(0.24)	(8.09)	(2.74)	(9.19)	(-0.22)	(5.77)	(3.16)	(2.13)	(-6.18)	(0.36)	(0.98)	(0.31)	
Trader Group: Non-Algorithmic Trader																	
1	-62.24***	0.38***	1.72***	0.18***	0.05	0.06***	0.26***	0.08***	0.01	0.04***	0.32***	0.01*	-0.5***	173.08**	8.13	88.61**	0.3628
	(-3.16)	(4.46)	(4.04)	(21.14)	(0.52)	(7.67)	(2.64)	(9.85)	(0.13)	(5.86)	(3.13)	(1.78)	(-5.76)	(2.54)	(1.15)	(2.47)	
2	30.5	0.21**	-0.76	0.22***	0.03	0.06***	0.27***	0.07***	0.02	0.04***	0.31***	0.01	-0.53***	219.97***	2.88	157.82	0.3552
	(1.55)	(2.52)	(-0.92)	(28.82)	(0.32)	(7.1)	(2.74)	(9.43)	(0.25)	(5.56)	(3.01)	(1.52)	(-5.98)	(3.18)	(0.41)	(1.63)	
3	18.95	0.03	1.38	0.22***	0.04	0.06***	0.22**	0.08***	0.02	0.04***	0.31***	0.01	-0.51***	136.48*	-1.35	70.83	0.3554
	(0.96)	(0.31)	(1.56)	(28.96)	(0.45)	(8.31)	(2.25)	(8.85)	(0.25)	(5.41)	(2.97)	(1.33)	(-5.82)	(1.93)	(-0.19)	(1.09)	
4	22.04	0.03	2.18***	0.22***	0.05	0.06***	0.21**	0.07***	0	0.04***	0.31***	0.01	-0.49***	102.84	28.25***	132.81**	0.3563
	(1.12)	(0.31)	(3.16)	(28.91)	(0.54)	(8.06)	(2.14)	(9.1)	(-0.06)	(4.47)	(3.02)	(1.49)	(-5.58)	(1.47)	(4.01)	(1.99)	
5	85.55***	0.02	0.15	0.22***	0.02	0.06***	0.27***	0.07***	-0.02	0.04***	0.32***	0.02**	-0.56***	25.38	6.9	23.51	0.3542
	(4.37)	(0.25)	(0.22)	(28.81)	(0.24)	(8.09)	(2.74)	(9.19)	(-0.22)	(5.77)	(3.16)	(2.13)	(-6.18)	(0.36)	(0.98)	(0.31)	

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): 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: Algorithmic Trader																	
1	-51.65***	-0.41***	-3.34***	0.18***	-1.28***	0.05***	1.34***	0.07***	1.82***	0.03***	1.79***	0.02**	-2.36***	804.67***	33.36***	-1133.45***	0.4776
	(-2.9)	(-5.37)	(-6.68)	(23.48)	(-8.86)	(6.82)	(9.43)	(9.79)	(11.34)	(4.82)	(10.63)	(2.32)	(-13.85)	(8.63)	(5.31)	(-15.85)	
2	51.06***	-0.12	-5.77***	0.21***	0.41***	0.06***	1.79***	0.07***	1.66***	0.03***	3.14***	0.01*	-3.54***	294.55***	7.86	-1244.67***	0.4306
	(2.75)	(-1.46)	(-9.74)	(28.94)	(2.94)	(6.96)	(11.77)	(9.14)	(9.8)	(4.39)	(18.37)	(1.91)	(-20.08)	(2.84)	(1.2)	(-13.98)	
3	32.05*	-0.01	-5.49***	0.21***	0.54***	0.05***	2.05***	0.07***	0.9***	0.03***	3.7***	0.01*	-3.62***	-381.01***	1.08	-568.32***	0.4195
	(1.71)	(-0.16)	(-7.2)	(28.63)	(3.8)	(7.12)	(13.36)	(8.98)	(5.15)	(4.36)	(20.97)	(1.78)	(-19.95)	(-3.61)	(0.16)	(-7.31)	
4	43.78**	-0.08	-0.49	0.21***	0.49***	0.05***	1.77***	0.06***	1.69***	0.03***	3.28***	0.01**	-4.04***	-271.69***	36.79***	-1002.52***	0.4197
	(2.35)	(-1.05)	(-0.58)	(28.51)	(3.44)	(6.7)	(11.9)	(8.68)	(9.74)	(4.19)	(19.16)	(2.1)	(-22.35)	(-2.64)	(5.52)	(-10.06)	
5	83.56***	0.02	0.94	0.21***	0.33**	0.05***	1.96***	0.06***	1.6***	0.03***	3.65***	0.02***	-4.43***	-355.97***	9.56	-723.17***	0.4178
	(4.5)	(0.27)	(1.06)	(28.38)	(2.29)	(6.84)	(13.27)	(8.6)	(9.35)	(4.68)	(21.18)	(2.72)	(-22.75)	(-3.49)	(1.44)	(-8.78)	
Trader Group: Non-Algorithmic Trader																	
1	-51.65***	0.41***	3.34***	0.18***	-1.28***	0.05***	1.34***	0.07***	1.82***	0.03***	1.79***	0.02**	-2.36***	804.67***	33.36***	-1133.45***	0.4776
	(-2.9)	(5.37)	(6.68)	(23.48)	(-8.86)	(6.82)	(9.43)	(9.79)	(11.34)	(4.82)	(10.63)	(2.32)	(-13.85)	(8.63)	(5.31)	(-15.85)	
2	51.06***	0.12	5.77***	0.21***	0.41***	0.06***	1.79***	0.07***	1.66***	0.03***	3.14***	0.01*	-3.54***	294.55***	7.86	-1244.67***	0.4306
	(2.75)	(1.46)	(9.74)	(28.94)	(2.94)	(6.96)	(11.77)	(9.14)	(9.8)	(4.39)	(18.37)	(1.91)	(-20.08)	(2.84)	(1.2)	(-13.98)	
3	32.05*	0.01	5.49***	0.21***	0.54***	0.05***	2.05***	0.07***	0.9***	0.03***	3.7***	0.01*	-3.62***	-381.01***	1.08	-568.32***	0.4195
	(1.71)	(0.16)	(7.2)	(28.63)	(3.8)	(7.12)	(13.36)	(8.98)	(5.15)	(4.36)	(20.97)	(1.78)	(-19.95)	(-3.61)	(0.16)	(-7.31)	
4	43.78**	0.08	0.49	0.21***	0.49***	0.05***	1.77***	0.06***	1.69***	0.03***	3.28***	0.01**	-4.04***	-271.69***	36.79***	-1002.52***	0.4197
	(2.35)	(1.05)	(0.58)	(28.51)	(3.44)	(6.7)	(11.9)	(8.68)	(9.74)	(4.19)	(19.16)	(2.1)	(-22.35)	(-2.64)	(5.52)	(-10.06)	
5	83.56***	-0.02	-0.94	0.21***	0.33**	0.05***	1.96***	0.06***	1.6***	0.03***	3.65***	0.02***	-4.43***	-355.97***	9.56	-723.17***	0.4178
	(4.5)	(-0.27)	(-1.06)	(28.38)	(2.29)	(6.84)	(13.27)	(8.6)	(9.35)	(4.68)	(21.18)	(2.72)	(-22.75)	(-3.49)	(1.44)	(-8.78)	

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

Table 6: 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**	$Model R^2$
Trader Group: Algorithmic Trader																	
1	-318.97***	-1.6***	-3.47*	0.01	0.16	0.03***	0.21	0.04***	-0.01	0.02**	0.18	-0.01	-0.25	120.18	-119.67***	284.42*	0.0801
	(-3.7)	(-4.17)	(-1.83)	(1.55)	(1.04)	(3.32)	(1.22)	(5.62)	(-0.08)	(2.23)	(1.08)	(-1.4)	(-1.61)	(0.39)	(-3.76)	(1.76)	
2	-173.86**	-1.31***	1.09	0.04***	0.25	0.02***	0.18	0.04***	-0.04	0.02**	0.17	-0.01	-0.28*	216.13	-50.43	367.18	0.0673
	(-2.01)	(-3.45)	(0.29)	(4.79)	(1.62)	(2.83)	(1.11)	(4.95)	(-0.24)	(2.19)	(1.03)	(-1.47)	(-1.78)	(0.7)	(-1.6)	(0.85)	
3	-184.63**	-0.34	-5.4	0.04***	0.26*	0.03***	0.19	0.03***	-0.09	0.01*	0.17	-0.01	-0.27*	136.68	15.17	203.36	0.0662
	(-2.14)	(-0.89)	(-1.35)	(5.25)	(1.72)	(4.34)	(1.1)	(4.3)	(-0.5)	(1.76)	(1)	(-1.55)	(-1.7)	(0.43)	(0.48)	(0.68)	
4	-115.6	-0.36	-2.94	0.04***	0.23	0.03***	0.17	0.04***	-0.03	0.01	0.12	-0.01*	-0.26	-127.45	55.95*	200.21	0.066
	(-1.35)	(-0.95)	(-0.95)	(5.22)	(1.5)	(4.43)	(0.99)	(5.29)	(-0.15)	(1)	(0.69)	(-1.8)	(-1.64)	(-0.4)	(1.76)	(0.66)	
5	132.96	-0.47	0.21	0.04***	0.25	0.03***	0.2	0.04***	-0.06	0.02**	0.19	-0.01	-0.3*	-15.35	45.33	113.52	0.0648
	(1.56)	(-1.25)	(0.07)	(5.21)	(1.61)	(4.5)	(1.18)	(5.49)	(-0.35)	(2.19)	(1.11)	(-1.57)	(-1.88)	(-0.05)	(1.43)	(0.32)	
Trader Group: Non-Algorithmic Trader																	
1	-318.97***	1.6***	3.47*	0.01	0.16	0.03***	0.21	0.04***	-0.01	0.02**	0.18	-0.01	-0.25	120.18	-119.67***	284.42*	0.0801
	(-3.7)	(4.17)	(1.83)	(1.55)	(1.04)	(3.32)	(1.22)	(5.62)	(-0.08)	(2.23)	(1.08)	(-1.4)	(-1.61)	(0.39)	(-3.76)	(1.76)	
2	-173.86**	1.31***	-1.09	0.04***	0.25	0.02***	0.18	0.04***	-0.04	0.02**	0.17	-0.01	-0.28*	216.13	-50.43	367.18	0.0673
	(-2.01)	(3.45)	(-0.29)	(4.79)	(1.62)	(2.83)	(1.11)	(4.95)	(-0.24)	(2.19)	(1.03)	(-1.47)	(-1.78)	(0.7)	(-1.6)	(0.85)	
3	-184.63**	0.34	5.4	0.04***	0.26*	0.03***	0.19	0.03***	-0.09	0.01*	0.17	-0.01	-0.27*	136.68	15.17	203.36	0.0662
	(-2.14)	(0.89)	(1.35)	(5.25)	(1.72)	(4.34)	(1.1)	(4.3)	(-0.5)	(1.76)	(1)	(-1.55)	(-1.7)	(0.43)	(0.48)	(0.68)	
4	-115.6	0.36	2.94	0.04***	0.23	0.03***	0.17	0.04***	-0.03	0.01	0.12	-0.01*	-0.26	-127.45	55.95*	200.21	0.066
	(-1.35)	(0.95)	(0.95)	(5.22)	(1.5)	(4.43)	(0.99)	(5.29)	(-0.15)	(1)	(0.69)	(-1.8)	(-1.64)	(-0.4)	(1.76)	(0.66)	
5	132.96	0.47	-0.21	0.04***	0.25	0.03***	0.2	0.04***	-0.06	0.02**	0.19	-0.01	-0.3*	-15.35	45.33	113.52	0.0648
	(1.56)	(1.25)	(-0.07)	(5.21)	(1.61)	(4.5)	(1.18)	(5.49)	(-0.35)	(2.19)	(1.11)	(-1.57)	(-1.88)	(-0.05)	(1.43)	(0.32)	

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 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	$ModelR^2$
Trader Group: Algorithmic Trader																	
1	-246.38***	-0.9***	-35.35***	0.02***	-4.81***	0.01**	5.47***	0.04***	4.35***	0.01	4.41***	0	-3.13***	7305.86***	39.73**	-6420.39***	0.6374
	(-4.56)	(-3.8)	(-22.97)	(4.82)	(-26.03)	(1.99)	(34.26)	(7.72)	(20.75)	(1.29)	(26.29)	(-0.91)	(-15.15)	(25.14)	(2.02)	(-29.12)	
2	12.92	-0.44	-19.45***	0.04***	-2.05***	0.01*	10.32***	0.04***	3***	0.01	6.83***	0	-4.19***	5859.76***	-2.5	-9247.85***	0.5076
	(0.21)	(-1.58)	(-9.18)	(6.66)	(-9.59)	(1.9)	(58.38)	(6.37)	(12.14)	(1.14)	(35.04)	(-0.78)	(-16.92)	(15.85)	(-0.11)	(-30.34)	
3	-49.1	-0.02	-10.42***	0.04***	-1.69***	0.01**	11.15***	0.03***	2.15***	0	7.03***	0	-3.97***	2523.66***	22.82	-3742.3***	0.4634
	(-0.75)	(-0.08)	(-3.76)	(6.5)	(-7.57)	(2.39)	(62.89)	(5.51)	(8.37)	(0.83)	(32.95)	(-0.84)	(-14.81)	(6.61)	(0.95)	(-14.04)	
4	45.77	-0.35	-3.8	0.04***	-2.45***	0.01**	11.08***	0.04***	2.69***	0	6.78***	0	-4.31***	2190.11***	92.5***	-5588.1***	0.4652
	(0.7)	(-1.23)	(-1.23)	(6.43)	(-11)	(2.4)	(63.06)	(6.3)	(10.47)	(0.59)	(33)	(-0.81)	(-16.85)	(5.76)	(3.85)	(-15.81)	
5	140.2**	-0.19	-2.75	0.04***	-2.53***	0.01**	11.16***	0.04***	3.2***	0.01	7.08***	0	-4.6***	3332.96***	50.92**	-1898.86***	0.4586
	(2.16)	(-0.66)	(-0.86)	(6.34)	(-11.23)	(2.37)	(62.68)	(6.19)	(11.94)	(1.09)	(34.77)	(-0.8)	(-16.97)	(8.89)	(2.11)	(-6.53)	
Trader Group: Non-Algorithmic Trader																	
1	-246.38***	0.9***	35.35***	0.02***	-4.81***	0.01**	5.47***	0.04***	4.35***	0.01	4.41***	0	-3.13***	7305.86***	39.73**	-6420.39***	0.6374
	(-4.56)	(3.8)	(22.97)	(4.82)	(-26.03)	(1.99)	(34.26)	(7.72)	(20.75)	(1.29)	(26.29)	(-0.91)	(-15.15)	(25.14)	(2.02)	(-29.12)	
2	12.92	0.44	19.45***	0.04***	-2.05***	0.01*	10.32***	0.04***	3***	0.01	6.83***	0	-4.19***	5859.76***	-2.5	-9247.85***	0.5076
	(0.21)	(1.58)	(9.18)	(6.66)	(-9.59)	(1.9)	(58.38)	(6.37)	(12.14)	(1.14)	(35.04)	(-0.78)	(-16.92)	(15.85)	(-0.11)	(-30.34)	
3	-49.1	0.02	10.42***	0.04***	-1.69***	0.01**	11.15***	0.03***	2.15***	0	7.03***	0	-3.97***	2523.66***	22.82	-3742.3***	0.4634
	(-0.75)	(0.08)	(3.76)	(6.5)	(-7.57)	(2.39)	(62.89)	(5.51)	(8.37)	(0.83)	(32.95)	(-0.84)	(-14.81)	(6.61)	(0.95)	(-14.04)	
4	45.77	0.35	3.8	0.04***	-2.45***	0.01**	11.08***	0.04***	2.69***	0	6.78***	0	-4.31***	2190.11***	92.5***	-5588.1***	0.4652
	(0.7)	(1.23)	(1.23)	(6.43)	(-11)	(2.4)	(63.06)	(6.3)	(10.47)	(0.59)	(33)	(-0.81)	(-16.85)	(5.76)	(3.85)	(-15.81)	
5	140.2**	0.19	2.75	0.04***	-2.53***	0.01**	11.16***	0.04***	3.2***	0.01	7.08***	0	-4.6***	3332.96***	50.92**	-1898.86***	0.4586
	(2.16)	(0.66)	(0.86)	(6.34)	(-11.23)	(2.37)	(62.68)	(6.19)	(11.94)	(1.09)	(34.77)	(-0.8)	(-16.97)	(8.89)	(2.11)	(-6.53)	

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

future realized volatility, indicating non-algorithmic traders are informed regarding future realized-volatility whereas algorithmic traders are not. The results are consistent across all definitions of realized volatility and for both type of announcements- pre-scheduled earnings announcements (Table 2, 4 & 6) and unscheduled corporate announcements (Table 3, 5 & 7). The fact that the coefficients have similar sign and significance level for the two type of announcements, seem to support our second hypothesis that volatility information based trading have 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 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. The exchange (NSE) reported realized volatility measures are based on a GARCH type modeling, where one-day lagged volatility has significant weight. While using this measure as our dependent variable, we find that only the first lag of the realized volatility term remains significant, while higher order lags become insignificant in most cases. Prior to announcement dates, however, lagged terms do provide additional information [5].

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 very small time. Agency algorithmic traders provide trade execution services for other investors. Results indicate that co-efficients corresponding to volatility demand for both these trader groups are negative, indicating none of them have

[5] 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.

prior information regarding future volatility. Similar to our first set of models, we use all three definitions of volatility for both scheduled (Table 8, 10 & 12) and unscheduled announcements (Table 9, 11 & 13). 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.

We also run robustness tests by using pooled regression models [6] (similar to Ni et al. (2008)) instead of fixed effect panel models, but the primary results are consistent.

6 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 towards their role in the spot market, especially in issues related to the provisioning of liquidity. However, the extent of literature devoted to the role of algorithmic traders in the derivative markets is considerably lesser. Existing literature seems to suggest that 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 suggests 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 identifiers for trades executed by algorithmic traders. We use six months of intraday data (Jan-Jun 2015) for both stock and options market [7] for 159 stocks to create

[6] Results not reported.

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

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): Stock volatility reported by NSE [Sqrt $(0.94 * Prev\_Day\_Volatility^2 + 0.06 * Same\_Day\_Return^2)$ or GARCH (1;1) model for INDIAVIX]

		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: Prop Algorithmic Trader																	
1	-7.83*	-0.05*	-0.82***	0.95***	0.2**	-0.01	0.06	-0.01	0.14	0.02*	-0.28**	-0.03***	-0.15*	-17.84	-4.41**	-1.15	0.9576
	(-1.77)	(-1.93)	(-5.09)	(109.98)	(2.22)	(-1.35)	(0.47)	(-0.66)	(0.98)	(1.8)	(-2.16)	(-3.63)	(-1.83)	(-1.17)	(-2.25)	(-0.13)	
2	5.66	-0.05*	-0.73***	0.96***	0.14	-0.01	0.11	-0.02	0.24*	0.02*	-0.38***	-0.03***	-0.15*	7.48	-2.87	-16.77	0.9572
	(1.28)	(-1.85)	(-2.96)	(123.92)	(1.62)	(-0.98)	(0.87)	(-1.43)	(1.72)	(1.73)	(-2.86)	(-3.81)	(-1.88)	(0.48)	(-1.49)	(-0.68)	
3	3.35	-0.02	-0.32	0.96***	0.14*	-0.02*	0.08	-0.01	0.17	0.02	-0.31**	-0.03***	-0.14*	7.34	-2.4	12.28	0.9572
	(0.76)	(-0.72)	(-1.42)	(124.3)	(1.69)	(-1.73)	(0.67)	(-0.79)	(1.18)	(1.52)	(-2.29)	(-3.62)	(-1.71)	(0.47)	(-1.24)	(0.69)	
4	6.91	-0.04	-0.44**	0.96***	0.15*	-0.02*	0.07	-0.01	0.18	0.02	-0.33**	-0.03***	-0.12	-27.59*	4.12**	-1.51	0.9572
	(1.59)	(-1.39)	(-2.06)	(124.24)	(1.75)	(-1.76)	(0.58)	(-0.95)	(1.27)	(1.46)	(-2.49)	(-3.15)	(-1.51)	(-1.72)	(2.13)	(-0.08)	
5	12.93***	-0.03	-0.34	0.96***	0.16*	-0.02*	0.11	-0.01	0.2	0.02*	-0.37***	-0.03***	-0.14*	-4	2.07	-41.02*	0.9572
	(3.04)	(-1.3)	(-1.36)	(124.13)	(1.84)	(-1.66)	(0.86)	(-1.01)	(1.36)	(1.85)	(-2.82)	(-3.68)	(-1.73)	(-0.25)	(1.1)	(-1.8)	
Trader Group: Agency Algorithmic Trader																	
1	-7.27	-0.11***	-0.73***	0.95***	0.16*	-0.01	0.07	-0.01	0.14	0.02*	-0.28**	-0.03***	-0.14*	-5.9	-1.58	50.26	0.9576
	(-1.64)	(-3.18)	(-4.67)	(111.72)	(1.88)	(-1.18)	(0.57)	(-0.6)	(0.99)	(1.81)	(-2.13)	(-3.62)	(-1.74)	(-0.36)	(-0.36)	(1.5)	
2	5.69	-0.02	-0.14	0.96***	0.14	-0.01	0.11	-0.01	0.23	0.02*	-0.41***	-0.03***	-0.12	11.42	-1.89	61.34	0.9572
	(1.28)	(-0.56)	(-0.43)	(123.83)	(1.63)	(-1.18)	(0.87)	(-1.33)	(1.63)	(1.75)	(-3.15)	(-3.78)	(-1.47)	(0.73)	(-0.44)	(1.18)	
3	4.1	-0.01	-0.41	0.96***	0.12	-0.02*	0.08	-0.01	0.18	0.02*	-0.32**	-0.03***	-0.12	16.42	6.39	176.22***	0.9573
	(0.93)	(-0.3)	(-1.03)	(124.37)	(1.41)	(-1.73)	(0.67)	(-1.03)	(1.24)	(1.76)	(-2.39)	(-3.63)	(-1.49)	(1.03)	(1.46)	(2.94)	
4	8.13*	-0.03	-0.26	0.96***	0.16*	-0.02*	0.06	-0.01	0.16	0.02*	-0.33**	-0.03***	-0.11	-20.78	19.29***	141.77***	0.9573
	(1.86)	(-0.91)	(-0.99)	(124.23)	(1.85)	(-1.71)	(0.5)	(-0.96)	(1.17)	(1.7)	(-2.49)	(-3.48)	(-1.36)	(-1.29)	(4.4)	(2.93)	
5	12.94***	0.02	-0.38*	0.96***	0.15*	-0.02*	0.12	-0.01	0.18	0.02*	-0.36***	-0.03***	-0.14*	9.67	8.63**	41.75	0.9572
	(3.04)	(0.6)	(-1.66)	(124.04)	(1.8)	(-1.66)	(0.89)	(-0.98)	(1.25)	(1.87)	(-2.71)	(-3.73)	(-1.74)	(0.62)	(1.97)	(1.03)	

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): Stock volatility reported by NSE [Sqrt $(0.94 * Prev\_Day\_Volatility^2 + 0.06 * Same\_Day\_Return^2)$ or GARCH (1;1) model for INDIAVIX]

		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	-8.06*	-0.08***	-0.34*	0.95***	0.51***	-0.01	-0.47*	-0.01	0.3	0.02**	-0.28	-0.03***	-0.05	57.38**	-2.69	-56.12***	0.9576
	(-1.82)	(-3.1)	(-1.76)	(109.77)	(3.31)	(-0.91)	(-1.67)	(-0.9)	(1.13)	(2.03)	(-1.51)	(-3.91)	(-0.39)	(2.4)	(-1.4)	(-2.68)	
2	6.16	-0.06**	-0.07	0.96***	0.95***	0	-1.14***	-0.02*	0.61**	0.02*	-0.27	-0.03***	-0.08	42.24*	-2.58	-46.82*	0.9572
	(1.39)	(-2.13)	(-0.44)	(123.3)	(7.52)	(-0.34)	(-4.24)	(-1.66)	(2.17)	(1.9)	(-1.42)	(-4.12)	(-0.65)	(1.65)	(-1.34)	(-1.76)	
3	3.69	-0.02	-0.53**	0.96***	1***	-0.01	-1.3***	-0.01	0.84***	0.02*	-0.44**	-0.03***	-0.04	28.37	-2.08	-57.3**	0.9572
	(0.84)	(-0.8)	(-2.05)	(123.69)	(8.11)	(-1.22)	(-5.38)	(-0.87)	(3.24)	(1.74)	(-2.24)	(-3.96)	(-0.3)	(1.11)	(-1.08)	(-2.4)	
4	7.18*	-0.05*	0.13	0.96***	1.04***	-0.01	-1.27***	-0.01	0.64**	0.02*	-0.36*	-0.03***	0	26.16	4.49**	0.14	0.9572
	(1.65)	(-1.78)	(0.37)	(123.58)	(8.44)	(-1.25)	(-5)	(-1.12)	(2.46)	(1.81)	(-1.89)	(-3.53)	(0.03)	(1.04)	(2.32)	(0.01)	
5	12.21***	-0.03	0.25	0.96***	1.03***	-0.01	-1.22***	-0.01	0.67***	0.02**	-0.37*	-0.03***	-0.05	42.24*	2.13	-32.82	0.9572
	(2.87)	(-1.31)	(0.85)	(123.49)	(8.42)	(-1.16)	(-5.05)	(-1.17)	(2.65)	(2.08)	(-1.91)	(-3.98)	(-0.43)	(1.73)	(1.13)	(-1.23)	
Trader Group: Agency Algorithmic Trader																	
1	-7.46*	-0.14***	-0.63*	0.95***	0.32**	-0.01	-0.38	-0.01	0.41	0.02**	-0.28	-0.03***	-0.06	49.46**	0.97	-136.02***	0.9576
	(-1.68)	(-4.13)	(-1.81)	(111.74)	(2)	(-0.88)	(-1.4)	(-0.86)	(1.61)	(2.05)	(-1.46)	(-3.93)	(-0.48)	(2.06)	(0.22)	(-3.9)	
2	6.36	-0.01	-0.85**	0.96***	0.94***	-0.01	-1.09***	-0.02	0.54**	0.02*	-0.33*	-0.03***	-0.02	38.18	-1.02	-186.32***	0.9572
	(1.43)	(-0.28)	(-2.16)	(123.3)	(7.42)	(-0.5)	(-4.45)	(-1.6)	(2.15)	(1.91)	(-1.77)	(-4.11)	(-0.14)	(1.47)	(-0.24)	(-2.94)	
3	4.44	-0.02	-0.34	0.96***	1.03***	-0.01	-1.32***	-0.01	0.75***	0.02**	-0.34*	-0.03***	-0.05	37.65	7.6*	-85.74	0.9572
	(1.01)	(-0.51)	(-0.67)	(123.7)	(8.34)	(-1.22)	(-5.36)	(-1.1)	(2.81)	(1.97)	(-1.76)	(-3.98)	(-0.41)	(1.44)	(1.74)	(-1.32)	
4	8.63**	-0.04	0.22	0.96***	1***	-0.01	-1.2***	-0.01	0.68***	0.02**	-0.39*	-0.03***	-0.03	15.15	21.8***	-101.18*	0.9573
	(1.98)	(-1.22)	(0.69)	(123.55)	(8.02)	(-1.19)	(-4.94)	(-1.14)	(2.68)	(2.09)	(-1.95)	(-3.92)	(-0.24)	(0.62)	(4.97)	(-1.69)	
5	12.47***	0.01	0.4	0.96***	1.03***	-0.01	-1.24***	-0.01	0.65***	0.02**	-0.32*	-0.03***	-0.05	46.34*	9.33**	-50.45	0.9572
	(2.93)	(0.38)	(0.72)	(123.4)	(8.45)	(-1.16)	(-5.21)	(-1.14)	(2.61)	(2.1)	(-1.72)	(-4.02)	(-0.4)	(1.92)	(2.13)	(-0.78)	

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

Table 10: 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	-65.11***	-0.33***	-2.42***	0.18***	0.06	0.06***	0.26***	0.08***	0.03	0.04***	0.31***	0.01*	-0.51***	147.3**	3.31	70.29*	0.362
	(-3.31)	(-2.84)	(-3.39)	(21.21)	(0.68)	(7.69)	(2.6)	(9.8)	(0.29)	(5.82)	(3.08)	(1.76)	(-5.79)	(2.19)	(0.39)	(1.89)	
2	27.93	-0.24**	-0.22	0.22***	0.04	0.06***	0.26***	0.07***	0.03	0.04***	0.32***	0.01	-0.53***	197.44***	-5.75	38.55	0.355
	(1.42)	(-2.13)	(-0.2)	(28.9)	(0.45)	(7.11)	(2.6)	(9.44)	(0.35)	(5.52)	(3.08)	(1.5)	(-6.04)	(2.89)	(-0.69)	(0.35)	
3	17.47	-0.17	-1.12	0.22***	0.04	0.06***	0.23**	0.08***	0.03	0.04***	0.31***	0.01	-0.52***	123.32*	-10.45	60.21	0.3555
	(0.89)	(-1.51)	(-1.12)	(28.95)	(0.47)	(8.3)	(2.28)	(8.81)	(0.29)	(5.44)	(2.99)	(1.35)	(-5.91)	(1.77)	(-1.25)	(0.79)	
4	18.43	-0.03	-1.16	0.22***	0.04	0.06***	0.24**	0.07***	0.02	0.04***	0.29***	0.01	-0.51***	99.64	20.83**	167.27**	0.3555
	(0.94)	(-0.28)	(-1.22)	(28.92)	(0.51)	(8.07)	(2.36)	(9.12)	(0.23)	(4.46)	(2.81)	(1.47)	(-5.79)	(1.42)	(2.49)	(2.18)	
5	84.85***	-0.06	0.58	0.22***	0.02	0.06***	0.27***	0.07***	-0.02	0.04***	0.32***	0.02**	-0.55***	41.54	6.86	99.41	0.3543
	(4.34)	(-0.56)	(0.52)	(28.83)	(0.27)	(8.09)	(2.72)	(9.2)	(-0.24)	(5.76)	(3.11)	(2.12)	(-6.07)	(0.59)	(0.82)	(0.99)	
Trader Group: Agency Algorithmic Trader																	
1	-65.7***	-0.6***	-1.92***	0.18***	0.03	0.06***	0.22**	0.07***	0.04	0.04***	0.31***	0.01*	-0.51***	122.42*	-4.48	-40.08	0.3622
	(-3.34)	(-4.04)	(-2.82)	(21.22)	(0.3)	(7.51)	(2.21)	(9.77)	(0.43)	(5.84)	(3.06)	(1.7)	(-5.83)	(1.71)	(-0.23)	(-0.28)	
2	29.68	-0.24*	2.74*	0.22***	0.01	0.06***	0.27***	0.07***	0.02	0.04***	0.3***	0.01	-0.52***	219.93***	8	361.09	0.3551
	(1.51)	(-1.65)	(1.88)	(28.87)	(0.14)	(7.15)	(2.77)	(9.37)	(0.2)	(5.51)	(2.95)	(1.49)	(-5.88)	(3.2)	(0.42)	(1.6)	
3	19.19	0.2	-0.75	0.22***	0.04	0.07***	0.23**	0.08***	-0.05	0.04***	0.34***	0.01	-0.51***	159.68**	9.46	821.79***	0.3558
	(0.98)	(1.39)	(-0.42)	(29)	(0.48)	(8.37)	(2.35)	(8.88)	(-0.58)	(5.45)	(3.3)	(1.31)	(-5.79)	(2.29)	(0.49)	(3.05)	
4	20.39	0	-4.65***	0.22***	0.04	0.06***	0.16	0.07***	0	0.04***	0.34***	0.01	-0.51***	97.42	69.52***	259.01	0.3563
	(1.04)	(-0.01)	(-4.05)	(28.91)	(0.41)	(8.06)	(1.6)	(9.17)	(0.04)	(4.46)	(3.19)	(1.48)	(-5.66)	(1.38)	(3.6)	(1.19)	
5	85.2***	0.05	-0.69	0.22***	0.02	0.06***	0.27***	0.07***	-0.02	0.05***	0.33***	0.02**	-0.57***	9.36	20.91	-90.68	0.3543
	(4.36)	(0.32)	(-0.68)	(28.81)	(0.21)	(8.08)	(2.74)	(9.2)	(-0.21)	(5.8)	(3.18)	(2.14)	(-6.28)	(0.13)	(1.08)	(-0.5)	

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

Table 11: 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.

j	Const.	D_TG^{σ} (t-j)	D_TG^{σ} (t-j) *UAD	OneDayRV (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	$abs(D\_TG^{\Delta})$ (t-j)	$abs(D\_TG^{\Delta})$ (t-j) *UAD	$ModelR^2$
Trader Group: Prop Algorithmic Trader																	
1	-56.34***	-0.47***	-3***	0.18***	-1.29***	0.05***	1.37***	0.07***	1.79***	0.03***	2.17***	0.02**	-2.82***	959.73***	32.45***	-1017.95***	0.4731
	(-3.16)	(-4.54)	(-4.3)	(23.4)	(-8.81)	(6.87)	(9.46)	(9.77)	(11.04)	(4.81)	(13.08)	(2.3)	(-16.62)	(10.35)	(4.31)	(-11.56)	
2	48.18***	-0.22**	-3.53***	0.21***	0.32**	0.06***	1.88***	0.07***	1.6***	0.03***	3.24***	0.01*	-3.84***	302.92***	2.04	-1525.55***	0.4293
	(2.6)	(-2)	(-5.84)	(28.93)	(2.24)	(6.89)	(12.34)	(9.14)	(9.4)	(4.38)	(19.04)	(1.91)	(-21.79)	(2.93)	(0.26)	(-13.97)	
3	31.06*	-0.13	-9.83***	0.21***	0.48***	0.05***	2.1***	0.07***	0.9***	0.03***	3.77***	0.01*	-3.64***	-393.34***	-7.36	-1042.81***	0.4221
	(1.67)	(-1.21)	(-9.36)	(28.69)	(3.38)	(7.13)	(13.87)	(8.96)	(5.2)	(4.4)	(21.4)	(1.81)	(-20.11)	(-3.74)	(-0.93)	(-10.48)	
4	38.87**	-0.09	-2.45*	0.21***	0.54***	0.05***	1.79***	0.06***	1.45***	0.03***	3.45***	0.01**	-3.91***	-204.67**	28.64***	-857.38***	0.4178
	(2.09)	(-0.85)	(-1.86)	(28.48)	(3.81)	(6.72)	(11.98)	(8.7)	(8.43)	(4.15)	(20.14)	(2.06)	(-21.55)	(-1.98)	(3.61)	(-7.92)	
5	82.56***	0.02	-0.8	0.21***	0.32**	0.05***	1.91***	0.06***	1.7***	0.03***	3.66***	0.02***	-4.55***	-315.42***	10.11	-1124.91***	0.4182
	(4.45)	(0.18)	(-0.7)	(28.42)	(2.18)	(6.84)	(12.94)	(8.6)	(9.85)	(4.68)	(21.3)	(2.72)	(-23.05)	(-3.14)	(1.28)	(-9.52)	
Trader Group: Agency Algorithmic Trader																	
1	-57.1***	-0.42***	-9.7***	0.18***	-0.67***	0.05***	0.94***	0.07***	1.79***	0.03***	1.8***	0.01**	-2.13***	643.75***	39.2**	-2733.1***	0.4829
	(-3.23)	(-3.18)	(-7.2)	(23.86)	(-4.78)	(6.7)	(6.58)	(9.69)	(11.24)	(4.76)	(10.78)	(2.13)	(-12.49)	(6.91)	(2.28)	(-20.5)	
2	49.62***	-0.01	-20.57***	0.21***	0.77***	0.06***	1***	0.07***	1.66***	0.03***	3.26***	0.01*	-3.62***	397.9***	24.44	-2015.28***	0.43
	(2.68)	(-0.08)	(-12.51)	(29)	(5.43)	(6.98)	(6.64)	(9.11)	(9.84)	(4.34)	(19.08)	(1.85)	(-20.58)	(3.8)	(1.36)	(-7.54)	
3	32.36*	0.18	-6.19***	0.21***	0.67***	0.05***	1.69***	0.07***	1.12***	0.03***	3.79***	0.01*	-3.67***	-273.48**	18.56	-1299.59***	0.4173
	(1.73)	(1.26)	(-3.02)	(28.58)	(4.64)	(7.14)	(11.34)	(8.94)	(6.58)	(4.37)	(21.34)	(1.73)	(-20.44)	(-2.57)	(1.01)	(-4.9)	
4	41.48**	-0.08	-6.61***	0.21***	0.45***	0.05***	1.57***	0.06***	2.52***	0.03***	3.05***	0.01**	-4.28***	-423.17***	100.25***	-4611.88***	0.4267
	(2.24)	(-0.59)	(-5.28)	(28.67)	(3.18)	(6.74)	(10.57)	(8.83)	(13.95)	(4.15)	(17.87)	(2.08)	(-23.9)	(-4.21)	(5.51)	(-17.93)	
5	84.13***	0.04	3.62	0.21***	0.56***	0.05***	1.75***	0.06***	1.52***	0.03***	3.63***	0.02***	-4.11***	-235.02**	27.56	-1329.25***	0.416
	(4.53)	(0.29)	(1.53)	(28.32)	(3.93)	(6.8)	(11.8)	(8.56)	(8.84)	(4.68)	(20.95)	(2.72)	(-21.73)	(-2.34)	(1.5)	(-4.78)	

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

Table 12: 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	-327.84***	-0.7	-6.98**	0.01*	0.17	0.03***	0.21	0.04***	0	0.02**	0.19	-0.01	-0.25	74.67	-168.93***	297.87*	0.0795
	(-3.81)	(-1.35)	(-2.2)	(1.7)	(1.11)	(3.37)	(1.23)	(5.48)	(-0.02)	(2.18)	(1.14)	(-1.42)	(-1.62)	(0.25)	(-4.42)	(1.77)	
2	-183.55**	-1.12**	0.06	0.04***	0.25	0.02***	0.18	0.04***	-0.04	0.02**	0.18	-0.01	-0.28*	172.87	-97***	188.23	0.067
	(-2.13)	(-2.18)	(0.01)	(4.86)	(1.62)	(2.92)	(1.08)	(4.98)	(-0.23)	(2.11)	(1.09)	(-1.49)	(-1.78)	(0.56)	(-2.58)	(0.39)	
3	-192.78**	-0.77	-6.15	0.04***	0.27*	0.03***	0.19	0.03***	-0.08	0.01*	0.18	-0.01	-0.27*	119.21	-21.73	254.84	0.0663
	(-2.24)	(-1.5)	(-1.38)	(5.24)	(1.78)	(4.33)	(1.13)	(4.31)	(-0.49)	(1.76)	(1.06)	(-1.55)	(-1.73)	(0.38)	(-0.58)	(0.73)	
4	-125.85	-0.48	-2.26	0.04***	0.24	0.03***	0.18	0.04***	-0.02	0.01	0.13	-0.01*	-0.27*	-141.79	26.92	127.18	0.0658
	(-1.47)	(-0.94)	(-0.53)	(5.23)	(1.57)	(4.43)	(1.03)	(5.29)	(-0.12)	(1.03)	(0.74)	(-1.8)	(-1.71)	(-0.45)	(0.71)	(0.37)	
5	128.39	-0.83	2.14	0.04***	0.24	0.03***	0.2	0.04***	-0.06	0.02**	0.19	-0.01	-0.31*	19.47	45.37	305.47	0.0648
	(1.51)	(-1.61)	(0.43)	(5.22)	(1.6)	(4.5)	(1.2)	(5.51)	(-0.38)	(2.21)	(1.13)	(-1.58)	(-1.89)	(0.06)	(1.2)	(0.67)	
Trader Group: Agency Algorithmic Trader																	
1	-310.62***	-3.77***	-1.75	0.01	0.18	0.02***	0.17	0.04***	-0.02	0.02**	0.17	-0.01	-0.25	57.32	-286.14***	322.85	0.0804
	(-3.61)	(-5.65)	(-0.57)	(1.48)	(1.19)	(3.21)	(1.02)	(5.64)	(-0.09)	(2.21)	(1.03)	(-1.41)	(-1.62)	(0.18)	(-3.33)	(0.49)	
2	-168.5*	-2.17***	3.44	0.04***	0.24	0.02***	0.2	0.04***	-0.04	0.02**	0.16	-0.01	-0.29*	200.68	-70.03	735.49	0.0671
	(-1.95)	(-3.28)	(0.52)	(4.78)	(1.54)	(2.83)	(1.17)	(4.91)	(-0.26)	(2.15)	(0.96)	(-1.51)	(-1.82)	(0.65)	(-0.81)	(0.7)	
3	-187.02**	0.26	0.5	0.04***	0.23	0.03***	0.2	0.03***	-0.12	0.01*	0.16	-0.01	-0.24	157.94	51.78	1776.65	0.0662
	(-2.17)	(0.39)	(0.06)	(5.28)	(1.52)	(4.39)	(1.17)	(4.35)	(-0.68)	(1.78)	(0.93)	(-1.59)	(-1.54)	(0.5)	(0.6)	(1.46)	
4	-117.44	-0.24	-4.95	0.04***	0.24	0.03***	0.16	0.04***	-0.05	0.01	0.12	-0.01*	-0.25	-104.92	157.02*	919.58	0.066
	(-1.37)	(-0.37)	(-0.96)	(5.23)	(1.57)	(4.43)	(0.95)	(5.3)	(-0.31)	(1.07)	(0.68)	(-1.8)	(-1.58)	(-0.33)	(1.8)	(0.94)	
5	124.93	-0.03	-1.35	0.04***	0.25	0.03***	0.19	0.04***	-0.05	0.02**	0.18	-0.01	-0.3*	-32.92	81.71	113.85	0.0646
	(1.46)	(-0.04)	(-0.3)	(5.23)	(1.62)	(4.52)	(1.16)	(5.51)	(-0.31)	(2.22)	(1.08)	(-1.5)	(-1.86)	(-0.11)	(0.94)	(0.14)	

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

Table 13: 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**	$ModelR^2$
Trader Group: Prop Algorithmic Trader																	
1	-265.5***	-0.88***	-36.3***	0.02***	-5.13***	0.01*	5.88***	0.04***	4.79***	0.01	4.39***	0	-3.45***	8343.74***	13.32	-5672.6***	0.6242
	(-4.84)	(-2.67)	(-16.53)	(4.69)	(-27.29)	(1.95)	(36.89)	(7.51)	(22.41)	(1.22)	(25.42)	(-0.92)	(-16.38)	(28.53)	(0.56)	(-21.21)	
2	6.64	-0.68*	-9.97***	0.04***	-2.58***	0.01*	10.6***	0.04***	3.18***	0.01	6.62***	0	-4.72***	6093.1***	-21.78	-11431.5***	0.5086
	(0.11)	(-1.79)	(-4.71)	(6.66)	(-12.12)	(1.89)	(60.67)	(6.38)	(12.94)	(1.12)	(33.91)	(-0.78)	(-19.07)	(16.56)	(-0.8)	(-30.75)	
3	-52.08	-0.15	-31.07***	0.04***	-1.69***	0.01**	11.03***	0.03***	2.61***	0	6.9***	0	-3.79***	2477.79***	-8.67	-6205.61***	0.4676
	(-0.8)	(-0.39)	(-8.11)	(6.5)	(-7.61)	(2.36)	(62.47)	(5.56)	(10.08)	(0.82)	(32.25)	(-0.84)	(-14.16)	(6.51)	(-0.31)	(-17.69)	
4	35.79	-0.4	18.19***	0.04***	-2.75***	0.01**	11.27***	0.04***	2.71***	0	6.69***	0	-4.3***	2706.66***	67.32**	-4649.15***	0.4629
	(0.55)	(-1.03)	(3.84)	(6.43)	(-12.29)	(2.39)	(64.01)	(6.27)	(10.5)	(0.61)	(32.42)	(-0.82)	(-16.67)	(7.13)	(2.35)	(-11.96)	
5	136.89**	-0.28	-3.58	0.04***	-2.47***	0.01**	11.13***	0.04***	3.17***	0.01	7.12***	0	-4.62***	3513.78***	55.43*	-2116.33***	0.4581
	(2.11)	(-0.71)	(-0.87)	(6.35)	(-11.05)	(2.37)	(62.26)	(6.2)	(11.66)	(1.1)	(34.92)	(-0.81)	(-16.97)	(9.51)	(1.93)	(-5.07)	
Trader Group: Agency Algorithmic Trader																	
1	-253.44***	-1.16***	-96.92***	0.03***	-4.6***	0.01**	4.25***	0.04***	4.92***	0.01	4.85***	0	-2.94***	6179.54***	33.71	-16736.4***	0.6576
	(-4.84)	(-2.92)	(-24.02)	(5.27)	(-25.57)	(2.1)	(25.95)	(7.92)	(24.06)	(1.31)	(30.06)	(-0.94)	(-14.63)	(21.78)	(0.64)	(-38.66)	
2	18.49	-0.29	-93.23***	0.04***	-1.63***	0.01*	9.63***	0.04***	3.45***	0.01	6.32***	0	-3.63***	7102.58***	31.96	-11558.2***	0.4933
	(0.29)	(-0.61)	(-15.82)	(6.58)	(-7.29)	(1.9)	(53.01)	(6.27)	(13.81)	(1.06)	(31.99)	(-0.82)	(-14.7)	(18.78)	(0.5)	(-11.99)	
3	-44.6	0.2	24.48***	0.04***	-2.08***	0.01**	11.2***	0.03***	1.84***	0	7.47***	-0.01	-4.15***	2803.6***	96.15	2976.88***	0.4579
	(-0.68)	(0.4)	(3.29)	(6.47)	(-9.24)	(2.39)	(62.58)	(5.51)	(7.18)	(0.85)	(35.56)	(-0.87)	(-15.49)	(7.25)	(1.45)	(3.05)	
4	38.69	-0.4	-58.69***	0.04***	-1.34***	0.01**	10.38***	0.04***	3.72***	0	6.84***	0	-4.77***	1002.19***	283.75***	-24701.1***	0.4799
	(0.6)	(-0.81)	(-13.15)	(6.48)	(-5.96)	(2.37)	(59.02)	(6.35)	(14.53)	(0.64)	(34.05)	(-0.87)	(-18.84)	(2.69)	(4.36)	(-27.54)	
5	134.75**	-0.08	-22.77***	0.04***	-2.53***	0.01**	11.29***	0.04***	2.82***	0.01	7.23***	0	-4.36***	3955.74***	101.94	-425.22	0.4574
	(2.07)	(-0.17)	(-2.59)	(6.35)	(-11.03)	(2.37)	(62.29)	(6.18)	(10.72)	(1.08)	(35.8)	(-0.74)	(-15.95)	(10.63)	(1.54)	(-0.43)	

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

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 exogenous shock. We find that different trader group behave similarly to both these type 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 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.

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