Journal of Behavioral and Experimental Finance 37 (2023) 100778

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

Do algorithmic traders exploit volatility?

Devika Arumugam [a,*], P. Krishna Prasanna [b], Rahul R. Marathe [b]

[a] Indian Institute of Management Indore, India
[b] Department of Management Studies, IIT Madras, India

ARTICLE INFO

Article history:
Received 17 April 2022
Received in revised form 18 October 2022
Accepted 29 November 2022
Available online 5 December 2022

JEL classification:
G12
G14
G20
G23
G40

Keywords:
Algorithmic trading
High-frequency trading
Volatility

ABSTRACT

This study examines the impact of trading by Algorithmic Traders (ATs) and Non-Algorithmic Traders (NATs) on volatility, and conversely, the impact of volatility shocks on ATs and Non-ATs. ATs are classified as High-Frequency Traders (HFTs) and Buy-side Algorithmic Traders (BATs). Using jump robust volatility estimates, we find that excessive directional and non-directional trading by BATs and HFTs increases volatility, whereas that by NATs marginally decreases volatility. Conversely, all traders increase their non-directional trading one hour following a volatility shock. BATs carry out more directional trades during a volatility shock, whereas HFTs withdraw from such activities.

1. Introduction

When markets are efficient, security prices reflect their true value; but the fact is that the markets are often inefficient, and this is reflected in the instances of excessive volatility and market crashes. In these circumstances, Algorithmic Traders (ATs) can take advantage of volatile periods to place directional bets and generate more volatility in future periods. Therefore, this is the classic chicken-and-egg dilemma, where causal evidence has not yet been found. This study aims to address this question by examining the dynamic relationship between traders' activity and market volatility. We investigate these dynamics by categorizing the ATs as High-Frequency Traders (HFTs) and Buy-side Algorithmic Traders (BATs); and by employing two jump robust estimates developed by Andersen et al. (2012).

ATs are a heterogeneous group, and HFTs form a small percentage of that group. On the one hand, HFTs engage in speed trading, hold securities for short intraday periods and maintain low inventory (Malceniece et al., 2019). They cancel most of their orders and exhibit high order-to-trade ratios. On the other hand, BATs employ algorithms to maintain large portfolios for their clients (Li et al., 2018). Unlike the HFTs, BATs hold these portfolios for a longer duration. We identify these trader groups using a unique dataset on the Futures market from the National Stock Exchange (NSE), India. During the sample period, BATs trade 1.6 times more NIFTY50 Futures than HFTs. While prior studies on spot markets are limited to a subset of ATs, i.e., HFTs, and ignore the impact of BATs, this study provides a holistic understanding of ATs in the derivatives market by considering all trader groups and their dynamic relationship with volatility, using the data on NIFTY50 Futures.

Extant literature is ambiguous on the impact of ATs on volatility. On the one hand, most studies use the conventional realized volatility (RV) measure and/or simulated data to find that ATs increase volatility (see, e.g., Casgrain and Jaimungal (2020), Scholtus et al. (2014)); on the other hand, a few studies find that ATs' are beneficial traders, as they reduce volatility (see, e.g., Aït-Sahalia and Brunetti (2020), Chaboud et al. (2014)). Our study adds to the literature by examining the differential impact of HFTs, BATs and Non-ATs (NATs) on volatility, using conventional as well as jump robust volatility estimates.

Empirical evidence predominantly suggests that HFTs enter the market at highly volatile periods to place directional bets and make profits (see, e.g., Hasbrouck and Saar, 2013). ATs would generate more profits by following volatility-based trading strategies (Ceffer et al., 2018). Contrarily, limited evidence suggests

* Corresponding author.
E-mail addresses: devikaa@iimidr.ac.in (D. Arumugam), pkp@iitm.ac.in (P.K. Prasanna), rrmarathe@iitm.ac.in (R.R. Marathe).
URLs: https://www.iimidr.ac.in/faculty/full-time-faculty/profile/?id=134 (D. Arumugam),
http://www.doms.iitm.ac.in/domsnew/index.php/krishna-prasanna-p (P.K. Prasanna), https://doms.iitm.ac.in/index.php/rrm (R.R. Marathe).

https://doi.org/10.1016/j.jbef.2022.100778
2214-6350/

that HFTs exit the market during highly volatile periods (Aït-Sahalia and Brunetti, 2020). This study contributes to this literature by examining whether volatility causes a differential impact on traders. We find that during volatility shocks, BATs enter while HFTs exit the market. Additionally, we examine the extent of directional trades by different traders during volatility shocks.

We employ the Bayesian Vector Autoregression (BVAR) and Impulse Response Functions (IRFs) to examine trading activity and volatility dynamics. Our results show that trading by NATs lowers volatility, whereas trading by BATs and HFTs raises the same. Similarly, extreme buying or selling pressure by BATs and HFTs raises volatility. Additionally, we find an hour's delay in traders' response to volatility shock, wherein all traders increase their trading volume, with BATs exhibiting the highest increase in trading volume. BATs carry out excessive buy or sell trades in response to volatility shock, whereas HFTs drastically reduce such trades.

The remainder of this paper is organized as follows: Section 2 discusses the related literature and the development of hypotheses. Section 3 discusses the data, measures of trading activity and volatility and methodology; Section 4 presents the empirical results and analysis. Section 5 discusses the results of the robustness checks, and Section 6 provides the concluding remarks in the final section.

2. Related literature and hypotheses

The theoretical background on the presence of heterogeneous traders and their differential impact on volatility can be traced back to De Long et al. (1990), who stated that noise traders and rational speculators act as two distinct heterogeneous groups that engage in positive feedback trading[1] and increase market volatility. Chaboud et al. (2014) observe that this theory is relevant to the present-day market environment, where ATs act as a group and create similar feedback effects. Therefore, we hypothesize the following:

H_{1a}: *The heterogeneous trader groups differ in their impact on volatility.*

H_{1b}: *Volatility produces a differential impact on heterogeneous trader groups.*

2.1. Impact of traders on volatility

Existing literature does not clearly answer whether subgroups of ATs increase or decrease volatility. Casgrain and Jaimungal (2020), using simulated models, show that increased disagreements between heterogeneous market agents increase volatility. Likewise, Scholtus et al. (2014), using NASDAQ data on S&P 500 Exchange-traded fund, find that ATs increase volatility and reduce market depth. Breedon et al. (2018) observe that ATs withdraw liquidity and increase volatility in foreign exchange markets. In their theoretical model, Cartea and Penalva (2012) classify traders into three groups, namely, liquidity traders, professional traders and HFTs, and find that HFTs increase volatility for liquidity traders, because of the 'intermediation' by HFTs between liquidity demanders and liquidity suppliers that enables faster liquidity provisioning. Thus, we hypothesize the following:

H_{2a}: *ATs' (both HFTs' and BATs') trading activity increases volatility.*

H_{2b}: *NATs' trading activity decreases volatility.*

H_{3a}: *ATs' (both HFTs' and BATs') buy/sell pressure increases volatility.*

H_{3b}: *NATs' buy/sell pressure decreases volatility.*

2.2. Impact of volatility on traders

Existing literature indicates several adverse effects of volatility for both investors and firms, resulting from ATs' trading. ATs' momentum and volatility-based strategies target high volatile stocks to make quick profits. One such volatility-based algorithm using Neural Networks by Ceffer et al. (2018) suggests that traders can make profits by entering (exiting) trades above (below) a threshold level of high volatility. Thus, we hypothesize the following:

H_{4a}: *Volatility encourages the trading activity of all ATs (both HFTs and BATs).*

H_{4b}: *Volatility discourages NATs' trading activity.*

Furthermore, the presence of intense trading by ATs creates an increased risk of a flash crash. Hasbrouck and Saar (2013) state that high volatility offers profitable opportunities for HFTs, who exploit such events in day trading. Our study differs from the existing literature by empirically examining the differential impact of volatility on trading volume and directional trades of different traders, namely, HFTs, BATs and NATs. Therefore, we hypothesize the following:

H_{5a}: *Volatility encourages ATs' (both HFTs' and BATs') to create excessive buy/sell pressure.*

H_{5b}: *Volatility discourages NATs' from creating buy/sell pressure.*

3. Data, measurement and methodology

3.1. Data

Existing research indicates that the futures market has faster information transmission and order execution, which is particularly prominent in index futures[2,3] Hence, we use the most widely traded index future in the National Stock Exchange (NSE), India, to evaluate the relationship between ATs' trading and volatility. We employ a proprietary dataset from the NSE and consider the widely traded NIFTY50 Index Futures. This contract has three month trading cycles, namely near month, next month and far month. The Futures market is open for trading from **09:15 to 15:30 IST**. We use three months of high-frequency data on near month NIFTY50 Futures, for the sample period of 1st July to 30th September, 2018. We analyze four near month contracts that expired on 26th July, 30th August, 27th September and 25th October, 2018, respectively.

Our dataset is unique in the following ways. During order placement, traders specify whether they are placing their own orders or clients' orders by choosing the "Proprietary" or the "Client"[4] option, respectively, in their trading interface. Additionally, traders must register themselves before employing trading algorithms.[5] Thus, the exchange precisely identifies the category of traders in this dataset. This information enables us to classify proprietary ATs as HFTs, and Non-proprietary ATs as BATs, following the classification of Li et al. (2018). All the other traders, who do not use algorithms are classified as NATs.[6]

1 When a positive feedback effect is present, ATs cause price deviations from the assets' fundamental value, leading to increased volatility during intraday intervals. However, Chaboud et al. (2014) conclude that ATs' trading activity decreases market volatility.

2 Fung et al. (2005) find a sizable amount of volatility spillover from index futures to the index market; however, the converse is not valid. They discover that the lead–lag link between index futures and index markets reduces the asymmetric reaction to positive or negative news.

3 Chen et al. (2016) observe that the E-mini index futures contribute significant information share to the price discovery process during volatile periods. They attribute this phenomenon to the increased participation of ATs, particularly HFTs in the trading process.

4 Clearing Mechanism - NSE India. https://www.nseindia.com/products-services/equity-derivatives-clearing-mechanism (accessed 2.23.21).

5 NIFM, 2017. A study on Algorithm Trading/ High Frequency Trading in the Indian Capital Market. Government of India. http://www.nifm.ac.in/sites/default/files/uploadfiles/Compendium.pdf (accessed 2.23.21).

6 A recent study by Arumugam and Prasanna (2021a) employs this NSE dataset and explains in detail the markers used to identify ATs.

3.2. Measurement and descriptive statistics

3.2.1. Trading measures

We calculate two measures of trading activity, namely, Volume of trade (VLM) and Absolute Net Position (ANP), following Benos et al. (2017). VLM is measured as the aggregate volume of futures traded by one of the three groups of traders; wherein the trader group participates in at least one side of the trade (buy/sell). We measure the number of futures traded by HFTs, BATs and NATs as VLM_HFT, VLM_BAT, and VLM_NAT, respectively, at time t and aggregated in one-hour intervals. VLM measures for the three trader groups are given in Eqs. (1), (2) and (3). ANP measures the absolute difference between aggregate buy-side and sell-side trade volumes, which indicates the intensity of directional trades placed by trader groups. ANP measures for the three trader groups are given in Eqs. (4), (5) and (6).

$$\mathrm{VLM\_HFT}_t = \sum_{j \epsilon HFT} VLM_t \tag{1}$$

$$\mathrm{VLM\_BAT}_t = \sum_{j \epsilon BAT} VLM_t \tag{2}$$

$$\mathrm{VLM\_NAT}_t = \sum_{j \epsilon NAT} VLM_t \tag{3}$$

$$\mathrm{ANP\_HFT}_t = \left| \sum_{j \epsilon HFT} VLM\_HFT(Buy)_t - VLM\_HFT(Sell)_t \right| \tag{4}$$

$$\mathrm{ANP\_BAT}_t = \left| \sum_{j \epsilon BAT} VLM\_\mathrm{BAT}(Buy)_t - VLM\_\mathrm{BAT}(Sell)_t \right| \tag{5}$$

$$\mathrm{ANP\_NAT}_t = \left| \sum_{j \epsilon NAT} VLM\_\mathrm{NAT}(Buy)_t - VLM\_\mathrm{NAT}(Sell)_t \right| \tag{6}$$

3.2.2. Volatility measures

Existing studies have used the conventional Realized Volatility (RV) estimate, which can be misleading in intraday statistical modeling. We measure the conventional RV as the standard deviation of logarithmic returns. As this conventional measure is not robust against intraday seasonality and produces U-shape patterns, Andersen et al. (2012) propose two jump robust measures: MedRV and MinRV, which are local realized volatility measures that are robust for intraday seasonality. MedRV calculates the median of three successive returns and squares it in intraday intervals, which removes jumps through two-sided truncation. Likewise, MinRV calculates the minimum of two successive returns and squares it. If there is a large return in the period, MinRV omits this observation; hence, it is robust for intraday jumps as it removes them through one-sided truncation.

Andersen et al. (2012) observe that MedRV is relatively more efficient than MinRV because of the latter's exposure to small or zero returns. Following their work, we use tick time sampling, where returns are calculated at the trading time at microsecond levels to deal with microstructure noise and seasonality. RV, MedRV and MinRV are given in Eqs. (7), (8) and (9), respectively, where r stands for logarithmic returns, t refers to one-hour intervals, $r_{t,i}$ stands for individual returns in the one-hour period t, and i varies from 1 to M.

$$RV_t = \sqrt{\frac{\sum_{i=1}^{M} \left(r_{t,i} - \bar{r}_t\right)^2}{M-1}} \tag{7}$$

$$MedRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi} \times \left(\frac{M}{M-2}\right) \sum_{i=2}^{M-1} med(\left|r_{t,i-1}\right|, \left|r_{t,i}\right|, \left|r_{t,i+1}\right|)^2 \tag{8}$$

$$MinRV_t = \frac{\pi}{\pi - 2} \left(\frac{M}{M-1}\right) \sum_{i=1}^{M-1} \min(\left|r_{t,i}\right|, \left|r_{t,i+1}\right|)^2 \tag{9}$$

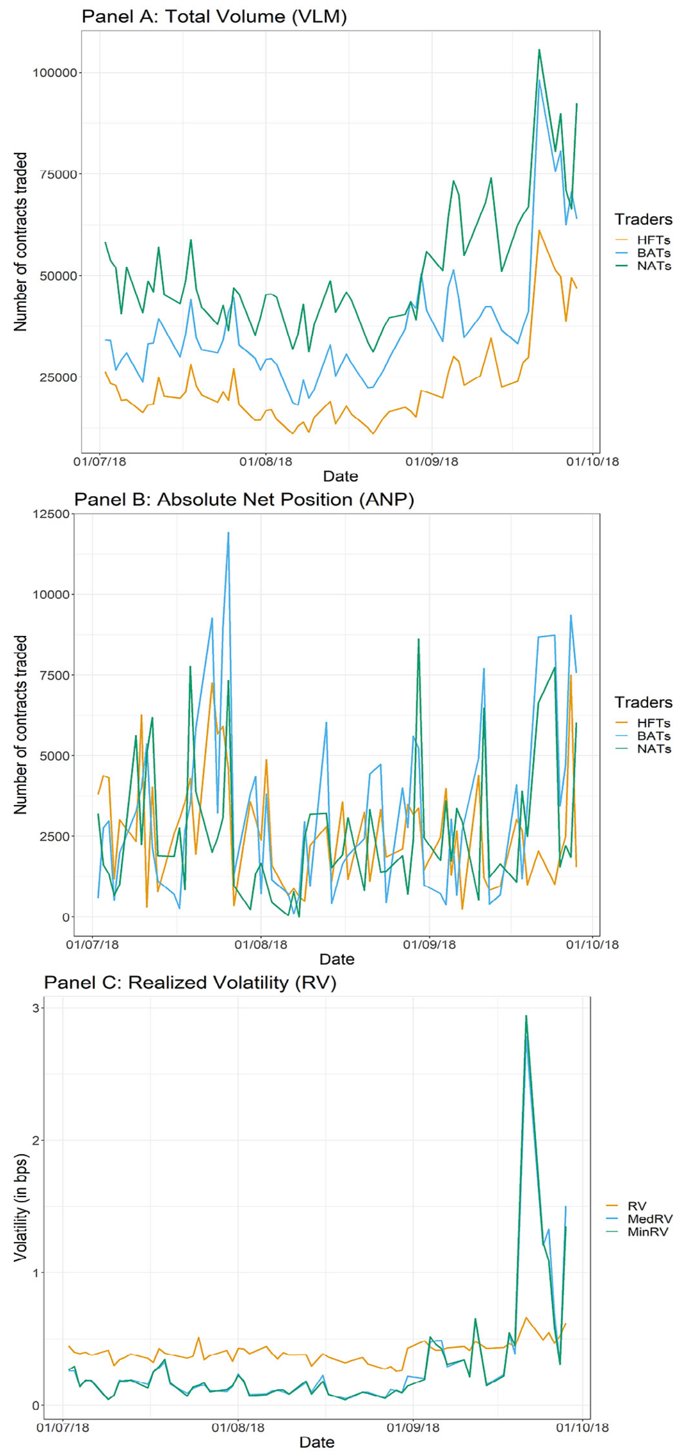

Fig. 1. Average daily trading activity and volatility.

3.2.3. Descriptive statistics

Table 1 presents the summary statistics of traders' activity and volatility measures calculated in one-hour intervals. We observe that the mean volume traded by NATs is the highest among all traders, followed by BATs. Contrarily, the mean absolute net position of BATs is the highest among all traders, followed by NATs. Fig. 1 depicts the daily averages of trading and volatility measures for ATs and NATs. Panel A and B show the total trade volume and absolute net position, respectively. Panel A indicates

Table 1
Summary Statistics of Traders' Activity and Volatility Measures.

Variable	Mean	Std. Dev.	25th %ile	Median	75th %ile
VLM_HFT	399624.9	261791.6	229125	328125	519300
VLM_BAT	648854.5	368430.3	398212.5	583200	783000
VLM_NAT	1061642	525938.4	674250	954975	1360163
ANP_HFT	67606.09	69359.48	21862.5	47850	91912.5
ANP_BAT	108699.4	101475.3	33787.5	81000	149700
ANP_NAT	104064.5	92908.86	34837.5	80250	145087.5
RV (bps)	0.3151	0.1538	0.272	0.3443	0.4066
MedRV (bps)	0.0421	0.0855	0.0107	0.021	0.0417
MinRV (bps)	0.0399	0.0927	0.0089	0.0187	0.0385

This table reports summary statistics over the sample period from 1st July to 30th September, 2018 during the regular trading hours, calculated in one-hour intervals. The sample consists of NIFTY50 Index Futures trading in the NSE. VLM_HFT, VLM_BAT, and VLM_NAT refer to the number of futures traded by HFTs, BATs and NATs, respectively. ANP_HFT, ANP_BAT and ANP_NAT measure the gap between aggregate buy-side and sell-side trade volumes of HFTs, BATs and NATs, respectively. RV is the standard deviation of logarithmic returns. MedRV and MinRV are the two jump robust estimates developed by Andersen et al. (2012).

Table 2
Unit root tests.

	ADF	PP	ADF	PP
	Constant		Constant and trend	
VLM_BAT	−2.84*	−11.7***	−3.59**	−12.15***
VLM_HFT	−2.83*	−13***	−3.71**	−14.13***
VLM_NAT	−2.6*	−14.9***	−3.64**	−15.12***
ANP_BAT	−15.98***	−16.15***	−16.22***	−16.23***
ANP_HFT	−19.98***	−19.98***	−19.96***	−19.96***
ANP_NAT	−17.37***	−17.95***	−18.02***	−18.02***
RV	−0.9	−19.07***	−1.66	−19.71***
MEDRV	−11.18***	−11.34***	−12.08***	−11.96***
MINRV	−12.13***	−12.11***	−12.84***	−12.84***

Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) denote unit root tests developed by Dickey and Fuller (1979) and Phillips and Perron (1988), respectively for testing stationarity. The null hypothesis assumes the presence of unit root.
*Denote rejection of the null hypothesis at 10%.
**Denote rejection of the null hypothesis at 5%.
***Denote rejection of the null hypothesis at 1%.

that three groups of traders' total volume show co-movement, where the upward (and downward) fluctuations of traders move concurrently. Panel B reveals a dissimilar trend in absolute net position among traders, wherein certain trader groups over-buy (or over-sell), while others do not do the same. Panel C depicts the trend of three volatility estimates, wherein MedRV and MinRV deviate from RV by a significant margin. The jump robust volatility estimates capture a considerable shift in the month of September, where the VLM estimates also shift upward. The conventional RV estimate does not capture this volatility shift.

3.3. Methodology

Following Hasbrouck and Seppi (2001), we first check for stationarity of variables, using Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests developed by Dickey and Fuller (1979) and Phillips and Perron (1988), respectively. The results are reported in Table 2, which shows that the variables are stationary. Hence, we use the level form of these variables in our analysis.

Additionally, this study uses a time series dataset, comprising 3843 observations at 1-hour frequency. While VAR is frequently used in models with jointly endogenous variables (Arumugam and Prasanna, 2021b), it requires the estimation of many parameters, which leads to an over-parameterization problem in small datasets. Therefore, we use Bayesian VAR (BVAR) method, which solves the over-parameterization problem through shrinkage by imposing restrictions on parameters using bayesian priors.

We examine the dynamic relationship between volatility and traders' activity using the BVAR model and the Impulse Response Functions (IRFs). We estimate six such BVAR models. Models 1, 2 and 3 include RV, MedRV and MinRV, respectively, along with three VLM measures as endogenous variables, and the results are reported in Table 3. Similarly, Models 4, 5 and 6 include RV, MedRV and MinRV, respectively, along with three ANP measures as endogenous variables, and the results are reported in Table 4. Schwarz Information Criterion (SIC) indicated one lag as the appropriate lag length, and the models use Litterman/Minnesota priors (Litterman, 1986). The general form of BVAR regression is given in Eq. (10), where X and Y are the vectors of endogenous variables, C is the vector of intercepts, t denotes the time in one-hour intervals and ε_t is the error term.

$$Y_t = AY_{t-1} + BX_{t-1} + C + \varepsilon_t \tag{10}$$

4. Results and analysis

4.1. Do traders affect volatility differently?

Panel A in Table 3 shows that a unit increase in HFT's VLM increases RV by 2.79 × 10 $^{-7}$ bps. Panel B and C in Table 3 also show that HFTs and BATs significantly increase MedRV and MinRV, respectively. We further evaluate the changes in their relationship using IRFs in Fig. 2, which shows that a one Standard Deviation (S.D) shock in trading volumes of NATs decreases volatility, while that of BATs and HFTs increases the same. Panel A in Fig. 2 depicts that a one S.D shock to the trading volume of NATs and BATs causes RV to drop by 0.023 bps. Contrarily, a one S.D shock to the trading volume of HFTs causes RV to soar by 0.017 bps. Similarly, Fig. 2 shows that NATs' trading cause MedRV

Table 3
Bayesian Vector Autoregression using Volume of trade (VLM) Measure.

Panel A:	Model 1			
	VLM_BAT	VLM_HFT	VLM_NAT	RV
VLM_BAT(−1)	0.37	0.16	0.4	−1.18E−07
	(0.06)***	(0.04)***	(0.09)***	(0.00)***
VLM_HFT(−1)	0.16	0.27	0.19	2.79E−07
	(0.09)*	(0.06)***	(0.13)	(0.00)***
VLM_NAT(−1)	0.04	0.01	0.11	5.82E−09
	(0.04)	(0.03)	(0.06)	(0.00)
RV(−1)	482431	370535.7	671267.1	0.017876
	(88265.8)***	(62977.7)***	(136523)***	(0.04)
R-sq.	0.37	0.38	0.30	0.19
Adj. R-sq.	0.37	0.37	0.29	0.18

Panel B:	Model 2			
	VLM_BAT	VLM_HFT	VLM_NAT	MedRV
VLM_BAT(−1)	0.32	0.13	0.36	3.2E−08
	(0.06)***	(0.04)***	(0.09)***	(0.00)**
VLM_HFT(−1)	0.2	0.3	0.31	8.21E−08
	(0.09)**	(0.06)***	(0.14)**	(0.00)***
VLM_NAT(−1)	0.01	−0.004	0.07	−1.43E−08
	(0.04)	(0.03)	(0.06)	(0.00)
MedRV(−1)	321107.9	246605.2	80700.85	0.259046
	(213659)	(152517)	(330429)	(0.05)***
R-sq.	0.32	0.31	0.24	0.32
Adj. R-sq.	0.31	0.31	0.24	0.32

Panel C:	Model 3			
	VLM_BAT	VLM_HFT	VLM_NAT	MinRV
VLM_BAT(−1)	0.33	0.13	0.36	3.21E−08
	(0.06)***	(0.04)***	(0.09)***	(0.00)**
VLM_HFT(−1)	0.21	0.31	0.31	8.31E−08
	(0.09)**	(0.06)***	(0.14)**	(0.00)***
VLM_NAT(−1)	0.02	−0.003	0.07	−1.46E−08
	(0.04)	(0.03)	(0.06)	(0.00)
MinRV(−1)	256610.5	208029.9	44223.25	0.235174
	(188066)	(134238)	(290854)	(0.05)***
R-sq.	0.32	0.31	0.24	0.27
Adj. R-sq.	0.31	0.31	0.24	0.26

The columns provide the coefficients and standard errors obtained from BVAR models of the form, $Y_t = AY_{t-1} + BX_{t-1} + C + \varepsilon_t$, where X and Y are the vectors of endogenous variables, C is the vector of intercepts, t denotes the time in one-hour intervals and ε_t is the error term. The model uses Litterman/Minnesota priors.
*Indicate significance at 10%.
**Indicate significance at 5%.
***Indicate significance at 1%.

and MinRV to drop by 0.013 and 0.017 bps, respectively. These results support hypotheses: H_{1a} and H_{2b}.

Panel B in Table 3 shows that a unit change in VLM of BATs and HFTs causes MedRV to increase by 3.2×10^{-08} and 8.21×10^{-08} bps, respectively. A similar response is seen on MinRV in Panel C (Table 3). Panel B in Fig. 2 shows that a one S.D shock in VLM of BATs and HFTs increases MedRV by 0.039 and 0.026 bps, respectively. We find a similar response on MinRV in Panel C in Fig. 2. Thus, Fig. 2 shows that jump robust volatility estimates increase considerably when BATs are trading than HFTs. These results support hypothesis H_{2a} and demonstrate the negative impact of ATs' trading on volatility. This is consistent with Breedon et al. (2018), Cartea and Penalva (2012), Casgrain and Jaimungal (2020) and Scholtus et al. (2014), but contrary to Chaboud et al. (2014), Hasbrouck and Saar (2013) and Saliba (2020). Further, it shows that BATs increase volatility more than HFTs. Besides, this evidence indicates that the decline in volatility resulting from NATs' trading is insufficient to compensate for the increase in volatility resulting from ATs' trading.

Furthermore, Panel C in Fig. 3 shows that MinRV reduces marginally by 0.0017 bps after NATs' activity, but volatility raises to 0.0076 bps in the second hour. Panels B and C in Table 4 show that a unit increase in the absolute net position of HFTs increases volatility by 1.62×10^{-07} and 1.86×10^{-07} bps, respectively. Panels B and C in Fig. 3 consistently show that HFTs' absolute net position has the highest adverse impact on volatility. They further illustrate that the absolute net position of HFTs and BATs increases volatility, and it peaks in the second hour. These results support our hypothesis H_{3a}. Thus, when traders increase their directional trade positions, volatility rises, and this effect is the highest when HFTs are trading actively. Panels B and C in Fig. 3 depict that a one S.D innovation in the absolute net position of BATs increases volatility by 0.0042 and 0.0057 bps, respectively. Similarly, a one S.D innovation in the absolute net position of HFTs increases volatility by 0.0085 and 0.01 bps. These results support hypothesis H_{3a}, which assumes that the buy/sell pressure of BATs and HFTs increases volatility. The results are consistent with Breedon et al. (2018), Casgrain and Jaimungal (2020) and Scholtus et al. (2014).

4.2. Does volatility affect traders differently?

Panel A in Table 3 shows that a unit change in RV substantially increases the VLM of BATs, HFTs and NATs. Similarly, Fig. 4 depicts

Table 4
Bayesian Vector Autoregression using Absolute Net Position (ANP) measure.

Panel A:	Model 4			
	ANP_BAT	ANP_HFT	ANP_NAT	RV
ANP_BAT(−1)	0.16	0.02	0.08	−6.41E−09
	(0.05)***	(0.03)	(0.04)	(0.00)
ANP_HFT(−1)	−0.008	0.01	0.02	−5.88E−08
	(0.06)	(0.04)	(0.06)	(0.00)
ANP_NAT(−1)	0.12	0.07	0.1	−4.82E−08
	(0.05)**	(0.03)*	(0.05)*	(0.00)
RV(−1)	74674.13	11671.96	78926.15	0.059289
	(28156.5)***	(19867.9)	(26251.3)***	(0.04)
R-sq.	0.09	0.02	0.06	0.01
Adj. R-sq.	0.08	0.01	0.05	0.00

Panel B:	Model 5			
	ANP_BAT	ANP_HFT	ANP_NAT	MedRV
ANP_BAT(−1)	0.14	0.02	0.05	−1.26E−08
	(0.05)***	(0.03)	(0.04)	(0.00)
ANP_HFT(−1)	−0.028	0.01	0.001	1.62E−07
	(0.06)	(0.04)	(0.06)	(0.00)***
ANP_NAT(−1)	0.1	0.07	0.08	9.58E−08
	(0.05)*	(0.03)*	(0.05)	(0.00)**
MedRV(−1)	184892.4	366.27	184650.2	0.427657
	(52806)***	(37261.6)	(49233.2)***	(0.03)***
R-sq.	0.10	0.02	0.07	0.31
Adj. R-sq.	0.09	0.01	0.06	0.30

Panel C:	Model 6			
	ANP_BAT	ANP_HFT	ANP_NAT	MinRV
ANP_BAT(−1)	0.13	0.02	0.05	−2.03E−08
	(0.05)***	(0.03)	(0.04)	(0.00)
ANP_HFT(−1)	−0.03	0.01	0	1.86E−07
	(0.06)	(0.04)	(0.06)	(0.00)***
ANP_NAT(−1)	0.11	0.07	0.09	0.00000012
	(0.05)*	(0.03)*	(0.05)*	(0.00)***
MinRV	176956.4	−11523.07	172856.5	0.378729
	(48191.1)***	(34005)	(44930.1)***	(0.04)***
R-sq.	0.10	0.02	0.07	0.27
Adj. R-sq.	0.09	0.01	0.06	0.26

The columns provide the coefficients and standard errors obtained from BVAR models of the form, $\boldsymbol{Y_t} = \boldsymbol{AY_{t-1}} + \boldsymbol{BX_{t-1}} + \boldsymbol{C} + \boldsymbol{\varepsilon_t}$, where X and Y are the vectors of endogenous variables, C is the vector of intercepts, t denotes the time in one-hour intervals and $\boldsymbol{\varepsilon_t}$ is the error term. The model uses Litterman/Minnesota priors.
*Indicate significance at 10%.
**Indicate significance at 5%.
***Indicate significance at 1%.

the impulse responses of traders' activity for one S.D innovation in volatility measures. Traders increase their activity after an hour of volatility shock. On the one hand, shocks to RV cause the highest increase in NATs' trading volumes, followed by BATs. These results support hypothesis H_{1b}. A one S.D shock in RV increases NATs, BATs and HFTs trading by 89441, 64280 and 49371 units, respectively. On the other hand, shocks to MedRV and MinRV cause the highest increase in BATs' trading volumes, followed by HFTs. A one S.D shock in MedRV increases NATs, HFTs and BATs trading by 4112, 12564 and 16360 units, respectively. Likewise, a one S.D shock in MinRV increases NATs, HFTs and BATs trading by 2617, 12312 and 15187 units, respectively. These results support hypothesis H_{4a} and is consistent with Ceffer et al. (2018), Hasbrouck and Saar (2013) and Zhang (2012), but contrary to Aït-Sahalia and Brunetti (2020).

Table 4 shows that NATs and BATs increase their directional trades for a unit change in volatility and rejects hypothesis H_{5b}. Fig. 5 depicts the impulse responses of traders' activity for a one S.D innovation in volatility measures. We notice that traders increase their absolute net position after an hour of volatility shock. Besides, BATs execute the highest number of directional trades, followed by NATs for a S.D shock in jump robust volatility estimates. A one S.D innovation in MedRV also produces the lowest increase in HFTs' absolute net position by 26 units. In contrast, a one S.D innovation in MinRV reduces HFTs' absolute net position by 906 units. These results partly support hypothesis H_{5a}, wherein BATs increase directional trades, while HFTs tend to withdraw from the market during extreme volatility.

Contrary to the market fleeing behavior among HFTs, Fig. 5 depicts that a one S.D innovation in MedRV and MinRV increases BATs' absolute net position by 13063 and 13920 units, respectively. Similar to BATs, NATs also increase their absolute net position after shocks in MedRV and MinRV by 13046 and 13598 units, respectively. While Fig. 4 shows that HFTs increase their trading activity after volatility shocks, Fig. 5 offers sufficient proof that HFTs' do not place aggressive unidirectional trades. Therefore, we find new evidence suggesting that among the ATs, only BATs increase their directional trades, thereby further aggravating the volatility shock.

5. Robustness checks

We perform additional robustness tests to verify the above results. We check for intraday seasonality by including two dummy

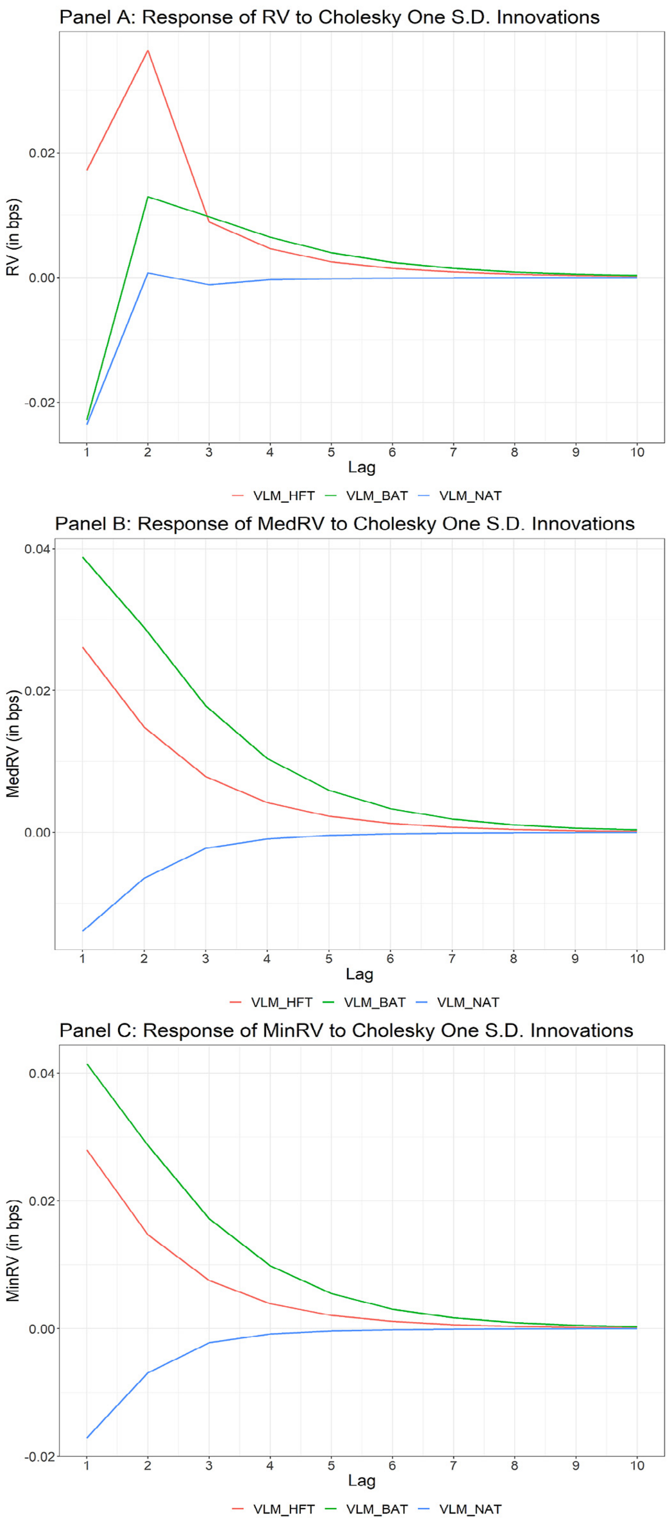

Fig. 2. Impulse response functions on response of volatility for innovations in Volume of trade (VLM) measure.

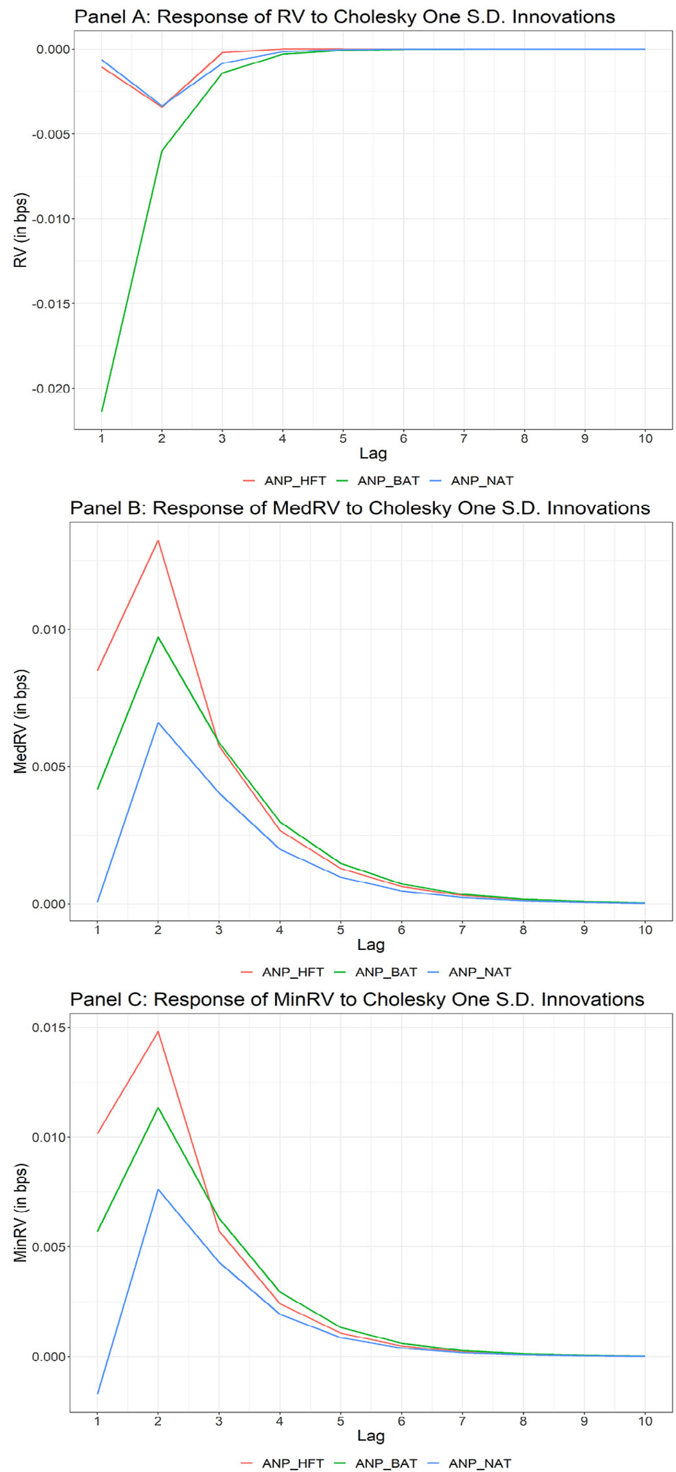

Fig. 3. Impulse response functions on response of volatility for innovations in Absolute Net Position (ANP) measure.

variables (Jain et al., 2016), one for the period from 9.15 A.M. to 11.00 A.M. (IST) and another for the period from 2.00 P.M to 3.30 P.M (IST). We find that the results obtained are similar to those presented above. To account for any impact of macroeconomic announcements on the volume and volatility during the sample period, we included a dummy variable for announcements. Data on announcements is obtained from the Economic calendar available in Bloomberg's database. We find that the announcement dummy is insignificant, and the results are similar.

6. Conclusion

This study investigates the differential impact of volatility shocks on traders and vice-versa. Using a unique dataset from

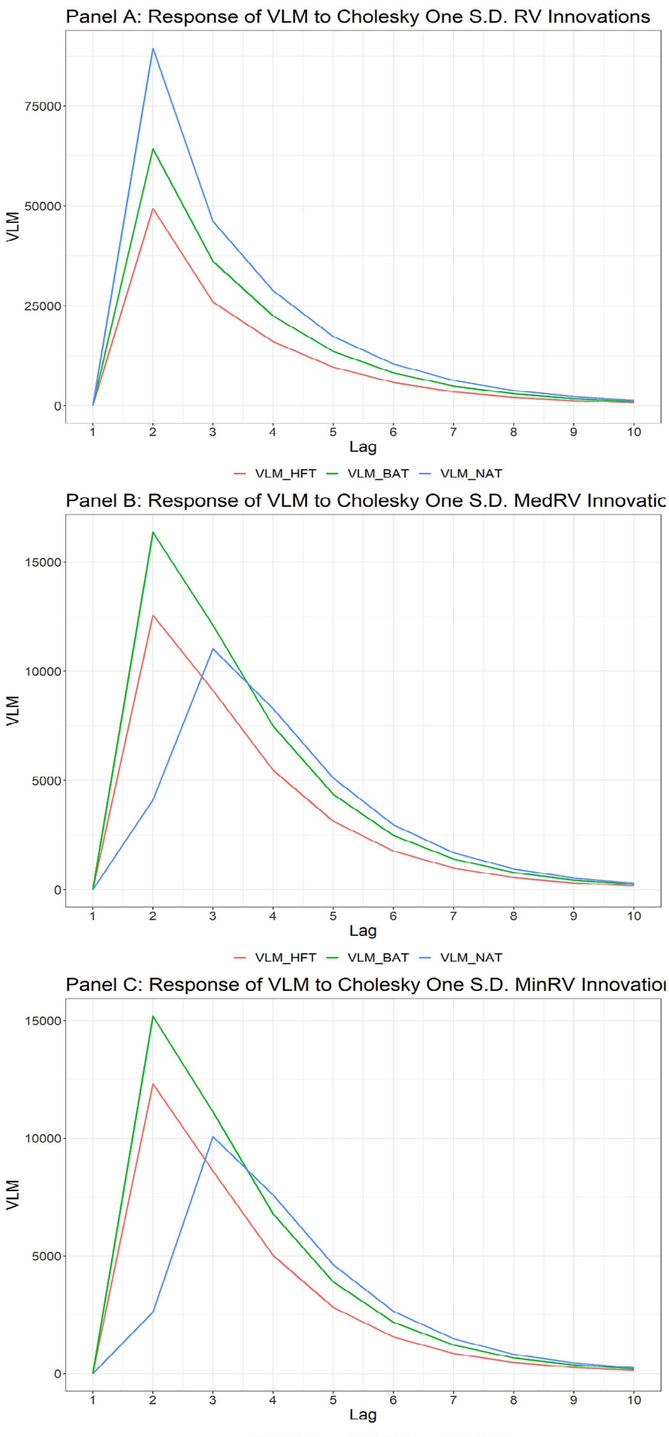

Fig. 4. Impulse response functions on response of traders' volume of trade (VLM) for innovations in volatility measures.

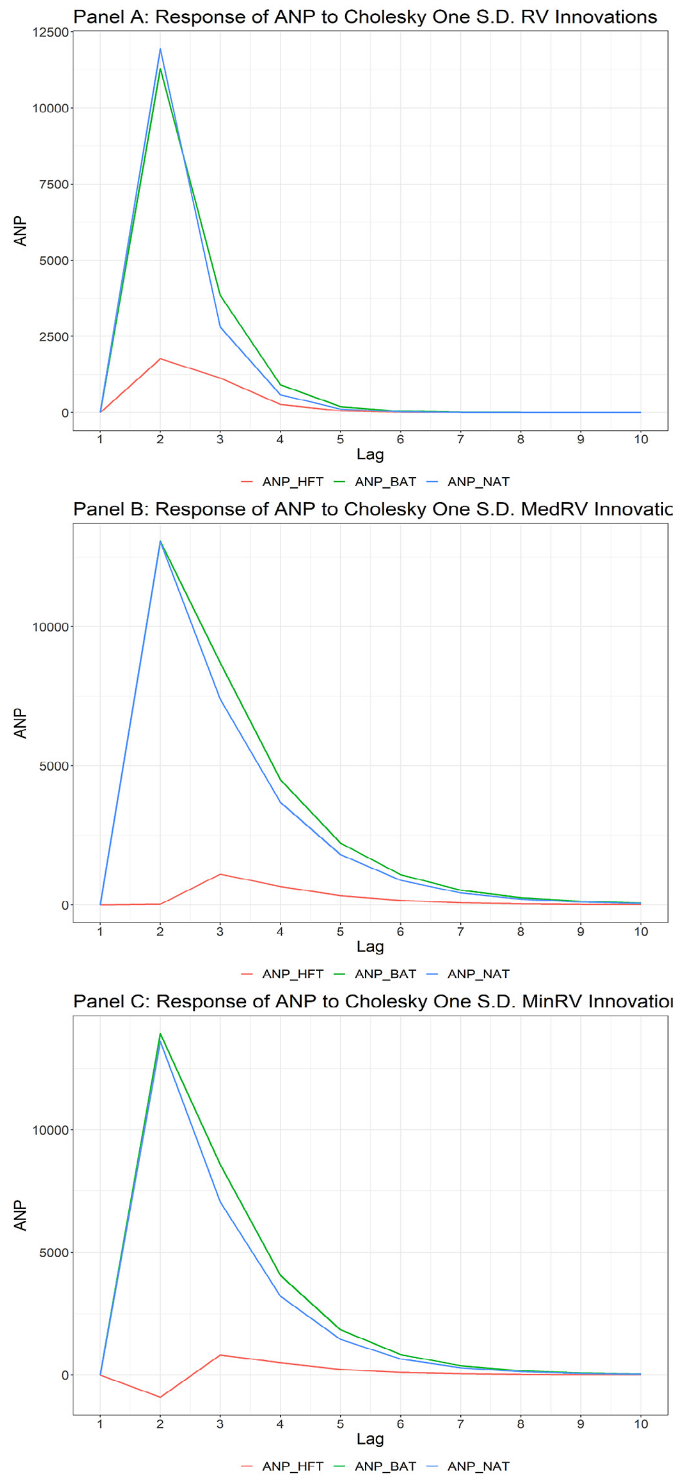

Fig. 5. Impulse response functions on response of traders' absolute net position (ANP) for innovations in volatility measures.

the NSE that identifies traders, we categorize them as HFTs, BATs and NATs. Trading activity is measured using aggregate volume and absolute net trades, where the latter provides the extent of buy/sell pressure. While existing studies have used the conventional RV estimate, we measure volatility using three measures, namely, conventional RV, MedRV and MinRV. Our study shows that BATs reduce conventional RV estimate, but increases jump robust volatility estimates. We also provide strong evidence for the presence of differential impact of volatility shocks on traders and vice-versa. Our results suggest that an increase in aggregate trading volume of NATs reduces volatility for other traders while that of ATs (both HFTs and BATs) increases the same. This study has important implications for market participants. NATs' returns are compromised due to increased volatility caused by ATs' trading. This relative disadvantage could discourage NATs from providing liquidity, causing them to flee the market for fear of volatility. Additionally, our results show that HFTs reduce their directional trades during volatility shocks, which brings down any unidirectional price movements caused by BATs' directional trades.

CRediT authorship contribution statement

Devika Arumugam: Conceptualization, Methodology, Writing – original draft. **P. Krishna Prasanna:** Writing – review & editing, Project administration, Funding acquisition, Supervision. **Rahul R. Marathe:** Writing – review & editing, Project administration, Funding acquisition, Supervision.

Acknowledgments

This work was supported by ICSR, IIT Madras fund for Exploratory Research.

References

Aït-Sahalia, Y., Brunetti, C., 2020. High frequency traders and the price process. J. Econometrics 217, 20–45. http://dx.doi.org/10.1016/j.jeconom.2019.11.005.
Andersen, T.G., Dobrev, D., Schaumburg, E., 2012. Jump-robust volatility estimation using nearest neighbor truncation. J. Econometrics 75–93. http://dx.doi.org/10.1016/j.jeconom.2012.01.011.
Arumugam, D., Prasanna, K., 2021a. A game of hide-and-seek between proprietary and buy-side algorithmic traders: Causal links with market quality. Appl. Econ. http://dx.doi.org/10.1080/00036846.2021.1907290.
Arumugam, D., Prasanna, P.K., 2021b. Commonality and contrarian trading among algorithmic traders. J. Behav. Exp. Finance 100495. http://dx.doi.org/10.1016/J.JBEF.2021.100495.
Benos, E., Brugler, J., Hjalmarsson, E., Zikes, F., 2017. Interactions among high-frequency traders. J. Financ. Quant. Anal. http://dx.doi.org/10.1017/S0022109017000485.
Breedon, F., Chen, L., Ranaldo, A., Vause, N., 2018. Judgement day: Algorithmic trading around the Swiss Franc cap removal. SSRN Electron. J. http://dx.doi.org/10.2139/ssrn.3126136.
Cartea, Á., Penalva, J., 2012. Where is the value in high frequency trading? Q. J. Finance 2, http://dx.doi.org/10.1142/S2010139212500140.
Casgrain, P., Jaimungal, S., 2020. Mean-field games with differing beliefs for algorithmic trading. Math. Finance 30, http://dx.doi.org/10.1111/mafi.12237.
Ceffer, A., Fogarasi, N., Levendovszky, J., 2018. Trading by estimating the quantized forward distribution. Appl. Econ. 50, 6397–6405. http://dx.doi.org/10.1080/00036846.2018.1486021.
Chaboud, A.P., Chiquoine, B., Hjalmarsson, E., Vega, C., 2014. Rise of the machines: Algorithmic trading in the foreign exchange market. J. Finance 69, 2045–2084. http://dx.doi.org/10.1111/jofi.12186.
Chen, W.P., Chung, H., Lien, D., 2016. Price discovery in the S & P 500 index derivatives markets. Int. Rev. Econ. Finance 45, 438–452. http://dx.doi.org/10.1016/J.IREF.2016.07.008.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation. J. Finance 45, 379–395. http://dx.doi.org/10.1111/j.1540-6261.1990.tb03695.x.
Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Amer. Statist. Assoc. 74, 427–431. http://dx.doi.org/10.1080/01621459.1979.10482531.
Fung, J.K.W., Lien, D., Tse, Y., Tse, Y.K., 2005. Effects of electronic trading on the Hang Seng Index futures market. Int. Rev. Econ. Finance 14, 415–425. http://dx.doi.org/10.1016/J.IREF.2004.03.004.
Hasbrouck, J., Saar, G., 2013. Low-latency trading. J. Financial Mark. 16, 646–679. http://dx.doi.org/10.1016/j.finmar.2013.05.003.
Hasbrouck, J., Seppi, D.J., 2001. Common factors in prices, order flows, and liquidity. J. Financ. Econ. 59, 383–411. http://dx.doi.org/10.1016/s0304-405x(00)00091-x.
Jain, P.K., Jain, P., McInish, T.H., 2016. Does high-frequency trading increase systemic risk? J. Financ. Mark. 31, 1–24. http://dx.doi.org/10.1016/j.finmar.2016.09.004.
Li, S., Wang, X., Ye, M., 2018. Who supplies liquidity, and when? SSRN Electron. J. http://dx.doi.org/10.2139/ssrn.3231166.
Litterman, R.B., 1986. Forecasting with bayesian vector autoregressions—five years of experience. J. Bus. Econom. Statist. 4, 25–38. http://dx.doi.org/10.1080/07350015.1986.10509491.
Malceniece, L., Malcenieks, K., Putniņš, T.J., 2019. High frequency trading and comovement in financial markets. J. Financ. Econ. 134, 381–399. http://dx.doi.org/10.1016/j.jfineco.2018.02.015.
Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346. http://dx.doi.org/10.1093/biomet/75.2.335.
Saliba, P., 2020. The information content of high-frequency traders aggressive orders: Recent evidence. Quant. Finance 20, 1779–1794. http://dx.doi.org/10.1080/14697688.2020.1748700.
Scholtus, M., Van Dijk, D., Frijns, B., 2014. Speed, algorithmic trading, and market quality around macroeconomic news announcements. J. Bank. Finance 38, http://dx.doi.org/10.1016/j.jbankfin.2013.09.016.
Zhang, F., 2012. High-frequency trading, stock volatility, and price discovery. SSRN Electron. J. http://dx.doi.org/10.2139/ssrn.1691679.