How do High-Frequency Traders Trade?*

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Abstract

We examine the order handling and trading behavior of high-frequency traders (HFTs) around firm-specific earnings surprises as well as unexpected interest rate changes. We find that HFTs do not change the order handling and trading behavior around earnings surprises. This shows that they do not withdraw from markets for the fear of losing to informed traders. Their profitability also does not change around earnings surprises. The results are different around macroeconomic shocks. We find that HFTs reduce their participation in trading activities. The reduced trading still leads to losses to HFTs. We also examine the trading of buy-side algorithmic traders. We find that their participation in trading activity is different from HFTs. They appear to trade more as well as more aggressively around earnings surprises, though their trades on average do not appear to be more profitable after earnings surprises.

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1. Introduction

High-frequency traders (HFTs) account for a large proportion of the trading volume in security markets today.[1] Despite this, there is very little understanding of how and why they trade. Are they more likely to demand or supply liquidity? Do they exit the market or increase participation when there is an exogenous information shock? Does their participation increase because they are informed or do they exit because they do not want to suffer losses to informed traders? HFTs typically end the trading day with very low inventory positions. Are they able to manage their inventories better when there is an exogenous information shock or do they end up with positions that are farther away from their preferred inventory positions? Our paper attempts to address these questions by comparing and contrasting their trading behavior around unexpected macroeconomic shocks as well as unexpected firm-level earnings surprises.

Recent studies focus on the impact of algorithmic trading and high frequency trading on various dimensions of market quality. Using the introduction of automated quote dissemination on the NYSE as an exogenous event, Hendershott et al. (2011) find that algorithmic trading improves liquidity and quote informativeness. They find that the impact on smaller stocks is not significant. They conclude that algorithmic trading improves market quality as algorithmic traders are more likely to supply liquidity than to demand liquidity. On the other hand, Hendershott and Moulton (2011) find that introduction of the Hybrid system on the NYSE raises the cost of immediacy because of increased adverse selection.

An alternate argument is that algorithmic traders consume liquidity, which leads to wider spreads and worse market quality. Foucault et al. (2013) predict that algorithmic traders' impact

[1] HFTs account for around one-third of volume in India and two-third of volume in the U.S. and in Europe (see http://articles.economictimes.indiatimes.com/2014-04-11/news/49058847_1_high-frequency-trading-hft-algorithmic-trading).

on liquidity is driven by the differential benefits bestowed on suppliers and consumers of liquidity. If algorithmic trading results in a larger decline in the market taker's monitoring cost, liquidity is consumed more quickly than it is supplied, leading to lower liquidity. However, if algorithmic trading results in a greater decline in market maker's cost of monitoring then liquidity is provided more quickly and hence it improves liquidity.

Other studies have studied the impact of HFTs, a subset of algorithmic traders, on market quality and efficiency measures. Brogaard et al. (2013) find that HFT lead to positive informational benefits. They document that price changes due to HFT are relatively more permanent, their trading activities are correlated with public information, and they help with better price discovery. However, HFTs lose money when they supply liquidity.

Hasbrouck and Saar (2013) find that HFTs improve traditional market quality measures and lower short-term volatility. Using publicly-available NASDAQ order-level data, time-stamped to the millisecond, for a period of relative stability and another period of declining prices and uncertainty, they find that HFTs enhance market quality in both periods and are not detrimental to long-term investors. They also document that HFTs help reduce volatility in smaller capitalization stocks more than in larger stocks. They conclude that this could be due to increased activity of HFTs in smaller stocks during both periods.

Brogaard (2010) also finds no evidence to support the hypothesis that HFT activity increases volatility. In a contrasting study, Kirilenko et al. (2011) investigate the origins of the Flash Crash of May 2010. They find that while HFTs did not trigger the crash, they could have potentially exacerbated the downward move and the associated spike in volatility.

While the evidence shows the impact of high frequency trading on bid-ask spreads, volatility, permanent and transitory volatility, it is not clear how high frequency traders trade.

The paper closest to ours is Menkveld (2013). He identifies one HFT across two markets, namely, the Chi-X and Euronext. He finds that the HFT employs a cross-market strategy, through which the HFT's position in the two markets mirror each other (net zero inventory across the two markets). Menkveld also finds that about 80 percent of the HFT's trades are through passive trades. He finds that overall the HFT trades profitably. This is contrary to Brogaard et al. (2013), who find that HFTs lose money when they supply liquidity. One reason for this could be the lack of competition from other HFTs on the Chi-X and Euronext. Menkveld's algorithm identifies only one possible HFT. Even if there are other HFTs in these markets, they may be much smaller. Menkveld focuses on the trading behavior of only one HFT and its impact on the market. Our study focuses on a larger cross-section of stocks and a larger number of HFTs around exogenous macroeconomic and firm-specific events. HFTs are likely to behave differently and more aggressively in a competitive environment.

We examine how HFTs trade in the BSE (Bombay Stock Exchange) 200 stocks around earnings surprises and macroeconomic shocks in 2011. Proprietary data from the BSE identifies which traders use smart order routers (SOR), whom we categorize as HFTs. The data also identifies traders using algorithms but without SOR and those with direct market access accounts also without SOR, both of whom we categorize as buy-side algos.

We identify 153 earnings surprises involving 102 firms and 2 macroeconomic shocks. We use 112 (86) stocks to examine the impact of a larger than expected increase in repurchase and reverse repurchase rates on May 3 (July 26), 2011 on HFTs and buy-side algos trading behavior. We have fewer than 200 stocks around the macroeconomic shocks as a number of the stocks have earnings announcements close to the macroeconomic shocks. We exclude these stocks from the sample of firms used to study the impact of the macroeconomic shock on HFT and buy-side algos trading in order to avoid any confounding effects.

We compare HFTs' and buy-side algos' average order handling, trading, and inventory balance management behavior and profitability on Days 0 and +1 relative to the event (we call this the event period) to that over the control period comprising of trading days -5 to -1 relative to the event. We find that HFTs do not change the number of orders or order size after an earnings surprise. However, they submit a third fewer orders after a macroeconomic shock and their order size falls by half. These results suggest that HFTs are likely not trading on information around earnings surprises but want to avoid trading against informed traders around macroeconomic shocks. We find the opposite results for buy-side algos. They submit more orders and larger orders after an earnings surprise than before. This suggests that they are informed and attempt to profit from their information advantage. They do not change their order handling behavior around macroeconomic shocks.

We, next, investigate if HFTs change their mix of order types after these information shocks. It is possible that HFTs submit reduce the number of one type of order while increasing other types of orders after earnings surprises. For example, if they are informed, they may increase the number of liquidity demanding orders while at the same time reducing liquidity-supplying orders. We find that HFTs do not significantly change the mix of limit and market orders. They, however, reduce the number of limit orders by a third after a macroeconomic shock. It is likely that they reduce their market participation to avoid being picked off by informed traders after a macroeconomic shock. Buy-side algos trade differently from HFTs. They increase both market as well as limit orders after earnings surprises but do not change the mix of order types after a macroeconomic shock. This shows that they trade aggressively after a firm-specific information shock, which implies that they are likely to be informed.

HFTs may not change the mix of limit and market orders but they could submit a larger or smaller number of aggressively-priced limit orders after an information shock. If they are informed, they may submit more liquidity-demanding orders and fewer liquidity-supplying orders. To this end, we examine the number of liquidity-demanding and supplying orders HFTs submit after an information shock. We find that they increase the daily number of liquidity-demanding orders submitted by 51 after an earnings surprise. This provides some evidence that they are likely informed and trade aggressively to profit from their information advantage. When we examine their orders around macroeconomic shocks, we find that they reduce the use of both liquidity-demanding as well as supplying orders. The reductions are both highly significant. When we investigate similar numbers for buy-side algos, we find that they increase both liquidity-demanding as well as supplying orders around earnings surprises but there is no change around macroeconomic shocks. These provide further evidence that buy-algos trade aggressively around firm-specific information shocks.

Next, we examine how aggressively HFTs price their limit orders. We measure order aggressiveness in two ways. One measure is the number of ticks the limit price of the order is away from the best quote on the same side.[2] A second measure is creating five order aggressiveness categories by comparing the limit price to the best quotes. The most aggressive order has a price that is equal to or better than the opposite side best quote. For example, if the best ask price is currently Rs. 1,000, a buy order with a limit price of Rs. 1,000 or higher is very aggressive as it will result in at least a partial execution almost instantaneously. The least

[2]The minimum price variation on the BSE is Rs. 0.05.

aggressive limit order has a limit price that is not among the five best prices on the same side.[3] On average, we find some weak evidence that HFTs increase orders at all levels of order aggressiveness around earnings surprises. On the other hand, they significantly reduce the number of orders submitted all levels of aggressiveness after a macroeconomic shock. These results are consistent with HFTs reducing market participation after a macroeconomic shock. Buy-side algos appear to increase the number of orders submitted across all levels of order aggressiveness both after earnings surprises as well as after macroeconomic surprises. All these results hold using both measures of order aggressiveness.

We also analyze the trading activity of HFTs around information shocks. HFTs do not change the daily rupee volume and number of shares traded after earnings surprises but they are involved in more number of trades. Consistent with our earlier results, we find that they reduce the daily rupee volume by Rs. 4 million and the number of shares by 21,000 after macroeconomic shocks. They are also involved in fewer trades. On the other hand, buy-side algos trade larger quantities, both in rupee terms as well as number of shares, after earnings surprises. This further supports our finding that buy-side algos are likely trading on private information.

We investigate how tightly HFTs manage their inventories during the event period. We measure their end-of-day net position scaled by gross volume traded that day and their minute-by-minute intraday inventory balance.[4] The intraday inventory balance measure is far away from zero for HFTs. While at first glance it appears that HFTs do not aggressively manage their intraday positions, it is likely they are trading the same stock on the National Stock Exchange of India (NSE). This is consistent with Menkveld's (2013) finding that an HFT manages his

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[3]The BSE publicly disseminates the five best prices on each side of the market.
[4] We discuss these measures in greater details in Section 3.

inventory across two markets. Since we do not have data from the NSE, it is difficult to test this conjecture. We do not find a significant change in the inventory measures around earnings surprises for HFTs but do find a significant decrease in these measures around macroeconomic surprises. The latter may not be due to HFTs better managing their positions. It is more likely because of their lower market participation after a macroeconomic shock. This result holds for both inventory measures. For buy-side algos, we find that their intraday inventory balance increases after an earnings surprise. This suggests that either they are worse off or are managing their positions across the BSE and the NSE. Similar to HFTs, we find a reduction in inventory positions after a macroeconomic shock. This may be related to the reduced participation in markets by buy-side algos.

Finally, we examine if HFTs and buy-side algos make more losses or profits around these information shocks by examining realized spreads. This gives a measure of how informed they are around the information shocks. Realized spread captures the loss a trader makes by trading with informed traders. It measures the change between the transaction price and the quote midpoint sometime after transaction.[5] A positive (negative) value implies losses (profits) to the trader. We find no change in realized spreads for HFTs around earnings surprises but find that they make losses to informed traders after a macroeconomic shock. Despite reducing their market participation after a macroeconomic shock, even their reduced trading activity still leads to losses for them. Buy-side algos tend to reduce their losses around macroeconomic shocks. They make losses prior to the shock as well as after the shock.

The rest of the paper is organized as follows. We describe our data and the events in Section 2. We discuss our results in Section 3 and conclude in Section 4.

[5] We use the quote midpoint 5, 30, and 60 minutes after the trade.

2. Data

Our data is from the BSE. We have complete order and trade book data for 2011. The order book data includes the BSE scrip code, date, time of order, type of order (limit, market, etc.), whether buy or sell, the limit price of the order, the displayed and total order size, whether the record is an order addition, update, or deletion, the trading member code, the client account number, and a unique order number. The trade book data includes the BSE scrip code, date, time of trade, the order numbers of the buy and sell orders involved in the trade, the trade price, and the trade size.[6] We use the order and trade data to generate the best five prices and associated depth at these prices on both sides of the market at all times. We generate the best five prices on both sides as the BSE disseminates this information publicly.

While the order and trade book is available for all BSE-listed stocks, we focus our analysis only on the BSE 200 Index stocks as of December 31, 2010. Aggarwal and Thomas (2014) find that algorithmic trading on the NSE is mostly in the larger stocks. Since high frequency trading is a form of algorithmic trading, the BSE 200 Index stocks are likely to have the largest proportion of high frequency trading.

To understand how HFTs trade, we investigate how they trade around exogenous information shocks. Specifically, we examine their trading around firm-specific earnings announcement surprises and unexpected interest rate changes by the RBI. We conjecture that if HFTs demand liquidity, they may have an advantage in processing firm-specific information and hence may trade profitably around earnings surprises. On the other hand, if they largely supply liquidity, they may exit the market around earnings surprises to avoid losing to informed traders.

[6]The unique order number helps us match the order data to the trade data.

Macroeconomic surprises affect the entire market. HFTs are less likely to have an information advantage around such surprises and hence more likely to withdraw from the market to avoid losses to informed traders.

We identify quarterly earnings announcements for the BSE 200 stocks during the calendar year 2011 from the S&P Capital IQ database. Using a market model with the BSE Sensex as the market index, we estimate the cumulative abnormal returns (CAR) over day 0 and +1 (Day 0 is the earnings announcement date).[7] We use the standardized CAR (SCAR) to identify earnings surprises.[8,9] We include those earnings announcements whose absolute SCAR is greater than 2. This results in 351 statistically significant earnings surprises.

We identify macroeconomic shocks in 2011 from Bloomberg. The RBI increased repurchase and reverse repurchase rates by more than expected twice during 2011. The first was on May 3, 2011 and the second was on July 26, 2011. The market expected a 25 basis point increase in both rates (as per market survey reported by Bloomberg) on both days but the RBI increased them by 50 basis points.[10] We examine trading by HFT around the macroeconomic shocks for the same BSE 200 firms.

For each event, both earnings as well macroeconomic shocks, we use the prior five trading days (Days -5 to -1 relative to the event) as the control period for trading behavior and compare it to that over Day 0 and +1 relative to the event (the event period). To get rid of any confounding information effects around the macroeconomic shocks, we exclude earnings

[7] We use returns data from the calendar year 2010 to estimate the market model and use the same estimates for all events of each firm in 2011.

[8] To determine earnings surprises, earnings forecasts are not available for BSE-listed firms. However, there is a large literature (e.g. Ball and Brown 1968) that shows that earnings surprises are accompanied by abnormal price reactions.

[9] We use the root mean square error from the market model to standardize the CAR.

[10] The repurchase (reverse repurchase) rate was increased from 6.75 (5.75) percent to 7.25 (6.25) percent on May 3, 2011. The similar numbers for the July 26, 2011 increase were 7.50 (6.50) and 8.00 (7.00) percent, respectively.

surprises whose seven days (Day –5 to +1) overlap with the seven days around the macroeconomic shocks. We exclude firms with such events from the sample of firms we examine around the macroeconomic shocks. This results in a final sample size of 153 earnings surprises (involving 102 firms), 112 firms for the macroeconomic shock on May 3, 2011, and 86 firms for the macroeconomic shock on July 26, 2011. The mean (median) CAR around the earnings surprises is -1.56 (-4.64) percent. The mean (median) SCAR is -0.62 (-2.17).

We treat a combination of a trading member code and client account number as a unique trader. The BSE order and trade data also identify the following trader types in addition to the client account numbers:

i) Normal

ii) Algorithmic trader (algo)

iii) Direct market access (DMA)

iv) DMA with algo

v) Smart order routing (SOR)

vi) Mobile

vii) SOR with algo

viii) DMA SOR with algo

HFTs tend to use smart order routers to route their orders to the locations with most profitable executions. So we categorize v), vii), and viii) above as HFTs. Algos and DMA are more likely to indicate buy-side algos and hence we categorize ii), iii), and iv) above as algos. The remaining traders are categorized as normal traders. In the rest of the paper, we examine the trading behavior of these three broad trader types, namely, normal, buy-side algo, and HFT.

In the rest of our analyses, we compare the HFTs order handling and trading behavior on the event date (Day 0) to those over a control period, which we define as Days -5 through -1 before the event. This helps us determine how HFTs react when there is an exogenous shock. Do they stop or reduce their participation in markets or are they more likely to demand or supply liquidity?

3. Results

A. Orders and Trades

First, we compare order handling (submissions, modifications, and cancellations) by the three different trader types during the event period to that over the control period. Results of traders' order handling are in Table I. We find that HFTs tend to submit more orders (around 150 orders) and larger orders (around 35,000 shares per order) than other types of traders. However, there is no significant difference in the number of new orders and order size between event and control periods around earnings surprises. This suggests that even though there is likely to be higher informed trading during the event window, since he is able to average his profits and losses across his orders, he does not change his order submission strategy. We also find that HFTs do not increase the number of order deletions around earnings surprises. There is some evidence that HFTs marginally reduce the number of modifications around earnings surprises. This is likely due to a larger proportion of his orders getting executed.

HFTs' order handling behavior is starkly different around macroeconomic shocks. We find that submit a third fewer orders in response to a macroeconomic shock and their order size falls by half. Order deletions do not change significantly but modifications fall by half. Taken in conjunction, these results suggest that HFTs reduce their trading in response to macroeconomic shocks. This is likely because they feel that they are at a disadvantage relative to informed traders and hence reduce the number of orders and order sizes to reduce their losses to informed traders.

Buy-side algos, on the other hand, trade differently from HFTs. They submit more orders and larger orders around earnings surprises. This suggests that they are informed and attempt to profit from their information advantage. Overall, they do submit fewer and smaller orders than HFTs but make far more order modifications. They do not change their order handling behavior much around macroeconomic shocks.

Next, we investigate the different types of orders HFTs uses. When there is an exogenous event, do HFTs trade more aggressively by submitting more market orders and aggressively priced limit orders? They may be trading on short-term information and hence trade aggressively. On the other hand, they may act purely as market makers and submit more orders during the event to provide more liquidity and capture more of the bid-ask spread. Tables II, III, and IV present results on different ways of measuring aggressive order types. In Table II, we separate new order submissions into limit, market, immediate-or-cancel (IOC) and stop-loss orders. From Table II, we find that HFTs do not change the number of market, limit, or stop-loss orders they submit around earnings surprises. So it is not the case that HFTs change the mix of orders around earnings surprises. They continue to submit the same number of the different order types. On the other hand, they reduce the number of limit orders they submit around macroeconomic announcements by a third. If their limit orders largely supply liquidity, this is consistent with them withdrawing from the market to avoid losing to informed traders. Algos increase the number of both market as well as limit orders around earnings surprises but do not change the number of different types of orders around macroeconomic shocks.

In Table III, we categorize orders as liquidity supplying or liquidity demanding. It is possible traders simply make their limit orders more or less aggressive around information shocks without actually changing the number of limit orders. To examine this, we determine if limit orders are liquidity demanding or liquidity supplying. We use the trade data to identify which order triggers the transaction, which we call the liquidity-demanding order. We compare the time stamp of the transaction to the latest time stamp of the two orders involved in the transaction. This latest time stamp could be from when the order was submitted with no subsequent modifications or from the last modification to the order. The order with time stamp closest to the trade is the liquidity-demanding order and the other order is the liquidity-supplying order. For example, a trade occurs at 10:00:00. The buy order was submitted at 9:45:00 with no further modifications. The sell order was first submitted at 9:30:00 and was last modified at 9:59:59. Our rule categorizes the sell order as the liquidity-demanding order and the buy order as the liquidity-supplying one.

We find that HFTs use 51 more liquidity-demanding orders after an earnings surprise than before. This increase is statistically significant at the 5 percent level and accounts for a more than 50 percent increase in liquidity-demanding orders. This suggests that HFTs do want to trade quickly right after an earnings surprise, which is consistent with them trading on information. Interestingly, we find that HFTs reduce the number of liquidity-supplying orders by more than 50 percent, from 84 orders per day before a macroeconomic shock to 31 orders per day after. They also reduce the number of liquidity-demanding orders by over 40 percent, from 109 orders per day to 62 orders per day after. Both changes are statistically significant at the 1 percent level. These results suggest that HFTs are not informed after a macroeconomic shock and hence withdraw from both sides of the market.

In Table III, we also find that buy-side algos trade more on both sides of the market after an earnings surprise but do not change their order submissions after a macroeconomic shock. Like HFTs, buy-side algos also appear to be informed after earnings surprises.

In Table IV, we categorize limit orders by the aggressiveness of their prices. We do this in two different ways. In Panel A, we determine the distance between an order's limit price and the best quote on the same side as the number of ticks.[11] This is calculated as the difference between best bid (limit) price and the limit (best ask) price divided by Rs. 0.05 for buy (sell) orders.[12] A negative number implies that the order is priced aggressively resulting in either at least a partial execution or simply improves the best quote on the same side. A zero indicates that the limit price is adding additional depth at the best quote on the same side. A positive number of ticks indicates that the limit order adds additional depth in the book behind the best quote on the same side. We find an increase, though marginally insignificant, in some of the HFTs' aggressively-priced orders after an earnings surprise. Further, consistent with our earlier results, we find that HFTs reduce order submissions at all levels of price aggressiveness after macroeconomic shocks. On the other hand, buy-side algos appear to increase the number of orders at all levels of price aggressiveness both after earnings surprises as well as after macroeconomic shocks.

In Panel B of Table IV, we categorize order aggressiveness as follows. Buy (sell) orders with limit price greater (less) than or equal to the best ask (bid) price are the most aggressively priced orders (Category 1) as they result in at least a partial execution. Category 2 is for buy (sell) orders whose limit price is greater (less) than the bid (ask) price but less (greater) than the ask (bid) price. These orders simply improve the current best quoted price on the same price

[11]Same side means the bid side of the book for buy orders and the ask side of the book for sell orders.
[12]The minimum price variation on the BSE is Rs. 0.05.

without any execution. Category 3 is for buy (sell) orders whose limit price is equal to the bid (ask) price. They add additional depth to the best quote. Category 4 is for buy (sell) orders whose limit price is at the four lower (higher) prices behind the best bid (ask) price. These orders add additional depth behind the best quotes to the publicly disseminated part of the order book. Finally, buy (sell) orders with limit price less (greater) than the five best prices on the buy (sell) side of the order book are in Category 5 (least aggressive). Our results are similar to those in Panel A of Table IV.

Next, we examine the trade executions of HFTs. Since some HFTs submit larger orders, we expect them to trade more. Results of HFT trading activity are in Table V. We find that daily gross traded value and number of shares traded is not different for HFTs after an earnings surprise. However, since HFTs submit larger orders, we find that they end up with 67 more trades per day after an earnings surprise, which is a statistically significant increase at the 5 percent level. Consistent with HFTs withdrawing from the market after a macroeconomic shock, we find that their traded value decreases by Rs. 4 million per day, the daily number of shares traded decreases by 21,000 shares, and the daily number of trades reduces by 92. All these decreases are highly statistically significant.

Table V also shows trading activity by buy-side algos. We find that they increase their trading significantly after an earnings surprise but no change after a macroeconomic shock. After an earnings surprise, they increase the daily value traded by Rs. 464,000, increase the daily number of shares traded by 1,400, and increase the daily number of trades by 19. All these increases are statistically significant at the 5 percent level. This further supports our previous findings that buy-side algos trade on firm-specific information right after an earnings surprise.

To summarize, HFTs submit more orders and larger orders than other types of traders. Their trading behavior largely does not change after an earnings surprise, but they appear to withdraw from the market after a macroeconomic shock. We find similar results when we examine HFTs' trading activity also. Their trading does not change much after an earnings surprise but they appear to withdraw after a macroeconomic shock. Buy-side algos, on the other hand, appear increase their participation in the market after an earnings surprise, which suggests that they are more likely to be trading information.

B. Inventory Management

In this section, we investigate how HFTs manage inventories during the event period when compared to the control period. Given the larger amount of trading due to the exogenous shock, do HFTs manage their inventories less or more aggressively? The larger volume may make it easier for HFTs to keep their inventory closer to zero at all times of the day. Alternatively, they may see profitable opportunities and be willing to move away from their optimal inventory levels

We use two measures of trader inventory. The first is an intraday inventory balance measure used by Kirilenko et al. (2011). We calculate the intraday inventory balance measure over each day of the control and event period as follows. For each trader in each stock on each day, we determine the net position for the day at the end of each minute (a total of 376 minutes[13]). We calculate the square of the deviation of this minute-by-minute net position from the end-of-day net position.[14] We sum these minute-by-minute squared deviations across the 376 minutes each day. We then scale the square root of this sum by the gross volume traded in that

[13] During our sample period, the BSE continuous session trading hours were from 9:15 am to 3:30 pm, which is a total of 375 minutes. A single market-clearing trade is executed during the pre-open session in each stock that is eligible to trade in the pre-open session. We include positions built up through this pre-open trade as a separate minute, time-stamped at 9:14 am. This gives a total of 376 minutes.

[14] The end-of-day net position is the difference between the number of shares bought and the number of shares sold in a stock by a trader on that day.

stock for that day.[15] Finally, we average this measure separately across the control and event periods for each trader-stock combination. Lower values of the intraday inventory balance measure show that HFTs aggressively manage their inventory intraday while higher values show that they do not manage their inventory very aggressively. The second measure is the end-of-day inventory balance, which is the ratio of the absolute value of the end-of-day net position to the gross volume traded for that day.

HFT inventory balance results are in Table VI. We find that HFTs have the highest intraday inventory imbalance, on average, during the control as well as event period for earnings surprises as well as macroeconomic shocks when compared to the other types of traders. While this suggests that they let their positions deviate substantially during the trading day, there is another explanation for the large level of the intraday inventory balance measure. The BSE 200 stocks constitute the largest stocks in the Indian markets and are cross-listed on the NSE. It is likely that HFTs, given their superior execution systems, manage their inventories close to zero across the two markets.[16] We find that there is no significant change in the intraday inventory measures for HFTs after earnings surprises. However, the measure halves after a macroeconomic shock and this decrease is statistically significant at the 1 percent level. This reduction in the intraday inventory measure could be due to their reduced participation in markets after macroeconomic shocks. As they trade smaller quantities, they are less likely to deviate from zero. We find similar results when we study the end-of-day inventory balances. HFTs' end-of-day inventory balance do not change significantly after an earnings surprise, but they halve after a macroeconomic shock.

[15] The gross volume traded by a trader in a stock is the sum of the number of shares bought and the number of shares sold on that day.
[16] Menkveld (2013) examines a single HFT's trading across two markets and shows that he manages his inventory across these two trading locations. We conjecture that this happens to HFTs trading cross-listed stocks on the BSE.

For buy-side algos, we find that their intraday inventory balance increases after an earnings surprise. This suggests that either they are worse off or are managing their positions across the BSE and the NSE. Similar to HFTs, we find a reduction in inventory positions after a macroeconomic shock. This may be related to the reduced participation in markets by buy-side algos.

C. Realized Spreads

Next, we examine how much money HFTs make from their trading around earnings surprises and macroeconomic shocks. We measure the information of HFTs by computing the realized spread after each transaction. The realized spread is defined as follows:

$$RealizedSpread_{i,t} = \frac{(TransactionPrice_{i,t} - QuoteMidpoint_{i,t+k})}{QuoteMidpoint_{i,t}} \times OrderDirection_{i,t},$$

where $TransactionPrice_{i,t}$ is the transaction price of the trade in stock i at time t, $QuoteMidpoint_{i,t}$ is the midpoint of the best ask and bid prices for stock i at time t, $QuoteMidpoint_{i,t+k}$ is the midpoint of the best ask and bid prices for stock i k minutes after the trade at time t (with k taking values of 5, 30, and 60), and $OrderDirection_{i,t}$ takes a value of +1 (-1) for buy (sell) orders. By design, the realized spread captures the loss made by traders trading against informed traders. Positive (Negative) values indicate losses (profits).

The descriptive statistics on realized spreads are in Table VII. Overall, the losses of none of the different trader types changes around earnings surprises. Around macroeconomic shocks, HFTs appear to go from negative realized spreads during the control period to marginally positive realized spreads during the event period, though this change is significant only for the 60-minute realized spread measure. This is consistent with them not having any information advantage around macroeconomic shocks. HFTs do not change their trading activity around earnings surprises. However, around macroeconomic shocks, they reduce their trading activity but still make some losses.

Buy-side algos tend to reduce their losses around macroeconomic shocks. They make losses prior to the shock as well as after the shock. This change is significant at the 1 percent level for all realized spread measures except at the 5-minute horizon.

4. Conclusions

We examine how HFTs respond to exogenous information shocks. Specifically, we examine their order handling and trading behavior, their inventory management, and the profitability around earnings surprises and macroeconomic shocks. We find that HFTs do not significantly change their order handling and trading behavior around earnings surprises but do reduce their participation in the market after a macroeconomic shock. HFTs also do not change the mix of order types that they use around earnings surprises, although they appear to increase the number of liquidity-demanding orders. On the other hand, they use fewer aggressively priced limit orders around macroeconomic shocks. The profitability of their orders does not change around earnings announcements. However, despite reducing their market participation after a macroeconomic shock, they still make losses to informed traders.

We also examine the trading behavior of buy-side algos. We find that they increase their market participation around earnings surprises and do not change it around macroeconomic surprises.

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Table I
HFT order handling behavior

This table presents order-handling behavior by different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. Firm-specific shocks

		Event period		Control period		
Trader type	N	Mean	Std Dev	Mean	Std Dev	Difference
	Number of new orders					
Normal	1,483,153	2.47	22.57	1.53	15.86	0.94*** (66.70)
Algo	35,434	28.73	233.95	14.16	117.22	14.56*** (13.56)
HFT	475	156.14	538.96	147.05	385.21	9.09 (0.34)
	Order size (number of shares)					
Normal	1,483,153	526.01	22,749.21	369.25	17,000.03	156.76*** (13.38)
Algo	35,434	5,513.01	96,159.85	2,437.10	31,605.99	3,075.91*** (6.02)
HFT	475	38,786.72	176,068.16	34,309.61	147,293.25	4,477.11 (0.49)
	Number of order deletions					
Normal	1,483,153	0.60	14.73	0.41	12.18	0.20*** (24.02)
Algo	35,434	11.84	106.79	7.65	86.36	4.19*** (10.17)
HFT	475	46.24	221.93	58.71	225.91	-12.47 (-1.27)
	Number of order modifications					
Normal	1,483,153	8.48	1,185.46	4.24	607.80	4.24*** (7.26)
Algo	35,434	667.37	9,336.38	243.00	3,639.33	424.37*** (11.38)

Trader type	N	Event period Mean	Event period Std Dev	Control period Mean	Control period Std Dev	Difference
HFT	475	65.61	236.56	92.34	293.14	-26.73* (-1.69)

Panel B. Macroeconomic shocks

Trader type	N	Event period Mean	Event period Std Dev	Control period Mean	Control period Std Dev	Difference
	Number of new orders					
Normal	1,037,726	1.55	17.14	2.02	15.76	-0.47*** (-33.99)
Algo	26,753	15.19	106.61	13.47	83.66	1.73*** (3.01)
HFT	323	101.44	278.98	166.18	343.35	-64.73*** (-2.86)
	Order size (number of shares)					
Normal	1,037,726	434.47	19,662.13	542.64	15,283.45	-108.17*** (-5.69)
Algo	26,753	2,590.46	28,954.89	3,199.83	62,680.07	-609.37 (-1.62)
HFT	323	24,088.99	148,984.91	44,160.96	139,633.66	-20,071.97* (-1.75)
	Number of order deletions					
Normal	1,037,726	0.47	13.05	0.55	12.07	-0.08*** (-8.19)
Algo	26,753	7.43	65.06	6.16	48.44	1.27*** (4.42)
HFT	323	51.60	164.35	64.22	180.57	-12.62 (-1.05)
	Number of order modifications					
Normal	1,037,726	5.63	662.04	5.15	551.33	0.49** (2.11)
Algo	26,753	321.11	3,992.20	214.92	2,182.27	106.19*** (6.88)

Trader type	N	Event period		Control period		Difference
		Mean	Std Dev	Mean	Std Dev	
HFT	323	43.68	165.07	93.76	272.72	-50.07*** (-3.15)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively

Table II
HFT order types

This table presents the different order types used by the different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. IOC orders refers to immediate-or-cancel orders. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. Firm-specific shocks

			Event period		Control period		
Trader type	Order type	N	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Normal	IOC orders	1,939	0.53	0.55	0.46	0.51	0.07*** (2.98)
	Market orders	92,034	0.90	11.85	0.65	2.17	0.25*** (6.32)
	Limit orders	1,426,123	2.43	22.72	1.51	16.13	0.92*** (64.28)
	Stop-loss orders	85,038	1.28	3.00	0.61	1.37	0.66*** (63.49)
Algo	IOC orders	14	1.93	1.97	0.35	0.50	1.58** (2.61)
	Market orders	4,281	9.86	72.11	2.81	18.74	7.06*** (6.94)
	Limit orders	33,042	29.43	238.51	14.78	120.35	14.65*** (12.92)
	Stop-loss orders	2,290	1.35	1.63	0.63	1.40	0.73*** (14.68)
HFT	Market orders	29	42.72	153.16	10.03	51.54	32.70 (1.07)
	Limit orders	468	155.80	541.91	148.63	387.67	7.18 (0.26)
	Stop-loss orders	7	1.71	2.14	0.39	0.61	1.33 (1.38)

Panel B. Macroeconomic shocks

Trader type	Order type	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
Normal	IOC orders	768	0.37	0.56	0.65	0.51	-0.28*** (-8.14)
	Market orders	60,188	0.58	3.13	0.93	11.95	-0.36*** (-7.35)
	Limit orders	998,963	1.54	17.37	1.99	15.72	-0.45*** (-32.31)
	Stop-loss orders	42,762	0.76	2.98	1.07	2.18	-0.31*** (-28.86)
Algo	IOC orders	2	1.50	2.12	0.25	0.35	1.25 (0.71)
	Market orders	2,827	3.18	23.56	5.27	104.89	-2.09 (-1.04)
	Limit orders	25,266	15.69	108.90	13.62	78.42	2.07*** (3.69)
	Stop-loss orders	1,214	0.85	1.64	1.07	1.46	-0.22*** (-3.22)
HFT	Market orders	12	126.29	384.96	1.53	4.72	124.76 (1.12)
	Limit orders	323	96.74	270.21	166.11	343.35	-69.37*** (-3.12)
	Stop-loss orders	4	0.75	0.96	0.75	0.96	0.00 (0.00)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively

Table III
HFTs' liquidity demanding orders

This table separates orders into liquidity-supplying and liquidity-demanding ones submitted by the different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. Liquidity-demanding orders are those trigger a trade and liquidity-supplying orders are those that trade against orders that trigger a trade. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. Firm-specific shocks

Trader type	Order type	N	Event period		Control period		Difference
			Mean	Std. Dev.	Mean	Std. Dev.	
Normal	Liquidity-supplying orders	1,268,402	1.95	21.01	1.11	10.31	0.84*** (51.15)
	Liquidity-demanding orders	1,268,402	1.80	17.65	1.07	7.81	0.73*** (51.27)
Algo	Liquidity-supplying orders	31,362	14.41	125.70	5.15	43.78	9.26*** (13.37)
	Liquidity-demanding orders	31,362	19.46	179.00	7.22	64.97	12.24*** (13.46)
HFT	Liquidity-supplying orders	441	102.30	278.75	80.83	213.57	21.47 (1.42)
	Liquidity-demanding orders	441	137.43	444.83	86.76	226.35	50.67** (2.11)

Panel B. Macroeconomic shocks

Trader type	Order type	N	Event period		Control period		Difference
			Mean	Std. Dev.	Mean	Std. Dev.	
Normal	Liquidity-supplying orders	842,914	1.04	10.67	1.44	9.00	-0.40*** (-32.74)
	Liquidity-demanding orders	842,914	0.98	8.91	1.44	8.61	-0.47*** (-40.51)
Algo	Liquidity-supplying orders	22,758	6.24	54.01	5.71	36.55	0.53 (1.51)
	Liquidity-demanding orders	22,758	8.59	67.57	8.41	67.26	0.17 (0.33)

Trader type	Order type	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
HFT	Liquidity-supplying orders	297	31.37	102.11	84.13	189.03	-52.77*** (-4.48)
	Liquidity-demanding orders	297	61.95	193.34	109.03	208.70	-47.09*** (-2.83)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively

Table IV
HFT limit order aggressiveness

This table presents limit order aggressiveness by the different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. Panel A measures order aggressiveness by the number of ticks from the best quote on the same side and Panel B categorizes order aggressiveness by comparing the limit price of an order to the best quote on the same side. Number of ticks from the best quote for a buy (sell) order is the difference between the best bid (limit) price and the limit (best ask) price divided by Rs. 0.05, which is the minimum tick size on the BSE. A negative value denotes that the limit price of a buy (sell) order is higher (lower) than the best bid (ask) price. Order aggressiveness in Panel B takes a value of 1 if the buy (sell) order's limit price is greater (less) than or equal to the best ask (bid) price, takes a value of 2 if the limit order improves on the current best quote on the same side, takes a value of 3 if the limit price is equal to the current best price on the same side, takes a value of 4 if the limit price is within the four best prices other than the best quote on the same side, and takes a value of 5 if the limit price is worse the five best prices on the same side. The mean percentage across all trader-stock-event combinations as presented. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. By number of ticks from same-side best quote

Panel A1. Firm-specific shocks

Trader type	Number of ticks from same –side best quote	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
Normal	Less than -10	383,793	1.09	4.45	0.62	3.18	0.48*** (63.65)
	-10 to -6	252,585	0.80	3.58	0.52	2.00	0.28*** (44.54)
	-5 to -1	574,319	1.29	13.18	0.94	7.97	0.35*** (26.62)
	0	271,298	1.08	10.78	0.67	7.84	0.40*** (28.86)
	1 to 5	289,173	1.19	8.05	0.70	5.12	0.49*** (40.18)
	6 to 10	187,226	0.92	4.60	0.52	3.23	0.39*** (44.45)
	Greater than 10	809,424	1.56	11.33	0.91	12.60	0.65*** (67.92)
Algo	Less than -10	10,720	6.03	49.65	3.05	26.32	2.97*** (6.58)

Trader type	Number of ticks from same –side best quote	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
	-10 to -6	7,836	7.09	42.79	3.13	19.15	3.97*** (9.66)
	-5 to -1	14,934	19.57	127.97	9.45	59.49	10.12*** (11.35)
	0	8,678	16.86	79.16	10.80	64.80	6.06*** (7.68)
	1 to 5	9,248	18.79	104.77	7.78	46.64	11.01*** (10.97)
	6 to 10	6,554	10.64	55.16	4.80	29.90	5.84*** (10.38)
	Greater than 10	19,640	8.65	82.15	4.72	67.04	3.93*** (8.71)
HFT	Less than -10	270	35.63	167.03	29.91	79.83	5.72 (0.50)
	-10 to -6	275	28.46	108.67	18.62	59.07	9.84 (1.33)
	-5 to -1	323	63.58	211.70	54.01	154.26	9.57 (0.68)
	0	303	54.60	157.41	60.90	147.27	-6.30 (-0.57)
	1 to 5	292	28.13	93.86	31.93	102.97	-3.80 (-0.50)
	6 to 10	196	14.29	48.78	12.50	36.06	1.79 (0.49)
	Greater than 10	304	24.09	157.32	27.90	140.43	-3.82 (-0.58)

Panel A2. Macroeconomic shocks

Trader type	Number of ticks from same –side best quote	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
Normal	Less than -10	202,638	0.68	3.94	0.83	2.42	-0.15*** (-16.71)
	-10 to -6	155,241	0.52	2.18	0.74	1.76	-0.21*** (-37.57)
	-5 to -1	422,702	0.91	9.37	1.27	8.09	-0.36*** (-26.57)
	0	168,424	0.79	9.44	0.99	7.73	-0.21*** (-8.58)
	1 to 5	182,976	0.80	6.32	1.04	5.41	-0.24*** (-18.35)
	6 to 10	119,668	0.60	4.93	0.78	4.09	-0.18*** (-18.31)
	Greater than 10	525,776	1.07	12.43	1.32	12.88	-0.25*** (-28.34)
Algo	Less than -10	6,717	3.99	36.36	4.35	46.30	-0.37 (-0.56)
	-10 to -6	5,483	3.63	16.67	3.12	11.47	0.52*** (2.79)
	-5 to -1	12,308	10.60	54.43	9.12	40.69	1.48*** (4.17)
	0	6,683	13.48	77.69	11.22	59.91	2.25*** (2.81)
	1 to 5	7,138	8.04	38.20	6.76	24.64	1.29*** (3.24)
	6 to 10	5,089	4.03	17.25	3.53	13.99	0.50** (2.01)
	Greater than 10	13,942	3.67	33.52	3.18	15.40	0.48** (2.16)
HFT	Less than -10	169	22.18	62.27	40.40	76.34	-18.22** (-2.42)
	-10 to -6	177	16.09	46.02	20.72	38.41	-4.63 (-0.98)

Trader type	Number of ticks from same –side best quote	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
	-5 to -1	240	36.68	114.08	64.38	134.88	-27.71** (-2.45)
	0	218	29.87	87.30	65.07	128.76	-35.20*** (-3.80)
	1 to 5	201	30.95	110.81	43.84	142.38	-12.89 (-1.24)
	6 to 10	141	8.42	35.42	11.86	31.56	-3.44 (-0.92)
	Greater than 10	186	10.29	56.86	16.15	50.95	-5.86 (-1.03)

Panel B. By order aggressiveness category

Panel B1. Firm-specific shocks

Trader type	Order aggressiveness	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
Normal	Most	880,915	1.34	10.76	0.81	5.04	0.53*** (53.03)
	2	255,381	1.12	9.11	0.88	7.26	0.24*** (20.10)
	3	255,038	1.04	10.41	0.69	7.86	0.34*** (25.43)
	4	360,385	1.36	13.36	0.84	13.07	0.52*** (32.69)
	Least	837,223	1.49	7.62	0.89	7.55	0.60*** (87.60)
Algo	Most	21,440	15.17	137.10	6.07	52.12	9.10*** (10.96)
	2	8,360	14.92	60.02	9.02	42.55	5.90*** (11.35)
	3	8,309	15.95	75.21	10.73	64.92	5.21*** (6.78)

Trader type	Order aggressiveness	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
	4	10,928	24.75	145.90	13.86	113.53	10.89*** (10.51)
	Least	20,094	5.96	46.52	2.11	16.76	3.85*** (13.05)
HFT	Most	389	88.46	347.64	67.37	179.41	21.08 (1.07)
	2	306	17.41	51.31	18.18	48.11	-0.77 (-0.21)
	3	294	52.47	149.91	60.67	146.48	-8.20 (-0.75)
	4	311	40.88	138.92	51.50	160.26	-10.63 (-1.02)
	Least	270	18.68	116.01	14.57	93.45	4.11 (1.03)

Panel B2. Macroeconomic shocks

Trader type	Order aggressiveness	N	Event period Mean	Event period Std. Dev.	Control period Mean	Control period Std. Dev.	Difference
Normal	Most	580,740	0.77	5.87	1.10	5.49	-0.33*** (-38.00)
	2	175,231	1.01	8.73	1.19	7.17	-0.18*** (-11.58)
	3	163,138	0.79	9.32	0.99	7.59	-0.20*** (-8.36)
	4	221,178	1.02	13.77	1.24	14.20	-0.22*** (-10.63)
	Least	555,232	1.01	8.28	1.28	8.03	-0.27*** (-50.48)
Algo	Most	15,857	7.23	51.37	6.65	43.27	0.58 (1.44)
	2	6,799	10.10	41.41	8.53	32.40	1.57*** (4.83)

Trader type	Order aggressiveness	N	Event period		Control period		Difference
			Mean	Std. Dev.	Mean	Std. Dev.	
	3	6,492	13.32	77.38	11.11	60.04	2.20*** (2.72)
	4	8,187	11.13	62.26	8.87	34.65	2.26*** (3.95)
	Least	14,405	2.47	14.63	2.51	11.39	-0.04 (-0.40)
HFT	Most	258	53.14	146.19	89.02	154.00	-35.88*** (-2.65)
	2	204	10.48	44.48	19.07	37.06	-8.58*** (-3.04)
	3	212	29.27	86.38	63.83	126.87	-34.56*** (-3.74)
	4	212	36.47	133.08	55.16	163.27	-18.69 (-1.53)
	Least	147	9.95	60.67	10.69	44.83	-0.73 (-0.12)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively

Table V
HFT trading behavior

This table presents trading behavior by the different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. Firm-specific shocks

Trader type	N	Event period Mean	Event period Std Dev	Control period Mean	Control period Std Dev	Difference
	Daily value traded (thousands Rs.)					
Normal	1,483,153	78.01	1,647.81	42.26	909.77	35.75*** (26.68)
Algo	35,434	770.11	8,455.73	306.37	4,292.56	463.74*** (9.96)
HFT	475	6,730.89	21,947.39	6,541.36	32,574.90	189.53 (0.10)
	Daily volume traded (number of shares)					
Normal	1,483,153	270.51	8,287.74	184.45	5,125.33	86.06*** (16.21)
Algo	35,434	2,507.49	34,401.03	1,084.29	16,305.52	1,423.20*** (7.40)
HFT	475	20,233.79	94,267.73	19,965.41	120,096.69	268.39 (0.04)
	Number of trades					
Normal	1,483,153	3.20	34.72	1.87	15.94	1.34*** (53.61)
Algo	35,434	29.98	273.30	10.95	88.38	19.02*** (14.03)
HFT	475	222.57	598.38	155.60	367.58	66.98** (2.14)

Panel B. Macroeconomic shocks

Trader type	N	Event period Mean	Event period Std Dev	Control period Mean	Control period Std Dev	Difference
	Daily value traded (thousands Rs.)					

Trader type	N	Event period		Control period		Difference
		Mean	Std Dev	Mean	Std Dev	
Normal	1,037,726	36.61	822.13	51.03	974.73	-14.41*** (-12.27)
Algo	26,753	313.72	4,990.77	414.49	9,856.67	-100.77 (-1.52)
HFT	323	1,786.37	6,002.98	5,890.91	16,143.06	-4,104.54*** (-4.29)
	Daily volume traded (number of shares)					
Normal	1,037,726	175.01	5,823.19	272.06	5,594.98	-97.06*** (-14.61)
Algo	26,753	1,076.62	14,460.65	1,535.62	27,620.90	-459.01** (-2.49)
HFT	323	9,310.23	49,632.48	30,481.84	116,978.03	-21,171.60*** (-2.97)
	Number of trades					
Normal	1,037,726	1.64	17.07	2.34	14.57	-0.70*** (-39.31)
Algo	26,753	12.61	99.53	12.01	82.27	0.60 (0.94)
HFT	323	85.81	246.95	177.62	344.43	-91.81*** (-3.98)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively

Table VI
HFT inventory balance management

This table presents inventory levels of different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. Firm-specific shocks

Trader type	N	Event period		Control period		Difference
		Mean	Std Dev	Mean	Std Dev	
	Intraday inventory balance					
Normal	1,483,153	4.43	6.09	4.14	6.03	0.29*** (37.36)
Algo	35,434	4.36	5.89	3.90	5.72	0.46*** (9.54)
HFT	475	6.16	7.12	6.27	7.06	-0.11 (-0.20)
	End-of-day inventory balance					
Normal	1,483,153	0.28	0.44	0.27	0.43	0.01*** (25.71)
Algo	35,434	0.28	0.43	0.25	0.42	0.03*** (8.46)
HFT	475	0.45	0.49	0.47	0.49	-0.02 (-0.42)

Panel B. Macroeconomic shocks

Trader type	N	Event period		Control period		Difference
		Mean	Std Dev	Mean	Std Dev	
	Intraday inventory balance					
Normal	1,037,726	3.36	5.85	5.64	6.49	-2.28*** (-239.3)
Algo	26,753	3.25	5.59	5.41	6.17	-2.16*** (-38.57)
HFT	323	4.23	6.29	8.15	6.67	-3.93*** (-7.02)

Trader type	N	Event period Mean	Event period Std Dev	Control period Mean	Control period Std Dev	Difference
	End-of-day inventory balance					
Normal	1,037,726	0.22	0.40	0.36	0.47	-0.15*** (-223.4)
Algo	26,753	0.20	0.39	0.34	0.46	-0.13*** (-34.03)
HFT	323	0.31	0.46	0.63	0.47	-0.32*** (-7.70)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively

Table VII
Realized spreads

This table presents realized spreads of different types of traders on the Bombay Stock Exchange around 153 earnings surprises and two macroeconomic shocks in the calendar year 2011. Event period refers to Days 0 and +1 relative to the event and Control period is days -5 through -1 relative to the event date. Realized spread is the difference between the transaction price and the quote midpoint either 5, 30, or 60 minutes after the transaction divided by the quote midpoint at the time of the transaction multiplied by 100. This multiplied by +1 for buy orders and -1 for sell orders. Difference is the mean paired difference of the corresponding measure, averaged over all trader-stock-event combinations. t-statistics of paired t-test is presented within parentheses below each mean difference.

Panel A. Firm-specific shocks

		Event period		Control period		
Trader type	N	Mean	Std Dev	Mean	Std Dev	Mean Diff
	After 5 minutes					
Normal	1,268,402	0.68%	1365.84%	1.31%	20.50%	-0.62% (-0.51)
Algo	31,362	0.28%	36.88%	1.09%	19.55%	-0.81% *** (-3.43)
HFT	441	0.68%	22.49%	0.12%	17.03%	0.57% (0.41)
	After 30 minutes					
Normal	1,268,402	0.47%	1413.09%	1.04%	41.45%	-0.57% (-0.45)
Algo	31,362	-13.90%	1721.53%	0.59%	39.56%	-14.49% (-1.49)
HFT	441	1.82%	38.52%	-0.61%	34.74%	2.43% (0.93)
	After 60 minutes					
Normal	1,268,402	0.20%	1058.38%	1.15%	53.31%	-0.94% (-1.00)
Algo	31,362	4.92%	706.65%	0.67%	50.57%	4.25% (1.06)
HFT	441	4.77%	61.23%	1.11%	42.82%	3.66% (0.99)

Panel B. Macroeconomic shocks

Trader type	N	Event period Mean	Event period Std Dev	Control period Mean	Control period Std Dev	Mean Diff
	After 5 minutes					
Normal	842,914	1.01%	16.61%	1.67%	30.62%	-0.66% *** (-17.36)
Algo	22,758	1.15%	15.71%	1.45%	30.61%	-0.30% (-1.32)
HFT	297	0.38%	9.87%	-0.69%	13.09%	1.07% (1.12)
	After 30 minutes					
Normal	842,914	0.76%	34.11%	2.18%	45.65%	-1.42% *** (-22.90)
Algo	22,758	1.40%	32.33%	2.53%	44.97%	-1.13% *** (-3.07)
HFT	297	-0.90%	23.22%	-2.90%	27.04%	2.00% (0.98)
	After 60 minutes					
Normal	842,914	0.41%	45.89%	2.00%	41.62%	-1.59% *** (-23.65)
Algo	22,758	1.07%	44.39%	2.27%	39.95%	-1.20% *** (-3.03)
HFT	297	0.71%	40.21%	-5.65%	38.11%	6.37% ** (2.04)

***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively