High-Frequency Trading and Extreme Price Movements*

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This paper examines the relation between high-frequency trading (HFT) and extreme price movements (jumps). Some market observers allege that HFT exacerbates or even causes price jumps, thus contributing to market instability. Contrary to these allegations, we find that during extreme price movements high-frequency traders act as net liquidity suppliers, while non-high-frequency traders act as net liquidity demanders. Moreover, high-frequency traders are active liquidity providers during price jumps that result in permanent price changes, absorbing the most informed order flow. Our evidence is consistent with HFT performing a stabilizing function in modern markets.

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1. Introduction

In the aftermath of the 2008-09 financial crisis, the fragility of financial markets is widely debated. The May 2010 Flash Crash has amplified one of the aspects of this debate: the relation between extreme price movements (EPMs) and high-frequency trading (HFT). EPMs (or price jumps) have long been a subject of concern in the finance literature, with a number of studies suggesting that they may have adverse effects on markets. For instance, EPMs may impair risk management (Duffie and Pan, 2001), derivative pricing (Bates, 2000; Eraker, Johannes, and Polson, 2003) and portfolio allocation (Jarrow and Rosenfield, 1984; Liu, Longstaff, and Pan, 2003). Despite the importance of EPMs and the recent proliferation of HFT, the relation between EPMs and HFT has not been directly studied by the academic literature.

Research often finds that high-frequency traders (HFTs) act as liquidity providers (Hasbrouck and Saar, 2013; Menkveld, 2013; Malinova, Park, and Riordan, 2014). Generally, the rise of HFT has been accompanied by a reduction in trading costs (Angel, Harris, and Spatt, 2011; Jones, 2013; Harris, 2013). Despite these findings, many investors worry that HFT liquidity provision is selective and limited to the times of low market stress. On this subject, Chordia et al. (2013) write: “There is growing unease on the part of some market observers that [...] violent price moves are occurring more often in financial instruments in which HFTs are active.” In this study, we shed light on this issue.

Our main finding is that on balance HFTs trade in the opposite direction of extreme price movements, supplying liquidity to non-HFTs (nHFTs). This result is driven mainly by the price jumps that result in permanent price changes. Put differently, an average HFT firm in our sample provides liquidity to aggressive, potentially informed traders during periods of extreme price fluctuations. As such, this firm acts to stabilize markets. It is important to note that HFTs do not act in a purely benevolent fashion during price jumps; we find that HFT liquidity demand increases too. Still, the increase in supply is of a higher magnitude, resulting in a net positive effect on liquidity provision. Overall, our results are consistent with the notion that HFTs dampen extreme market moves and inconsistent with the claims that HFTs cause or exacerbate such moves.

We use two techniques to define extreme price movements. First, we define EPMs as ten-second returns in the 99.99th percentile according to magnitude.[1] Second, we use the Lee and Mykland's (2012) jump-detection methodology. The two techniques identify 4,560 EPMs, or 4.75 EPMs in every stock-month. EPM returns are more than 26 times larger than the average return. Consistent with Christensen, Omen, and Podolskij (2014), EPMs are not instantaneous; rather they develop over sequences of multiple trades (about 110 trades).

To connect EPMs and HFT activity, we use the dataset provided by NASDAQ that identifies two types of market participants, HFT and nHFT. This dataset has been used by a number of other researchers (e.g., Carrion, 2013; Brogaard, Hendershott, and Riordan, 2014; O'Hara, Yao, and Ye, 2014). In addition to identifying the two types of market participants, the dataset also discloses which participant is taking and providing liquidity for each trade.

Some market observers claim that HFTs only supply liquidity in normal times and withdraw liquidity in times of stress. We observe the opposite; during EPMs, HFTs supply more liquidity than they demand, compensating for the net liquidity demand from nHFTs. Some observers also claim that HFTs may trigger price jumps through aggressive trading. If this were the case, we would likely observe an increase in net HFT liquidity demand prior to the jumps. We find no such increase.

Extreme price movements may be either information-related (permanent) or liquidity-related (transitory). With the former, the price adjusts permanently due to new information being revealed to the market. With the latter, the price adjusts temporarily, likely due to a mismatch between liquidity supply and demand. We consider a price jump to be transitory if the price reverts by more than 2/3 of the jump return within one minute and

[1] The results are similar when we use alternative jump interval lengths that produce smaller/larger samples. The results are also similar when we use alternative percentile cutoffs.

permanent if the price does not revert more than 1/3 of the jump return.[2] We find that HFTs provide liquidity during both permanent and transitory jumps, whereas nHFTs take liquidity. These results are consistent with the notion that HFTs stabilize markets even at times of highly informed order flow.

The mechanism behind price jumps is not yet fully understood. Farmer et al. (2004) suggest that large price fluctuations in a short time period may be driven by the stock-specific time-varying liquidity supply. Jiang, Lo, and Verdelhan (2010) and Miao, Ramchander, and Zumwalt (2012) find that most jumps cluster around pre-scheduled macroeconomic news. To examine this angle, we define idiosyncratic and systematic jumps and examine them separately. Systematic jumps are instances when at least two stocks undergo an extreme price movement in the same direction during the same time interval, whereas idiosyncratic jumps are instances when EPMs are observed in only one sample stock.

We posit that EPMs in a single stock may be conceptually different from simultaneous movements in several stocks due to HFT capital constraints. Firstly, if the critics are correct in that HFT firms cause jumps via undue price pressure, they are more likely to be successful moving prices in one stock than do so in several stocks simultaneously. Contrary to the critics' claims, we find no evidence of net price pressure from HFTs during both systematic and idiosyncratic jumps. Secondly, constrained capital may prevent HFTs from providing liquidity in stocks experiencing simultaneous jumps. Our findings are consistent with this notion: neither HFTs, nor nHFTs act as net liquidity providers during the systematic jumps.

Finally, we ask if HFT and nHFT trading may lead to EPMs, and if there is a material difference in return sensitivity to HFT and nHFT trading during jumps compared to normal periods. We find that during normal periods returns are more sensitive to HFT trading than nHFT trading. We find the opposite results during EPMs, suggesting that during these periods nHFTs take the lead from HFTs in terms of volume-return relation. In a probit

[2] Our results are robust to alternative thresholds.

analysis, we show that HFT activity is associated with a lower probability of a price jump in the subsequent interval, further alleviating concerns that jumps may be caused by HFTs.

Some of the existing empirical literature finds that HFT activity is associated with improved market quality. Hanson (2011) and Menkveld (2013) describe HFTs as the new market makers. Hagströmer and Nordén (2013) show that the market-making HFTs dominate other HFTs when measured by market presence. Hasbrouck and Saar (2013) find that increased low-latency (high-frequency) activity is associated with narrower spreads, wider displayed depths, and lower short-term volatility. Despite these findings, HFTs are often accused of negatively impacting various aspects of market quality. For instance, notwithstanding the findings by the joint CFTC-SEC advisory committee[3] and by Kirilenko et al. (2014), some commentators continue to allege that HFTs caused the May 6th, 2010 Flash Crash. Golub, Keane, and Poon (2013) document that individual stock mini-crashes have increased in recent years and suggest the link between these crashes and HFT. Leal et al. (2014) model a market, in which HFT play a fundamental role in generating flash crashes.[4] Our results are consistent with the studies that find a generally positive effect from HFT. We find that even during extreme price movements, and especially those price movements associated with new information coming to the market, HFTs act as net suppliers of liquidity thereby benefiting market stability.

Why do HFTs provide liquidity during EPMs? After all they provide liquidity voluntarily, and HFT technology certainly allows for quick withdrawal of limit orders as EPMs develop. Voluntary liquidity provision is a relatively new characteristic of the U.S. equity marketplace. In the past, equity market makers had several incentives to ensure market stability. First, competition between the NYSE and NASDAQ business models incited the specialists and dealers to ensure price stability even at a loss to their immediate bottom

[3] http://www.sec.gov/news/studies/2010/marketevents-report.pdf

[4] Madhavan (2012) argues that the fragmented nature of modern markets played a primary role in proliferation of the Flash Crash and generally exacerbates propagation of all liquidity shocks. Hendershott (2011) suggests that the short-lived crashes may originate from several sources: proliferation of HFT, market structure changes, trading fragmentation, and/or the disappearance of designated market makers.

line. By doing so, liquidity providers on the two competing markets tried to demonstrate the advantage of the specialist vs. the dealer system to their clients.[5] In addition to these competitive incentives, Panayides (2007) reports that the price continuity obligations of NYSE specialists required them to maintain continuous prices, i.e., prevent discrete price jumps.[6] Such obligations do not apply to the HFT firms in our sample; moreover, modern rules for NASDAQ market makers do not focus on price continuity. In addition, competition between the NYSE and NASDAQ models has largely ceased to exist. Bessembinder, Hao, and Lemmon (2011) point out that the endogenous liquidity providers in modern markets have no obligations to stabilize the price if it rises or plunges due to buy and sell imbalances.[7] Given these characteristics of modern liquidity provision, it is not immediately clear why HFTs provide liquidity during EPMs.

We suggest that there are two possible explanations to HFT behavior. First, it is possible that liquidity provision during EPMs is a byproduct of a non-market making trading strategy. HFTs are known for engaging in various arbitrage activities (e.g., Harris, 2013, Jones, 2013). Meanwhile, Gromb and Vayanos (2002, 2010) show that arbitrageurs provide liquidity when they push against price dislocations. Such arbitrage-driven liquidity provision is consistent with our results. Second, HFTs' behavior may also be driven by accumulated inventory. For instance, if an HFT firm has accumulated a long position prior to a positive jump in price, it may act as a net seller during the jump providing liquidity to the aggressive buyers. We note that our data do not allow us to reconcile these possibilities because we do not observe trading positions of HFT firms. Our data are also not suitable to check the possibility that during EPMs, HFTs provide liquidity on NASDAQ while demanding liquidity on other venues. We suggest that future research that may be in possession of HFT data from

[5] S. Wunsch, "Market Maker Obligations for High-Frequency Traders Are Not the Answer," Wall Street & Technology, October 15, 2010 (http://goo.gl/vt3qmk).
[6] As an example, in the early 2000s, the NYSE defined discrete price jumps as changes in consecutive prices by more than $0.12. Most of EPMs in our sample are of similar or larger magnitude, but they develop over sequences of several trades rather than between two consecutive trades. As such, it is not clear if the affirmative obligations of the past would entirely prevent EPMs examined in this study.
[7] See also N. Mehta, "SEC Questions Trading Crusade as Market Makers Disappear," Bloomberg, September 12, 2010 (http://goo.gl/IXdhbj).

a larger set of trading venues, data on inventory figures, and data on strategic characteristics of HFTs may be better equipped to shed light on this issue.

The remainder of the paper is as follows. Section 2 describes the data, discusses the methodology and summary statistics. Section 3 reports the empirical results. Section 4 discusses robustness checks. Section 5 concludes.

2. Data, EPM detection methods, and summary statistics

HFT data

The HFT data come from NASDAQ and span 2008 and 2009. The data are uniquely suited for this study as they contain an indicator for whether an HFT or an nHFT participates on each side of a trade. The dataset identifies 26 firms that act as independent HFT proprietary trading firms. NASDAQ determines whether a participant is an HFT firm based on its knowledge of the firm's activity. A firm is more likely to be identified as HFT if it trades frequently, holds small intraday inventory positions, and ends the day with nearly zero inventory. Large firms, such as investment banks, may use the same MPID for both high- and lower-frequency activity. Such accounts are conservatively labelled nHFT by NASDAQ. Although the dataset is unique in that it allows us to separate HFT and nHFT trading activity, it is limited to NASDAQ. As such, we are unable to analyze trading activity on the other trading venues. We however note that NASDAQ executes a sizeable portion of trading activity for the stocks in our sample.

EPM detection

To construct a sample of EPMs, we first construct the National Best Bid and Offer (NBBO) midpoints using the Trade and Quote database (TAQ) provided by the New York Stock Exchange (NYSE). Then, we use the absolute returns computed from the NBBO midpoints to identify extreme price movements. To avoid focusing on price dislocations that may be caused by market opening and closing, we remove returns that occur before 9:35 a.m. or after 3:55 p.m.

For jump detection, we focus on relatively short (10-second) time intervals. Our choice of the 10-second sampling frequency is based on the following two offsetting considerations. Firstly, modern trading occurs on a sub-second time scale, and therefore we would like our time intervals to be as short as possible. Secondly, and somewhat offsetting the first consideration, one of our jump-detection techniques, i.e., the Lee and Mykland (2012) method discussed shortly, requires time intervals of at least several seconds. The data show that the 10-second interval is long enough for prices to vary substantially, but short enough so as to capture relatively short-lived jumps.[8] To check if our choice of 10-second intervals survives an examination on a more granular level, we describe a second-by-second analysis in one of the subsequent sections.

Our NASDAQ HFT dataset includes 120 stocks in three size categories (40 stocks in each category): large, medium, and small. In large stocks, the choice of 10-second time intervals represents a compromise between the two abovementioned considerations. In medium in small stocks however, using 10-second intervals is not an effective solution because such intervals often do not contain sufficient (if any) numbers of trades. Due to this constraint, we restrict the sample to the 40 largest stocks by market capitalization.[9] Twenty of these stocks are listed on NASDAQ, and the other twenty are listed on the NYSE. The filtered database contains nearly 45.6 million 10-second intervals.

We use two techniques to detect EPMs. The first technique assigns the 99.99th percentile of 10-second absolute NBBO midpoint changes as the cutoff for a price jump. Put differently, out of nearly 45.6 million 10-second intervals, we identify 0.01% of intervals with

[8] In the Appendix, we explain our choice of 10-second intervals for the Lee-Mykland technique in more detail. Our results are robust to using alternative interval lengths. These results are available upon request.

[9] In a similar application and driven by similar considerations, Andersen et al. (2001) also focus on the largest stocks when detecting jumps. Our results remain qualitatively similar when we examine longer (1- and 5-minute) time intervals that allow us to include medium and small stocks.

the largest absolute midpoint return, for a total of 4,560 EPM intervals.[10] This technique is simple to understand and implement, but it has two limitations. First, the cutoff is for each stock, and therefore each stock is assumed to be equally likely to undergo a jump. As such, the 99.99 technique may (over-) under-sample stocks that are (less) more prone to jumps. This concern is somewhat alleviated due to our focus on large stocks. The second concern is that by weighting each time interval equally the technique assumes static volatility. That is, in each time interval the price change is evaluated based on its magnitude, regardless of the volatility conditions. We note that our question of interest (i.e., How do HFTs and nHFTs behave around jumps?) is equally relevant regardless of whether the jump is due to these conditions or an isolated process. This said, our second jump-detection technique is more immune to this concern.

The second technique is based on Lee and Mykland (2012) (LM), who define jumps as EPMs that are abnormal given the level of volatility. The details of the LM methodology are discussed in the Appendix. To ensure that our 99.99 and LM samples are of similar sizes, after identifying EPMs with the LM methodology, we restrict the LM sample to include the same number of EPMs as the 99.99 sample, or 4,560 instances. These instances include the highest-magnitude LM jumps for each stock.[11] The two samples have 2,748 observations in common. For both methodologies, the number of positive jumps is approximately equal to the number of negative jumps.

Figure 1 plots the intraday frequency of jumps using both techniques. A significant portion of the jumps (53.1% in the 99.99 sample and 44.1% in the LM sample) occur between 9:35 a.m. and 10:00 a.m. The remaining jumps are distributed relatively evenly through the trading day, with a small yet noticeable spike close to the end of the day. In the robustness section, we examine early morning jumps separately from the rest. We find no significant

[10] Expectedly, this approach captures relatively large EPMs. We find similar results when we use several alternative jump magnitude cutoffs. We report a complete list of EPMs in the Internet Appendix (http://bit.ly/1BEELbN).
[11] Our results are similar when we examine all jump events identified by the Lee and Mykland (2012) technique. These events represent about 0.54% of all intervals.

differences between HFT activity around these jumps and around the jumps occurring later in the day.

INSERT FIGURE 1 ABOUT HERE

Figure 2 plots the frequency of EPMs across the entire 2008-2009 sample period for both methodologies. The plots show (perhaps expectedly) that EPMs are more likely to occur during the months of September-November 2008, the height of the financial crisis. This period contains 68.4% of all EPMs in the 99.99 sample and 54.6% of all EPMs in the LM sample. In the robustness section, we examine the crisis and non-crisis sub-periods separately. We find no significant differences between HFT activity around jumps during the two sub-periods.[12]

INSERT FIGURE 2 ABOUT HERE

We use NBBO midpoint changes instead of transaction price changes because the former occur more frequently. As a robustness check, we repeat the analysis using transaction prices. Our results are similar. Finally, we observe similar HFT behavior for both price increases and declines (up and down jumps). For brevity, the subsequent analyses combine up and down jumps.

Summary Statistics

To better understand the jump events, in Table 1 we examine several return, volume and liquidity characteristics for the full sample of 10-second intervals (Panel A) as well as for the two jump event subsamples (Panels B and C). We define return as the log-price change between the first price and the last price in an interval if the jump is positive. For negative jumps, we multiply the return by -1. To measure trading activity, we compute the number of trades during an interval, $\# trades$; the dollar volume, $\$VOL$; and the number of shares

[12] Furthermore, one of our robustness checks restricts the number of EPMs to be equal in each month. With this restriction, the results are similar.

traded, $sh.VOL$. To capture liquidity, we compute quoted spreads and relative quoted spreads. The relative spread metric is the time-weighted average of the differences between the NBBO ask and bid prices scaled by the contemporaneous midpoint.

INSERT TABLE 1 ABOUT HERE

The mean absolute EPM return is 0.809% in the 99.99 sample (Panel B) and 0.735% in the LM sample (Panel C). As such, jump returns are more than 26 times (or more than 15 standard deviations) larger than the full-sample returns. Expectedly, trading activity increases substantially, with the number of trades surging more than tenfold during the EPMs compared to the average interval, from an average of 10 to more than 113. Dollar trading volume also increases more than tenfold, from $76,285 to $825,763 in the 99.99 sample and to $867,541 in the LM sample. Share volume increases by similar magnitudes. Finally, the spreads often double during the EPMs. For instance, the mean relative spread increases from 4.6 bps to 9.5 bps in the 99.99 sample and to 7.9 bps in the LM sample.

We suggest that EPMs may occur for two distinct reasons. First, EPMs may be a consequence of new information coming to the market and being quickly incorporated into prices. Second, jumps may be triggered by uninformed activity, whereby a trader or a group of traders generate substantial order flow in one direction (perhaps while rebalancing a large stock position), causing the price to temporarily deviate from the efficient price. Jumps tied to information are likely to result in a permanent price shift, while jumps triggered by the uninformed traders may be followed by a price drift back towards the pre-jump level. We use this intuition to separate jumps into permanent and transitory. Specifically, we define EPMs as permanent if they are reversed by no more than 1/3 within one minute. Meanwhile, an EPM is identified as transitory if it is reversed by more than 2/3 within the one minute.[13] We note that this division leaves out some jumps (about 30%); those with price reversals between 1/3 and 2/3 of the original EPM.

[13] Our results are robust to a set of alternative cutoffs and to extending the post-jump period to more than one minute.

Table 2 reports summary statistics similar to those in Table 1, while distinguishing between the permanent and transitory jumps. We find that more of the jumps are permanent (2,398 in the 99.99 sample and 2,575 in the LM sample) than transitory (respectively, 779 and 814). It is perhaps not surprising that the transitory jumps are relatively rare. Modern order routing strategies are sophisticated enough to avoid demanding liquidity too aggressively and walking the book as a result. In addition, modern limit order books may have high levels of resiliency as a result of competition among liquidity providers.

Transitory jumps are somewhat lower in magnitude than permanent jumps. The permanent jump return in the 99.99 (LM) sample is 0.790% (0.717%), while the transitory jump return is 0.747% (0.695%). Lower return magnitude of the transitory jumps is accompanied by relatively fewer trades and lower trading volume. Specifically, the number of trades during permanent jumps is 112 (110) in the 99.99 (LM) sample, whereas transitory jumps are accompanied by 101 (98) trades. When it comes to volume, the permanent jumps are associated with more volume than the transitory jumps no matter which volume metric (i.e., dollar volume or share volume) we use. For instance, the permanent jumps in the 99.99 sample are accompanied by an average of 26,537 shares traded, whereas the transitory jumps see an average share volume of 23,630. The results for spread statistics are mixed. Whereas dollar quoted spreads are somewhat higher during the permanent EPMs than during the transitory EPMs (e.g., $0.055 vs. $0.051 in the 99.99 sample), the results are reversed when we use the relative spread metric (e.g., 8.7 bps vs. 9.1 bps in the 99.99 sample).

INSERT TABLE 2 ABOUT HERE

Table 3 reports summary statistics for the idiosyncratic (Panels A and B) and the systematic (Panels C and D) EPMs. Systematic EPMs are instances when at least two stocks jump in the same direction during the same time interval, whereas idiosyncratic EMPs are instances when significant price movements are observed in only one sample stock. As we mention earlier, HFT behavior for these two types of jumps may be different. In a subsequent section, we examine HFT behavior during systematic and idiosyncratic EPMs in more detail. Here, we discuss descriptive statistics.

An average systematic jump has 2.8 and 2.6 stocks simultaneously experiencing an EPM in the 99.99 and LM samples, respectively.[14] The maximum number of simultaneous jumps is 15 and 20 in the respective samples. Idiosyncratic jumps are 2-3 times more likely to occur compared to the systematic jumps. Because the likelihood of randomly observing two simultaneous jumps is lower than the actual observed frequency, we suggest that the systematic jumps represent a distinct event type, corroborating the need to study them separately.

We find no consistent differences in returns between the two jump types. Specifically, the average return is higher during the idiosyncratic jumps than it is during the systematic jumps in the 99.99 sample (0.813% vs. 0.799%), but it is lower in the LM sample (0.734% vs. 0.740%). The differences are more consistent when we compare spreads and trading activity. All trading activity metrics are noticeably higher during the idiosyncratic jumps than during the systematic jumps. For example, share volume is 33,325 and 29,798 in, respectively, 99.99 and LM samples of idiosyncratic EPMs, and 15,207 and 19,712 in the samples of systematic EPMs. Both spread metrics are also significantly higher during the idiosyncratic jumps (e.g., $0.064 and 10.8 bps in the 99.99 sample) than during the systematic jumps (e.g., $0.054 and 6.8 bps).

INSERT TABLE 3 ABOUT HERE

3. HFT and nHFT activity around EPMs

The main goal of this study is to examine HFT and nHFT activity around EPMs. To measure these two types of trading activity, we use volume imbalances computed as the difference between trading activity in the direction of the price movement and trading activity

[14] Our results are similar when we force systematic jumps to include at least 3 or at least 5 stocks.

in the opposite direction. To ease the reader's navigation through the results, we assign positive (negative) values to volume executed in the direction of (opposite to) the price movement. For example, if HFTs demand 20 shares in the direction of the price movement and demand 1 share in the opposite direction, the HFT demand imbalance (HFT_D) is +19 (=20-1).[15] Similarly, if HFTs supply 20 shares of liquidity against the direction of the price movement and supply 4 shares in the direction of the movement, the HFT supply imbalance (HFT_S) is -16 (=-20+4). As such, if HFTs exacerbate (dampen) price movements, we should see positive (negative) imbalances. As such, we examine four volume imbalance metrics: HFT_D, HFT_S, nHFT_D, and nHFT_S.

In addition to the four abovementioned metrics, we introduce two net imbalance metrics, HFT_NET and nHFT_NET, computed as the sum of HFT_D and HFT_S (nHFT_D and nHFT_S) in each period.[16] Net imbalances indicate the direction in which the net trading activity by a particular trader type is moving the stock price. For example, a positive (negative) net imbalance originated by HFTs indicates that their aggregate trading is pushing the price in the direction (opposite) of the price movement.

In addition to examining trading activity during the jump interval itself, we are also interested in studying trading that precedes and follows jumps. We begin by discussing several graphics and later switch to a more comprehensive set of statistics. Figures 3 and 4 report cumulative returns (CRET) and trader activity in the [-10; +10]-interval window around the jump return for, respectively, the 99.99 and the LM samples.[17] For brevity, we focus the following discussion on the 99.99 sample. The results for the LM sample are similar.

[15] It may appear strange that a trader would demand liquidity in the direction opposite to the price movement. We note that prices may change direction during our 10-second sampling intervals. As such, the overall 10-second price movement may not be representative of the price movement at every instance during the interval.

[16] We note that because (n)HFT_S has a negative sign by construction, the sum of (n)HFT_D and (n)HFT_S is in effect the difference between liquidity demanding and liquidity providing volume.

[17] In the figures, returns are scaled by 10,000 to facilitate exposition.

Figure 3a contains the results for the full sample of EPMs. We find that after a period of relatively flat returns, prices jump in interval 0 and reverse somewhat during the remaining 10 intervals. There is a small increase in nHFT_D in the several intervals prior to the jump, followed by a markedly larger increase in the jump interval with a share imbalance of nearly 9,800. Expectedly, this increase is in the direction of the jump. In the meantime, HFT_D does not appear to increase much prior to the jump. During a jump, HFT_D increases by 2,400 shares, about five times less than nHFT_D. As such, the data suggest that nHFTs demand considerably more liquidity than HFTs during EPMs.

INSERT FIGURES 3 AND 4 ABOUT HERE

Notably, HFT_NET is negative during jumps, suggesting that HFT liquidity supply is not only larger than HFT liquidity demand, but also partly absorbs the imbalances created by nHFTs, thereby dampening EPMs.[18] We note that although HFT_NET inhibits EPMs, HFT_D is commonly in the direction of the price movement. Put differently, just like nHFTs, HFTs execute trades in the direction of the jump and demand liquidity while doing so. On balance however, their activity is liquidity providing and counteracts the net activity of nHFTs, who execute substantial volume in the direction of EPMs. The results obtained for the LM sample in Figure 4a are similar.

Next, we use the previously discussed division into permanent and transitory EPMs to try disentangling trader activity during the information-based price jumps and the jumps driven by fleeting price pressures. Figures 3b and 3c split EPMs into permanent and transitory. The split appears to be successful; after the permanent EPMs prices remain at the new price level and even exhibit signs of momentum, whereas prices almost completely revert to the pre-jump levels after the transitory jumps.

As previously, there is evidence of both HFT and nHFT demanding liquidity in the direction of the jump, with nHFTs creating imbalances of substantially larger magnitude

[18] Our net imbalance metrics are designed so that HFT_NET=-nHFT_NET.

(about 9,500 shares during the permanent jumps and about 8,500 shares during the transitory jumps) than HFTs (about 2,500 shares and 2,400 shares, respectively). In addition, we observe moderate increases in nHFT_D, as much as 30 seconds before the transitory jumps, while HFT_D does not appear to increase before jumps. HFT_NET is negative for both jump types, consistent with the notion that, on balance, HFT activity impedes extreme price movements. We note that this result is more pronounced for the permanent jumps than for the transitory jumps. The results obtained for the LM sample of EPMs (Figures 4b and 4c) are similar, although in the LM sample net liquidity provision by HFTs is observed for both the permanent and transitory EPMs.

Finally, we turn to the split into idiosyncratic and systematic EPMs. Figures 3d and 3e describe HFT and nHFT behavior that is consistent with the earlier results, although volume imbalance magnitudes are lower for the systematic EPMs compared to the idiosyncratic ones, particularly for nHFT_D. Specifically, nHFT_D is nearly 12,000 shares during the idiosyncratic jumps and is less than 5,000 shares during the systematic jumps. The HFT_NET metric points to HFTs' being net liquidity providers during idiosyncratic jumps, yet staying away from net liquidity provision during systematic jumps. The results obtained for the LM sample (Figures 4d and 4e) are similar.

The results in Figures 3 and 4 are informative, but they are silent on issues of statistical significance. We fill this gap in Tables 4 through 6 that examine [-2; +2]-interval windows around EPMs. Corroborating our prior discussion, Table 4 reports a statistically significant HFT_NET in the opposite direction of the jump return in intervals t and t+1. Further, upon splitting HFT activity into demand and supply, we observe (expectedly) that HFTs trade in the direction of the jump with their liquidity demanding trades (HFT_D is 2,400 and 2,440 shares in the 99.99 and LM samples) and in the opposite direction with their liquidity supplying trades (HFT_S is 3,443 and 3,967 shares). The negative sign of HFT_NET is due to the HFT_S being larger than HFT_D.

INSERT TABLE 4 ABOUT HERE

Next, we turn our attention to nHFT_NET, which is statistically significant in the direction of the jump. In the meantime, nHFT_D (nHFT_S) are in the direction (opposite) of the jump. We note that nHFT_D is 4-4.7 times larger than HFT_D depending on the sample. In addition, HFT_D and HFT_S as well as nHFT_D and nHFT_S show some evidence of abnormal activity one interval prior to the jump interval. In interval -1 however, these metrics cancel out so that statistically and economically significant HFT_NET and nHFT_NET are only observed during the jump interval. Overall, the results are consistent with the notion that, on balance, HFTs stabilize the markets during EPMs, whereas nHFTs exacerbate EPMs.

Table 5 contains HFT and nHFT activity around permanent and transitory jumps. At the time of permanent jumps, HFTs act as net suppliers of liquidity as their aggregate trading (HFT_NET) is in the direction opposite of the jump. During transitory jumps, HFT involvement is less clear; HFT_NET is negative but statistically insignificant in the 99.99 sample and negative and significant in the LM sample. nHFTs act as net liquidity demanders during permanent jumps in both the 99.99 sample and the LM sample. nHFTs also exhibit signs of net liquidity demand during transitory jumps in the LM sample. We note that in both samples, the _NET imbalances are larger around permanent jumps than around transitory jumps.

INSERT TABLE 5 ABOUT HERE

In Table 6, we report the results for the systematic vs. idiosyncratic jumps. HFT_NET and nHFT_NET are statistically insignificant during the systematic jumps. Meanwhile, during the idiosyncratic jumps HFTs act as liquidity suppliers to nHFTs. These results are consistent in both the 99.99 sample and the LM sample. Overall, Table 6 confirms the notion that HFTs do not exacerbate EPMs and even play a net positive role during idiosyncratic EPMs.

In summary, the results reported in Figures 3 and 4 and in Tables 4 through 6 point to the generally benevolent behavior of HFTs during the extreme price movement episodes.

None of the results discussed thus far is consistent with the notion that HFTs cause of exacerbate EPMs. Instead, the majority of results point to nHFTs as drivers of large price changes, with HFTs playing the role of liquidity providers to nHFTs.

INSERT TABLE 6 ABOUT HERE

The results discussed thus far provide little evidence on the impact of HFT and nHFT on jump returns and on the likelihood of observing a jump. To better understand these two dimensions of the HFT-jump relation and to examine this relation in a more robust multivariate setting, we next examine several regression setups. The first two models relate the magnitude of jump returns to HFT and nHFT volume imbalances. The third model estimates the relation between HFT and nHFT activity and the likelihood of observing a jump.

To facilitate interpretation of the subsequent multivariate analyses, we begin by estimating the bivariate correlations of the variables of interest. In Table 7, we report correlations of HFT and nHFT imbalances, jump returns and trading volume during normal market conditions and during EPMs. Supportive of our earlier results, returns are positively correlated with HFT_D and nHFT_D during both normal (Panel A) and extreme (Panel B) conditions, whereas HFT_S and nHFT_S are negatively correlated with returns during both types of conditions. We note that the correlations substantially increase during extreme conditions.

INSERT TABLE 7 ABOUT HERE

Our univariate results suggest that, on balance, HFTs provide liquidity during EPMs, and nHFTs demand liquidity. Next, we ask if these results persist when reexamined in a multivariate regression framework that controls for the contemporaneous and lagged returns, (n)HFT activity, and liquidity. We estimate the following regression models:

$$HFT\_D_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 nHFT\_D_{it} + \beta_5 nHFT\_D_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (1)$$

$$HFT\_S_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 nHFT\_S_{it} + \beta_5 nHFT\_S_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (2)$$

$$nHFT\_D_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 HFT\_D_{it} + \beta_5 HFT\_D_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it} \quad (3)$$

$$nHFT\_S_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 HFT\_S_{it} + \beta_5 HFT\_S_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (4)$$

$$HFT\_NET_{it} = \beta_1 Ret_{it} + \beta_2 Ret_{it} * J_{it} + \beta_3 J_{it} + \beta_4 Vol_{it} + \beta_5 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (5)$$

where HFT_D_{it} is HFT demand, $nHFT\_D_{it}$ is nHFT demand, HFT_S_{it} is HFT supply, $nHFT\_S_{it}$ is nHFT supply, HFT_NET_{it} is net HFT imbalance, Ret_{it} is the absolute return in stock i during period t, J_{it} is a dummy variable equal to one if the current 10-second interval is identified as an EPM and is equal to zero otherwise, Vol_{it} is the traded share volume, $RQSpr_{it}$ is the percentage quoted spread, and $\boldsymbol{Lags_{kit-\sigma}}$ is a vector of σ lags for the dependent and each of the independent variables, with $\sigma \in \{1, 2, \dots, 10\}$ and the variables indexed with a subscript k. All variables are standardized to ensure comparability across stocks. The estimated coefficients are reported in Table 8.

INSERT TABLE 8 ABOUT HERE

The multivariate results confirm and expand our previous findings. The coefficient estimates for the J dummy in Panel A of Table 8 suggest that liquidity demand by both types of traders increases during EPMs. Notably, this increase is significantly more pronounced for nHFTs than for HFTs. Specifically, nHFT liquidity demand increases by 2.5 (4.0) standard deviations in the 99.99 (LM) sample. In the meantime, the increase in HFT liquidity demand is only observed in the LM sample, and even there the increase is relatively low – only 1.3 standard deviations.

Also of note is the relation between HFT_D, nHFT_D, and returns during normal periods and during EPMs. We find that the expectedly positive relation between HFT_D and returns observed during normal periods substantially declines in magnitude during the jump periods. Specifically, during normal periods there is a 0.338 and 0.337 standard deviation increase in HFT liquidity demand for each standard deviation change in return in the 99.99 and LM samples, respectively. During EPMs, the magnitude of this relation declines so that there is only 0.041 (=0.338-0.297) and 0.019 standard deviation increase in HFT liquidity demand for each standard deviation of return in the respective samples. As such, the data suggest that HFTs substantially reduce liquidity demand per unit of return during an average EPM episode.

Compared to the HFT-return dynamic during EPMs, the relation between nHFT liquidity demand and returns is stronger. Specifically, the coefficient estimates on Ret and $Ret * J$ indicate that liquidity demand by nHFTs remains at 0.289 standard deviations per standard deviation of return in the 99.99 sample and falls to 0.094 (=0.287-0.193) in the LM sample. Either way, nHFTs appear to demand noticeably more liquidity per unit of return than HFTs during EPMs.

In Panel B of Table 8, we turn our attention to liquidity supply. The coefficient estimates for the dummy variable J indicate that HFTs do not change their liquidity supply during EPMs, whereas nHFTs increase liquidity supply by 2.3 and 2.9 standard deviations in the 99.99 and LM samples, respectively. During the normal periods, liquidity supplied by HFTs increases by 0.258 and 0.257 standard deviations (in the 99.99 and LM samples) per one standard deviation change in return. Meanwhile during EPMs, a one standard deviation in return is accompanied by only a 0.111 (=-0.258+0.147) and 0.081 standard deviations increase in liquidity supplied by HFTs. As such, although liquidity supply per unit of return declines during EPMs, we note that HFTs continue to provide liquidity performing a stabilizing function. When it comes to liquidity supply by nHFTs, the return-supply relation in the 99.99 sample declines in magnitude during the jumps from -0.312 to -0.038 (=-

0.312+0.274). It declines to 0.019 in the LM sample. Notably, the jump itself brings more nHFT liquidity supply irrespective of the jump return as indicated by the J coefficient estimate.

Finally, in the HFT_NET equation, we shed more light on the net effect from HFT. Recall that by construction HFT_NET=-nHFT_NET, and as such our results here may be easily reinterpreted for nHFTs. The regression results in Panel B of Table 8 show that during the normal times, net HFT aligns with returns in that there is a 0.119 standard deviation increase in net HFT liquidity demand per every standard deviation of return. During the jump periods, the direction of HFT activity changes. Specifically, for every standard deviation increase in jump return, there is a 0.021 increase in liquidity supply by HFTs in the 99.99 sample and a 0.023 increase in liquidity supply in the LM sample.[19] As such, the multivariate results in Table 8 confirm that HFTs act as net liquidity providers during extreme price movements.

Our next goal is to examine return sensitivity to HFT and nHFT during normal periods and during EPM episodes. To do so, we fit the following linear models with fixed effects and ten lags of dependent and independent variables:

$$Ret_{it} = \beta_1 HFT\_D_{it} + \beta_2 nHFT\_D_{it} + \beta_3 HFT\_D_{it} * J_{it} + \beta_4 nHFT\_D_{it} * J_{it} + \beta_5 Vol_{it} + \beta_6 J_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (6)$$

$$Ret_{it} = \beta_1 HFT\_S_{it} + \beta_2 nHFT\_S_{it} + \beta_3 HFT\_S_{it} * J_{it} + \beta_4 nHFT\_S_{it} * J_{it} + \beta_5 Vol_{it} + \beta_6 J_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (7)$$

and

$$Ret_{it} = \beta_1 HFT\_NET_{it} + \beta_2 HFT\_NET_{it} * J_{it} + \beta_3 Vol_{it} + \beta_4 J_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it,} \quad (8)$$

where Ret_{it} is the return in stock i during period t, HFT_D_{it} is HFT demand, $nHFT\_D_{it}$ is nHFT demand, HFT_S_{it} is HFT supply, $nHFT\_S_{it}$ is nHFT supply, Vol_{it} is the traded share

[19] Specifically, in the 99.99 sample, the Ret coefficient and the incremental $Ret * J$ coefficient add up to -0.021 (=0.119-0.140), where the negative sign indicates net liquidity supply.

volume, J_{it} is a dummy variable equal to one if the current 10-second interval is identified as an EPM and is equal to zero otherwise, HFT_NET_{it} is net HFT imbalance, and $\boldsymbol{Lags_{kit-\sigma}}$ is a vector of σ lags for the dependent and each of the independent variables, with $\sigma \in \{1, 2, \ldots, 10\}$ and the variables indexed with a subscript k. The estimated coefficients are reported in Table 9.

We note the rather low correlations between HFT_D (HFT_S) and nHFT_D (nHFT_S) reported in Table 7. Because these correlations are not close to one, multicollinearity is less of a concern when running regressions of returns on HFT and nHFT liquidity demand pairs and on HFT and nHFT liquidity supply pairs.

The estimated coefficients from eq. 6 indicate that during normal periods returns are more strongly associated with HFT_D than with nHFT_D. Specifically, a one standard deviation change in HFT_D is associated with a 0.305 standard deviation change in return, whereas a similar change in nHFT_D is associated with only a 0.262 standard deviation change in return. During EPMs, the relation between HFT_D and returns does not change (the interaction coefficient of HFT_D*J is statistically insignificant), whereas the relation between returns and nHFT_D strengthens by 0.128 and by 0.130 in, respectively, the 99.99 and the LM samples. As such, during EPMs the relation between returns and nHFTs (0.390=0.262+0.128 in the 99.99 sample and 0.392 in the LM sample) is stronger than the relation between returns and HFTs, which remains around 0.305 in both samples.

Similarly to the rest of this study, eq. 6 setup uses 10-second sampling intervals. As such, we are unable to make bold claims about the causal relation between returns and trading activity. This said, we posit that the abovementioned results are generally consistent with two possibilities: during normal times, HFTs are either (i) more sensitive to recent price changes than nHFTs, or (ii) are more informed about (have more effect on) short-term future price changes. During EPMs, this relation reverses in favor of the nHFTs. We suggest that it is unlikely that the nHFTs' ability to react to recent returns should significantly improve during EPMs and especially outpace that of the HFTs. What is perhaps more likely is that nHFTs' effect on short-term future price changes increases temporarily during the jump episodes. If so, the coefficient estimates from eq. 6 suggest that liquidity demand from nHFTs has more influence on the jump returns than liquidity demand form HFTs.

INSERT TABLE 9 ABOUT HERE

The estimated coefficients from eq. 7 suggest that returns are more associated with the nHFT liquidity supply than with the HFT supply during the normal trading periods. In particular, the coefficients on HFT_S and nHFT_S are, respectively, -0.237 and -0.304. This relation reverses during EPMs, when every standard deviation change in HFT_S is associated with a -0.463 (=-0.237+(-0.226)) standard deviations change in return, and every standard deviation change in nHFT_S is associated with only a -0.394 standard deviations change in return in the 99.99 sample. The results obtained for the LM sample are similar.

What may explain a stronger relation between nHFT liquidity supply and returns during normal times? As previously, causality of these relations is difficult to pinpoint, and we consider the following two possibilities. The first possibility is that during normal times nHFTs may be engaged in more arbitrage activities than HFTs. When prices change, nHFTs view the change as an arbitrage opportunity and push back against the price movement providing additional liquidity in the process. The second possibility is that nHFT liquidity is located in layers of the limit order books that are thinner and more remote from the inside quotes compared to HFT liquidity. During normal times, as traders walk the book they reach nHFT liquidity after the price has changed by a sufficient amount. Furthermore, the following price change is larger because the next layer of liquidity is thinner than the previous one. We note that the two possibilities outlined above are not mutually exclusive, and unfortunately, our data do not allow us to reconcile them. We leave this issue for future research.

For the purposes of our study it is perhaps more important to understand why HFTs begin to dominate the relation between return and liquidity supply during EPMs. Given our logic above, the switch in dominance may be explained in two ways. First, during EPMs HFTs may take the lead from nHFTs in implementing arbitrage strategies. Second, HFTs may continue the practice of providing liquidity at the top of the book as the best quotes change in the direction of the jump return. As the jump develops, and new orders execute against the retreating best quotes, liquidity provision by the HFTs appears to dominate. We leave the final word on reconciling these possibilities to future research that may have access to detailed order book data. Either way, our results suggest that HFT liquidity plays a more important role in dampening EPMs than nHFT liquidity.

The estimated coefficients from eq. 8 offer a confirmation to the notion that the relation between the overall HFT activity and returns changes during EPMs. Specifically, controlling for volume and a number of lag dependencies, we verify that the net HFT imbalance changes from going along with returns during normal times to going against returns at the time of jumps. This relation is stronger in the LM sample, where each standard deviation change in the jump return is associated with a -0.039 (=0.116-0.155) standard deviations change in HFT_NET. A similar relation is weaker (-0.003 standard deviations) in the 99.99 sample. As such, at a minimum net HFT activity appears not to exacerbate price jumps and there is some evidence that it inhibits the jumps. Given that HFT_NET=-nHFT_NET, the effect of the net nHFTs activity is the opposite.

Next, we discuss the relation between HFT and nHFT trading and the likelihood of EPMs. To do so, we estimate probit regressions of lagged HFT and nHFT demand and supply on the dummy variable equal to one when an EPM occurs in a particular interval and zero otherwise. Similarly to the linear regressions, we estimate three specifications with HFT and nHFT demand, HFT and nHFT supply, and HFT_NET. We control for relative quoted spreads and total traded volume. All independent variables are defined as before.

INSERT TABLE 10 ABOUT HERE

The estimated coefficients and the marginal effects are reported in Table 10. The probability of a jump in our sample is 1/10,000, and we scale the marginal effects by a factor of 10,000 to improve readability. The results suggest that higher nHFT_D is associated with a higher probability of an EPM in the subsequent interval. Specifically, the scaled marginal effects of nHFT_D estimated for both the 99.99 sample and the LM sample are 0.025. As such, the probability of a jump increases by 2.5% of the unconditional probability with every standard deviation increase in the pre-jump nHFT_D. In the meantime, HFT_D does not appear to affect the probability of EPMs as its estimated coefficient is statistically insignificant.

Liquidity supply from both HFT and nHFT is associated with a reduced probability of a jump in the subsequent interval. Specifically, the probability of a jump declines by 4.2% (1.6%) and 3.8% (1.6%) of the unconditional probability with every standard deviation increase in HFT_S (nHFT_S) in, respectively, the 99.99 and the LM samples. Finally, a one standard deviation increase in HFT_NET is associated with a decline of 1.6% (1.5%) of the unconditional jump probability in the 99.99 (LM) sample. When it comes to control variables, we find that EPMs tend to be preceded by periods of higher volume and wider spreads.

Overall, the probit results corroborate our previous discussion. First, there appears to be no evidence that the HFT liquidity demand causes jumps in the next interval. Such evidence however exists for the nHFT liquidity demand. Second, both the HFT and nHFT liquidity supply act as deterrents of EPMs in the next interval; however, the effect of the HFT liquidity supply is economically stronger. Finally, net HFT activity deters EPMs from developing, whereas the net nHFT activity increases the likelihood of EPMs.

4. Robustness

Throughout the manuscript, we mention a number of robustness checks. These include retesting the results using interval lengths other than 10 seconds, using jump cutoffs other than the 99.99^{th} percentile, using the entire sample of LM jumps instead of matching the LM sample size to that of the 99.99 sample, using alternative thresholds to distinguish between permanent and transitory jumps, adding medium and small stocks to the sample, and restricting the definition of the systematic jumps to include more than two stocks. Our conclusions do not change when we perform these checks.

In addition, our earlier discussion of Figures 1 and 2 suggests that EPMs may be arranged into groupings by the time and month of occurrence. Specifically, there is a sizeable group of early-morning EPMs that stands out from the rest. The early-morning EPMs comprise 53.1% of all EPMs in the 99.99 sample and 44.1% in the LM sample. There is also some evidence that EPMs that occur before the close may comprise a distinct group. In addition, there is a sizeable group of the 'financial crisis' EPMs (68.4% of all EPMs in the 99.99 sample and 54.6% in the LM sample). Given the distinct nature of these groupings, checking whether our results apply across all groupings appears warranted. In Tables A2 and A3 of the Appendix, we report the results of these checks. These results are consistent with our findings for the main sample.

Our investigation so far has focused on 10-second intervals. As we mention earlier, the choice of these intervals is dictated by the requirements of jump identification methodologies, particularly the LM technique. In Figure 5, we increase the granularity of our investigation and examine HFTs and nHFTs at the second-by-second frequency. Generally, we find that HFT liquidity demand does not precede nHFT liquidity demand in the seconds before the largest jump return. During most of the one-second time periods, and especially during the second with the largest return, HFTs are net liquidity suppliers to nHFTs. The results for the 99.99 sample (Panel A) and the LM sample (Panel B) are similar.

INSERT FIGURE 5 ABOUT HERE

Finally, we ask if our results change if we use a liquidity supply and demand metrics that are simpler than the main metrics. While our main metrics account for liquidity demand and supply in relation to the return direction, the simpler metrics examine liquidity demand

and supply without conditioning on returns. Going back to our original example in Section 3, if HFTs demand 20 shares in the direction of the price movement and demand 1 share in the opposite direction, our main metric, HFT_D, is +19 (=20-1). The simpler alternative examined here (HFT total demand) is 20 (=19+1). The results using this metric corroborate the main results and are in fact noticeably stronger. In Table A4 of the Appendix, we report that HFTs provide nearly 5,000 shares of liquidity to nHFTs during the EPMs in both the 99.99 and LM samples.

5. Conclusion

In this study, we take advantage of the NASDAQ HFT dataset to investigate the relation between HFT and nHFT activity and extreme price movements (jumps). We detect jumps using two approaches: a straightforward 99.99% return technique and a more advanced econometric identification approach of Lee and Mykland (2012). We find that overall HFTs trade in the opposite direction of extreme price movements consistent with liquidity provision. In the meantime, nHFTs trade in the direction of price jumps, exacerbating them. This result applies to jumps of several different types: permanent, transitory, and idiosyncratic.

In a regression that relates the sensitivity of prices to the HFT and nHFT volume, we find that during normal periods returns are more sensitive to HFT liquidity demand rather than nHFT demand. During jumps however, the relation between prices and HFT liquidity demand remains the same, while it becomes significantly more sensitive to the nHFT demand. Our discussion suggests that this evidence is consistent with jump returns being a function of aggressive nHFT trading. When liquidity demand and supply are combined in a regression setting, we find that overall prices are positively related to net HFT activity during normal periods and negatively during the extreme periods, corroborating the notion that the net activity by HFTs inhibits extreme price movements, while the net activity of nHFTs exacerbates these movements.

Finally, in an analysis of the probability of extreme price movements we find that such movements are more likely to be preceded by the nHFT liquidity demand. There is no evidence of them being preceded by the HFT demand. Furthermore, the HFT liquidity supply plays a larger role in preventing the jumps than the nHFT supply. Overall, our results point to a positive role of HFT in stabilizing markets during periods of instability.

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Table 1. Summary statistics

The table reports summary statistics for the full sample of 10-second intervals (Panel A) and the two subsamples of extreme price movements (EPMs) (Panels B and C). Panel B reports EPMs that are identified as the 10-second intervals with the returns above the 99.99th percentile. Panel C reports EPMs that are the 4,560 highest-magnitude observations identified as jumps by the Lee and Mykland (2012) jump-detection algorithm. Returns are computed as the absolute value of the 10-second midpoint return. *# trades* represents the number of trades. *$VOL* and *sh.VOL* are the total dollar and share volume traded during the interval. *qspread* and *rqspread* are quoted and relative quoted NBBO spreads.

	abs. return, %	# trades	$VOL	sh. VOL	qspread, $	rqspread, %
Panel A: Full sample						
mean	0.028	10.1	76,285	1,991	0.026	0.046
median	0.009	3.0	14,038	318	0.010	0.040
std	0.048	19.9	231,397	6,055	0.057	0.033
N	45.6 M					
Panel B: 99.99 percentile EPMs						
mean	0.809	115.8	825,763	27,493	0.060	0.095
median	0.731	64.0	289,959	8,903	0.019	0.075
std	0.332	150.0	1,714,278	53,980	0.236	0.316
N	4,560					
Panel C: LM 2012 top 4,560 EPMs						
mean	0.735	113.6	867,541	27,562	0.053	0.079
median	0.662	67.0	318,770	9,581	0.017	0.067
std	0.334	137.7	1,716,172	51,287	0.190	0.272
N	4,560					

Table 2. Summary statistics for the permanent and transitory EPMs

The table reports the summary statistics for the subsamples of extreme price movements (EPMs). Panels A and B report the statistics for the permanent EPMs. Panels C and D report the statistics for the transitory EPMs. An EPM is identified as permanent if it is reversed by no more than 1/3 within one minute. AN EPM is identified as transitory if it is reversed by more than the 2/3 within the one minute. Panels A and C report EPMs from the 99.99 percentile sample. Panels B and D report EPMs that are the 4,560 highest magnitude jumps from the LM sample. Returns are computed as the absolute value of the 10-second midpoint return. *# trades* represents the number of trades. *$VOL* and *sh.VOL* are the total dollar and share volume traded during the interval. *qspread* and *rqspread* are quoted and relative quoted NBBO spreads.

	abs. return, %	# trades	$VOL	sh. VOL	qspread, $	rqspread, %
Panel A: 99.99 percentile permanent EPMs						
mean	0.790	112.3	783,405	26,537	0.055	0.087
median	0.721	66.0	297,263	9,185	0.017	0.074
std	0.298	134.6	1,569,239	47,665	0.193	0.261
N	2,398					
Panel B: Lee and Mykland 2012 permanent EPMs						
mean	0.717	110.0	829,908	26,467	0.050	0.075
median	0.649	67.0	310,446	9,449	0.016	0.067
std	0.301	124.5	1,699,045	45,757	0.173	0.216
N	2,575					
Panel C: 99.99 percentile transitory EPMs						
mean	0.747	101.4	743,462	23,630	0.051	0.091
median	0.693	58.0	262,268	8,152	0.019	0.073
std	0.233	112.4	1,412,991	45,112	0.223	0.291
N	779					
Panel D: Lee and Mykland 2012 transitory EPMs						
mean	0.695	98.1	753,539	23,482	0.047	0.079
median	0.653	58.0	279,640	8,382	0.019	0.068
std	0.245	106.7	1,336,455	45,671	0.162	0.176
N	814					

Table 3. Summary statistics for the idiosyncratic and systematic EPMs

The table reports the summary statistics for the subsamples of extreme price movements (EPMs). Panels A and B report statistics for the idiosyncratic EPMs. Panels C and D report statistics for the systematic EPMs. An EPM is identified as systematic if it occurs in at least two sample stocks at the same time. An EPM is identified as idiosyncratic if only one stock experiences it in a given interval. Panels A and C report EPMs from the 99.99 sample. Panels B and D report EPMs that are the 4,560 highest-magnitude jumps from the LM sample. Returns are computed as the absolute value of the 10-second midpoint return. *# trades* represents the number of trades. *$VOL* and *sh.VOL* are the total dollar and share volume traded during the interval. *qspread* and *rqspread* are quoted and relative quoted NBBO spreads. We also report the average and maximum number of stocks that experience simultaneous jumps.

	abs. return, %	# trades	$VOL	sh. VOL	qspread, $	rqspread, %
Panel A: 99.99 percentile idiosyncratic EPMs						
mean	0.813	135.1	996,172	33,325	0.064	0.108
median	0.737	79.0	365,217	12,167	0.018	0.075
std	0.338	167.3	1,954,331	60,734	0.189	0.272
N	3,093					
Panel B: Lee and Mykland 2012 idiosyncratic EPMs						
mean	0.734	121.0	946,420	29,798	0.062	0.097
median	0.663	74.0	354,351	10,863	0.018	0.069
std	0.326	144.8	1,844,937	53,726	0.170	0.217
N	3,549					
Panel C: 99.99 percentile systematic EPMs						
mean	0.799	75.1	466,733	15,207	0.054	0.068
median	0.716	45.0	186,130	5,510	0.020	0.074
std	0.320	92.0	945,743	32,559	0.313	0.392
N	1,467					
avg. stocks	2.8					
max stocks	15					
Panel D: Lee and Mykland 2012 systematic EPMs						
mean	0.740	87.4	590,643	19,712	0.024	0.013
median	0.655	51.0	235,985	6,675	0.014	0.057
std	0.358	105.1	1,112,989	40,669	0.243	0.402
N	1,011					
avg. stocks	2.6					
max stocks	20					

Table 4. Volume imbalances around EPMs

The table reports the direction of trading volume around the extreme price movements (EPMs). HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. HFT_NET (nHFT_NET) are the differences between HFT (nHFT) liquidity demand and supply. *p*-Values are in parentheses. Asterisks *** and ** indicate significance at the 1% and 5% levels.

	99.99 percentile					**Lee and Mykland 2012**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-82.1	5.6	-1042.2***	-353***	-125.7	-76.6	24.1	-1527.2***	-318.6***	-17.3
	(0.36)	(0.96)	(0.00)	(0.00)	(0.16)	(0.27)	(0.78)	(0.00)	(0.00)	(0.82)
HFT_D	-75.1	288.5***	2400.7***	-479.7***	-197.1**	7.9	222.2***	2440.1***	-600.9***	-211.3***
	(0.36)	(0.00)	(0.00)	(0.00)	(0.03)	(0.90)	(0.00)	(0.00)	(0.00)	(0.00)
HFT_S	-7.0	-283***	-3442.9***	126.7	71.5	-84.5	-198.1***	-3967.3***	282.2***	194.0***
	(0.94)	(0.00)	(0.00)	(0.19)	(0.41)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)
nHFT_NET	82.1	-5.6	1042.2***	353.0***	125.7	76.6	-24.1	1527.2***	318.6***	17.3
	(0.36)	(0.96)	(0.00)	(0.00)	(0.16)	(0.27)	(0.78)	(0.00)	(0.00)	(0.82)
nHFT_D	203.7	654.7***	9756.6***	1233.8***	383.7**	193.2	562.2***	11462.3***	898.2***	109.3
	(0.24)	(0.00)	(0.00)	(0.00)	(0.04)	(0.13)	(0.00)	(0.00)	(0.00)	(0.42)
nHFT_S	-121.6	-660.3***	-8714.4***	-880.8***	-258.1	-116.6	-586.2***	-9935.1***	-579.6***	-92.0
	(0.49)	(0.00)	(0.00)	(0.00)	(0.16)	(0.33)	(0.00)	(0.00)	(0.00)	(0.45)

Table 5. Volume imbalances around permanent and transitory EPMs

The table reports the direction of trading volume around the permanent and transitory EPMs. An EPM is identified as permanent if it is reversed by no more than 1/3 within one minute. An EPM is identified as transitory if it is reversed by more than 2/3 within one minute. HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. HFT_NET and nHFT_NET are the differences between HFT and nHFT liquidity demand and supply. *p*-Values are in parentheses. Asterisks *** and ** indicate significance at the 1% and 5% levels.

Panel A: 99.99 percentile sample

	Permanent jumps					**Transitory jumps**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	120.2	-1095.7	-1095.7***	-481.3***	-167.1	-357.8	-145.7	-344.7	-353.2	-74.9
	(0.31)	(0.09)	(0.00)	(0.00)	(0.13)	(0.06)	(0.48)	(0.22)	(0.14)	(0.65)
HFT_D	-53.4	323.4***	2521.8***	-351.0**	-141.8	92.0	197.9	2352.8***	-1018.8***	-426.7***
	(0.59)	(0.01)	(0.00)	(0.01)	(0.29)	(0.59)	(0.21)	(0.00)	(0.00)	(0.00)
HFT_S	173.6	-84.7	-3617.5***	-130.3	-25.3	-449.8**	-343.6	-2697.5***	665.6***	351.8**
	(0.10)	(0.49)	(0.00)	(0.27)	(0.80)	(0.01)	(0.06)	(0.00)	(0.00)	(0.04)
nHFT_NET	-120.2	-238.7	1095.7***	481.3***	167.1	357.8	145.7	344.7	353.2	74.9
	(0.31)	(0.09)	(0.00)	(0.00)	(0.13)	(0.06)	(0.48)	(0.22)	(0.14)	(0.65)
nHFT_D	-310.0	17.9	9538.2***	1384.9***	632.6**	1299.4***	914.3***	8418.5***	-98.8	-572.3**
	(0.18)	(0.95)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.75)	(0.01)
nHFT_S	189.8	-256.6	-8442.4***	-903.6***	-465.5	-941.6**	-768.6**	-8073.8***	452.0	647.2***
	(0.43)	(0.23)	(0.00)	(0.00)	(0.09)	(0.02)	(0.01)	(0.00)	(0.07)	(0.00)

Panel B: LM sample

	Permanent jumps					Transitory jumps				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-14.0	298.0**	-1510.7***	-365.0***	-146.7	-168.1	-282.8	-1002.1***	-25.9	222.7
	(0.88)	(0.01)	(0.00)	(0.00)	(0.14)	(0.31)	(0.06)	(0.00)	(0.87)	(0.12)
HFT_D	-66.8	361.3***	2504.7***	-484.2***	-158.3	148.1	22.7	2019.7***	-785.2***	-380.9***
	(0.36)	(0.00)	(0.00)	(0.00)	(0.12)	(0.35)	(0.85)	(0.00)	(0.00)	(0.00)
HFT_S	52.8	-63.3	-4015.4***	119.2	11.6	-316.1**	-305.5**	-3021.8***	759.3***	603.6***
	(0.55)	(0.55)	(0.00)	(0.20)	(0.89)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
nHFT_NET	14.0	-298.0**	1510.7***	365.0***	146.7	168.1	282.8	1002.1***	25.9	-222.7
	(0.88)	(0.01)	(0.00)	(0.00)	(0.14)	(0.31)	(0.06)	(0.00)	(0.87)	(0.12)
nHFT_D	-153.8	122.6	11146.4***	1198.2***	568.8***	1144.4***	981.6***	9834.4***	-142.9	-802.2***
	(0.32)	(0.61)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.57)	(0.00)
nHFT_S	167.8	-420.6**	-9635.8***	-833.2***	-422.1***	-976.4**	-698.8***	-8832.3***	168.8	579.4***
	(0.23)	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.48)	(0.00)

Table 6. Order Imbalances for idiosyncratic and systematic extreme price movements

The table reports the direction of trading volume around the idiosyncratic and systematic extreme price movements (EPMs). An EPM is identified as systematic if it occurs in at least two sample stocks at the same time. We consider the rest of EPMs to be idiosyncratic. HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. HFT_NET and nHFT_NET are the differences between HFT and nHFT liquidity demand and supply. *p*-Values are given in parentheses. Asterisks *** and ** indicate significance at the 1% and 5% levels.

Panel A: 99.99 percentile sample

	Systematic jumps					Idiosyncratic jumps				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-165.6	125.7	-38.2	-47.7	-152.5	-42.9	-51.4	-1518.7***	-497.9***	-112.9
	(0.07)	(0.18)	(0.83)	(0.71)	(0.08)	(0.73)	(0.72)	(0.00)	(0.00)	(0.36)
HFT_D	-167.2**	301.5***	1843.1***	-261.2***	-229.1***	-31.8	282.4**	2665.3***	-583.4***	-181.9
	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.78)	(0.02)	(0.00)	(0.00)	(0.16)
HFT_S	1.6	-175.7**	-1881.2***	213.5*	76.6	-11.0	-333.8***	-4184.1***	85.5	69.0
	(0.98)	(0.02)	(0.00)	(0.06)	(0.27)	(0.93)	(0.01)	(0.00)	(0.52)	(0.57)
nHFT_NET	165.6	-125.7	38.2	47.7	152.5	42.9	51.4	1518.7***	497.9***	112.9
	(0.07)	(0.18)	(0.83)	(0.71)	(0.08)	(0.73)	(0.72)	(0.00)	(0.00)	(0.36)
nHFT_D	37.9	468.7***	4671.8***	236.5	3.9	281.7	743.0***	12170.0***	1707.3***	564.0**
	(0.81)	(0.01)	(0.00)	(0.20)	(0.98)	(0.25)	(0.01)	(0.00)	(0.00)	(0.04)
nHFT_S	127.7	-594.4***	-4633.6***	-188.8	148.6	-238.9	-691.6***	-10651.3***	-1209.4***	-451.1
	(0.39)	(0.00)	(0.00)	(0.22)	(0.40)	(0.34)	(0.00)	(0.00)	(0.00)	(0.08)

Panel B: LM sample

	Systematic jumps					Idiosyncratic jumps				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-157.7	86.6	119.8	91.3	-56.9	-53.6	6.2	-1996.4***	-435.6***	-6.0
	(0.08)	(0.52)	(0.66)	(0.60)	(0.60)	(0.53)	(0.95)	(0.00)	(0.00)	(0.95)
HFT_D	-40.2	328.1***	2821.4***	-309.8**	-168.1	21.5	192.0**	2331.4***	-683.9***	-223.6**
	(0.62)	(0.01)	(0.00)	(0.01)	(0.08)	(0.78)	(0.01)	(0.00)	(0.00)	(0.01)
HFT_S	-117.5	-241.5**	-2701.6***	401.2**	111.2	-75.1	-185.8**	-4327.8***	248.3**	217.6**
	(0.17)	(0.03)	(0.00)	(0.01)	(0.24)	(0.35)	(0.04)	(0.00)	(0.02)	(0.01)
nHFT_NET	157.7	-86.6	-119.8	-91.3	56.9	53.6	-6.2	1996.4***	435.6***	6.0
	(0.08)	(0.52)	(0.66)	(0.60)	(0.60)	(0.53)	(0.95)	(0.00)	(0.00)	(0.95)
nHFT_D	118.8	637.0***	6697.5***	177.0	114.0	214.2	540.8**	12819.7***	1103.9***	108.0
	(0.34)	(0.00)	(0.00)	(0.48)	(0.55)	(0.18)	(0.01)	(0.00)	(0.00)	(0.52)
nHFT_S	38.9	-723.6***	-6817.3***	-268.3	-57.1	-160.6	-547.1***	-10823.3***	-668.4***	-102.0
	(0.72)	(0.00)	(0.00)	(0.19)	(0.75)	(0.29)	(0.00)	(0.00)	(0.00)	(0.49)

Table 7. Correlations

The table reports the correlation coefficients for the main variables of interest. HFT_D (nHFT_D) is the standardized share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. Panel A reports the correlations for the subsample of observations when the price movement was not identified as extreme. Panel B reports the correlations for the subsample in which extreme price movements were identified either via the 99.99 percentile method or the Lee and Mykland (2012) method. Standardization is done on the stock level.

	99.99 percentile sample					**LM sample**				
Panel A: non-EPMs										
	Ret	**HFT_D**	**HFT_S**	**nHFT_D**	**nHFT_S**	**Ret**	**HFT_D**	**HFT_S**	**nHFT_D**	**nHFT_S**
HFT_D	0.045					0.044				
HFT_S	-0.038	-0.562				-0.038	-0.562			
nHFT_D	0.022	0.076	0.087			0.022	0.076	0.087		
nHFT_S	-0.022	-0.244	-0.308	-0.897		-0.021	-0.244	-0.308	-0.897	
Vol	0.000	-0.121	0.083	-0.262	0.229	0.000	-0.121	0.083	-0.262	0.229
Panel B: EPMs										
	Ret	**HFT_D**	**HFT_S**	**nHFT_D**	**nHFT_S**	**Ret**	**HFT_D**	**HFT_S**	**nHFT_D**	**nHFT_S**
HFT_D	0.141					0.141				
HFT_S	-0.242	-0.417				-0.269	-0.413			
nHFT_D	0.238	0.053	-0.149			0.270	0.051	-0.191		
nHFT_S	-0.178	-0.260	-0.123	-0.885		-0.201	-0.261	-0.088	-0.883	
Vol	0.010	-0.087	0.053	-0.210	0.199	0.020	-0.086	0.052	-0.199	0.192

Table 8. Multivariate analysis: HFT and EPMs

The table reports estimated coefficients from the following regressions of HFT and nHFT liquidity demand and supply on returns:

$$HFT\_D_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 nHFT\_D_{it} + \beta_5 nHFT\_D_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$
$$nHFT\_D_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 HFT\_D_{it} + \beta_5 HFT\_D_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$
$$HFT\_S_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 nHFT\_S_{it} + \beta_5 nHFT\_S_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$
$$nHFT\_S_{it} = \beta_1 Ret_{it} + \beta_2 Ret * J_{it} + \beta_3 J_{it} + \beta_4 HFT\_S_{it} + \beta_5 HFT\_S_{it} * J_{it} + \beta_6 Vol_{it} + \beta_7 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$
$$HFT\_NET_{it} = \beta_1 Ret_{it} + \beta_2 Ret_{it} * J_{it} + \beta_3 J_{it} + \beta_4 Vol_{it} + \beta_5 RQSpr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it,}$$

where HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the price movement through HFT (non-HFT) liquidity demanding orders; HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders; HFT_NET (nHFT_NET) is the net volume imbalance; the dummy J is equal to one if the interval is identified to contain an EPM and is equal to zero otherwise; Vol is the standardized total trading volume; RQSpr is the percentage quoted spread. All non-dummy variables are standardized by stock. Regressions are estimated with fixed effects. To save space, we do not report the intercept. Ten lags of return and the independent variables are included in each regression specification. Columns labeled 99.99 correspond to the subsample of price changes larger than the 99.99th percentile. LM columns correspond to the largest 4,560 jumps obtained using the Lee and Mykland (2012) algorithm. p-Values associated with the double-clustered standard errors are in parentheses. Asterisks *** and ** denote significance at the 1% and 5% levels.

Panel A: HFT_D and HFT_S

	HFT_D			**nHFT_D**	
	99.99	**LM**		**99.99**	**LM**
J	0.912	1.329**	**J**	2.522**	3.980***
	(0.15)	(0.03)		(0.03)	(0.00)
Ret	0.338***	0.337***	**Ret**	0.289***	0.287***
	(0.00)	(0.00)		(0.00)	(0.00)
Ret*J	-0.297***	-0.318***	**Ret*J**	-0.170	-0.193**
	(0.00)	(0.00)		(0.06)	(0.03)
HFT_D	0.081***	0.082***	**HFT_S**	0.082***	0.082***
	(0.00)	(0.00)		(0.00)	(0.00)
HFT_D*J	-0.074***	-0.093***	**HFT_S*J**	-0.087***	-0.127
	(0.00)	(0.00)		(0.16)	(0.07)
Vol	0.007**	0.007**	**Vol**	0.008	0.008
	(0.02)	(0.02)		(0.11)	(0.11)
RQSpr	0.002***	0.002***	**RQSpr**	0.000	0.000
	(0.01)	(0.01)		(0.98)	(0.96)
Adj. R^2	0.14	0.14	**Adj. R^2**	0.13	0.13

Panel B: nHFT_D, nHFT_S, HFT_NET

	HFT_S			nHFT_S			HFT_NET	
	99.99	**LM**		**99.99**	**LM**		**99.99**	**LM**
J	-0.162	-0.756	**J**	-2.263***	-2.863***	**J**	-0.027	-0.303
	(0.87)	(0.37)		(0.00)	(0.00)		(0.96)	(0.56)
Ret	-0.258***	-0.257***	**Ret**	-0.312***	-0.311***	**Ret**	0.119***	0.119***
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
Ret*J	0.147**	0.176***	**Ret*J**	0.274***	0.292***	**Ret*J**	-0.140***	-0.142***
	(0.05)	(0.01)		(0.00)	(0.00)		(0.00)	(0.00)
nHFT_D	0.203***	0.203***	**nHFT_S**	0.192***	0.192***			
	(0.00)	(0.00)		(0.00)	(0.00)			
nHFT_D*J	0.032	0.069	**nHFT_S*J**	0.150**	0.227***			
	(0.51)	(0.18)		(0.04)	(0.00)			
Vol	0.004	0.004	**Vol**	-0.012**	-0.012**	**Vol**	0.009***	0.009***
	(0.09)	(0.09)		(0.04)	(0.04)		(0.01)	(0.01)
RQSpr	0.000	0.000	**RQSpr**	-0.001	-0.001	**RQSpr**	0.002***	0.002***
	(0.91)	(0.92)		(0.27)	(0.25)		(0.00)	(0.00)
Adj. R^2	0.15	0.15	**Adj. R^2**	0.15	0.19	**Adj. R^2**	0.02	0.02

Table 9. Sensitivity of Returns

The table reports estimated coefficients from regressions of return sensitivity to liquidity demand and supply by HFTs and nHFTs during normal and extreme periods. The regression models are as follows:

$$Ret_{it} = \beta_1 HFT\_D_{it} + \beta_2 nHFT\_D_{it} + \beta_3 HFT\_D_{it} * J_{it} + \beta_4 nHFT\_D_{it} * J_{it} + \beta_5 Vol_{it} + \beta_6 J_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (4)$$

$$Ret_{it} = \beta_1 HFT\_S_{it} + \beta_2 nHFT\_S_{it} + \beta_3 HFT\_S_{it} * J_{it} + \beta_4 nHFT\_S_{it} * J_{it} + \beta_5 Vol_{it} + \beta_6 J_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (5)$$

and

$$Ret_{it} = \beta_1 HFT\_NET_{it} + \beta_2 HFT\_NET_{it} * J_{it} + \beta_3 Vol_{it} + \beta_4 J_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (6)$$

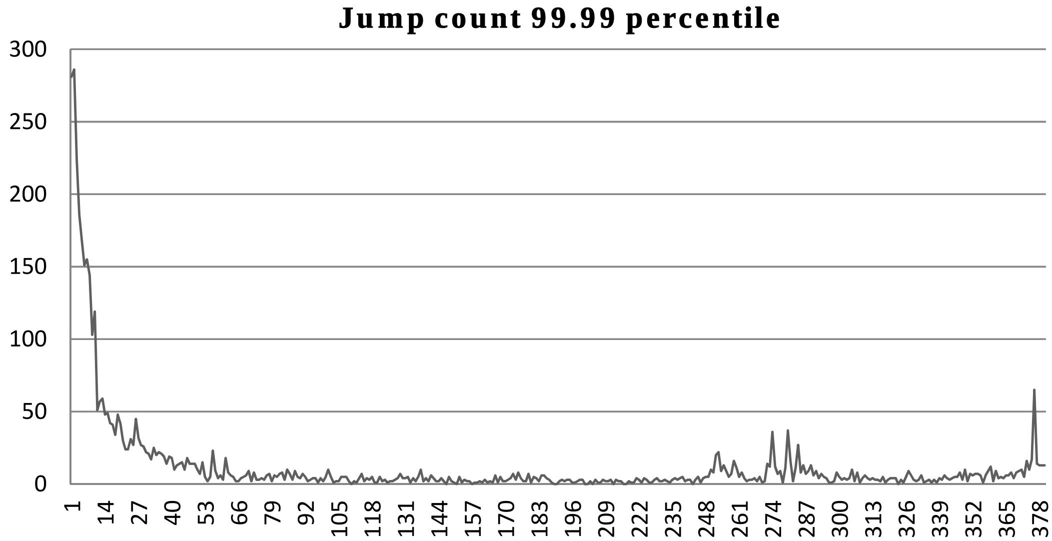
where the dependent variable is the standardized return. All other non-dummy variables are also standardized on the stock level. The dummy variable J is equal to one if the interval is identified to contain an extreme price movement and is equal to zero otherwise. HFT_D (nHFT_D) is the standardized share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. Vol is the standardized total trading volume. HFT_NET (nHFT_NET) is the net HFT (nHFT) imbalance. Regressions are estimated with fixed effects. The 10 lags of return and the independent variables are included in each regression specification (not reported). 99.99 columns correspond to the subsample of price changes larger than the 99.99th percentile. LM columns correspond to the top 4,560 jumps obtained through the Lee and Mykland (2012) algorithm. p-Values associated with the double-clustered standard errors are in parentheses. Asterisks *** and ** denote significance at the 1% and 5% levels.

	99.99	**LM**		**99.99**	**LM**		**99.99**	**LM**
HFT_D	0.305***	0.305***	**HFT_S**	-0.237***	-0.237***	**HFT_NET**	0.116***	0.116***
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
nHFT_D	0.262***	0.262***	**nHFT_S**	-0.304***	-0.304***	**HFT_NET*J**	-0.119***	-0.155***
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
J	0.958**	1.206***	**J**	0.902**	1.041***	**J**	0.581	0.872***
	(0.04)	(0.01)		(0.02)	(0.00)		(0.09)	(0.01)
HFT_D*J	0.116	0.091	**HFT_S*J**	-0.226***	-0.207***			
	(0.08)	(0.11)		(0.00)	(0.00)			
nHFT_D*J	0.128***	0.130***	**nHFT_S*J**	-0.090***	-0.083***			
	(0.00)	(0.00)		(0.00)	(0.00)			
Vol	-0.002	-0.002	**Vol**	-0.001	-0.001	**Vol**	0.003	0.003
	(0.35)	(0.32)		(0.80)	(0.77)		(0.11)	(0.13)
Adj. R^2	0.194	0.194		0.195	0.194		0.014	0.014

Table 10. Probability of EPMs

The table reports the coefficients (first line) and the marginal effects (second line) obtained from a probit model of jump occurrence. Dependent variable is equal to one if the interval is identified to contain an extreme price movement and zero otherwise. HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. HFT_NET is the net HFT imbalance. Vol is total traded volume. RQSpr is the percentage quoted spread. All variables are standardized by stock. All independent variables are lagged by one period. 99.99 columns correspond to the subsample of the price changes higher than 99.99 percentile. LM columns correspond the top 4,564 jumps obtained using the Lee and Mykland 2012 algorithm. The marginal effects are scaled by a factor of 10,000. *p*-Values are in parentheses. Asterisks *** indicate significance at the 1% level.

	99.99	**LM**		**99.99**	**LM**		**99.99**	**LM**
Intercept	-3.7513***	-3.7407***	**Intercept**	-3.7516***	-3.7409***	**Intercept**	-3.7506***	-3.7401***
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
HFT_D (t-1)	-0.0017	-0.0021	**HFT_S (t-1)**	-0.0112***	-0.0099***	**HFT_NET (t-1)**	-0.0042***	-0.0040***
	-0.006	-0.008		-0.042	-0.038		-0.016	-0.015
	(0.24)	(0.17)		(0.00)	(0.00)		(0.00)	(0.00)
nHFT_D (t-1)	0.0067***	0.0065***	**nHFT_S (t-1)**	-0.0042***	-0.0041***			
	0.025	0.025		-0.016	-0.016			
	(0.00)	(0.00)		(0.00)	(0.00)			
Vol (t-1)	0.0675***	0.0600***	**Vol (t-1)**	0.0672***	0.0596***	**Vol (t-1)**	0.0672***	0.0596***
	0.253	0.230		0.251	0.228		0.252	0.228
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
RQSpr (t-1)	0.0160***	0.0091***	**RQSpr (t-1)**	0.0160***	0.0091***	**RQSpr (t-1)**	0.0160***	0.0091***
	0.060	0.035		0.060	0.035		0.060	0.035
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
Pseudo-R^2	0.055	0.035		0.056	0.035		0.055	0.034



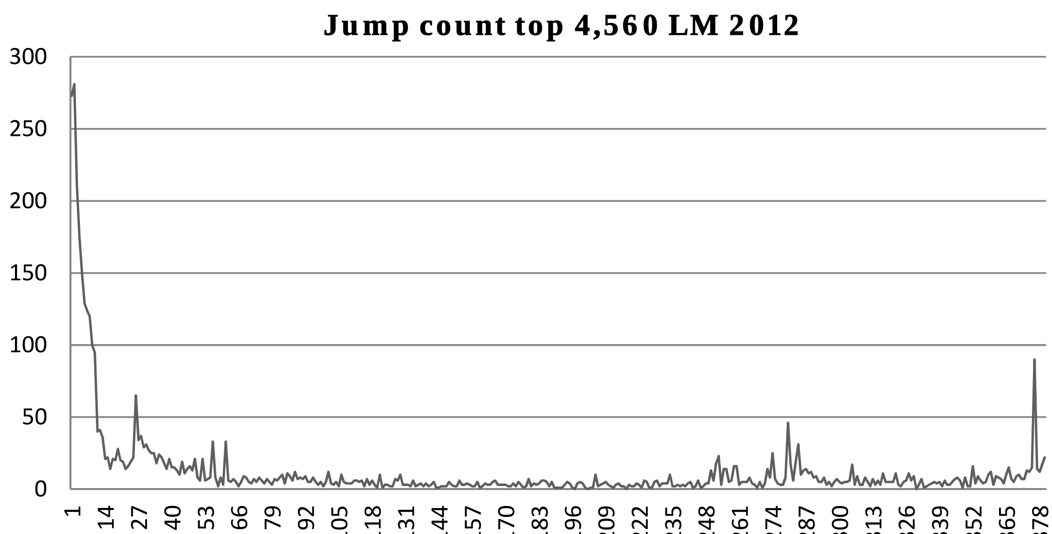


Figure 1: Intraday Distribution of Extreme Price Changes
The horizontal axis contains a counter of minutes between 9:35 a.m. and 3:55 p.m. The vertical axis reflects the number of extreme price movements (EPMs) in a given minute. The upper figure contains EPMs estimated as absolute returns above the 99.99 percentile, while the bottom chart contains EPMs estimated as the 4,560 largest-magnitude jumps detected with the Lee and Mykland (2012) methodology.

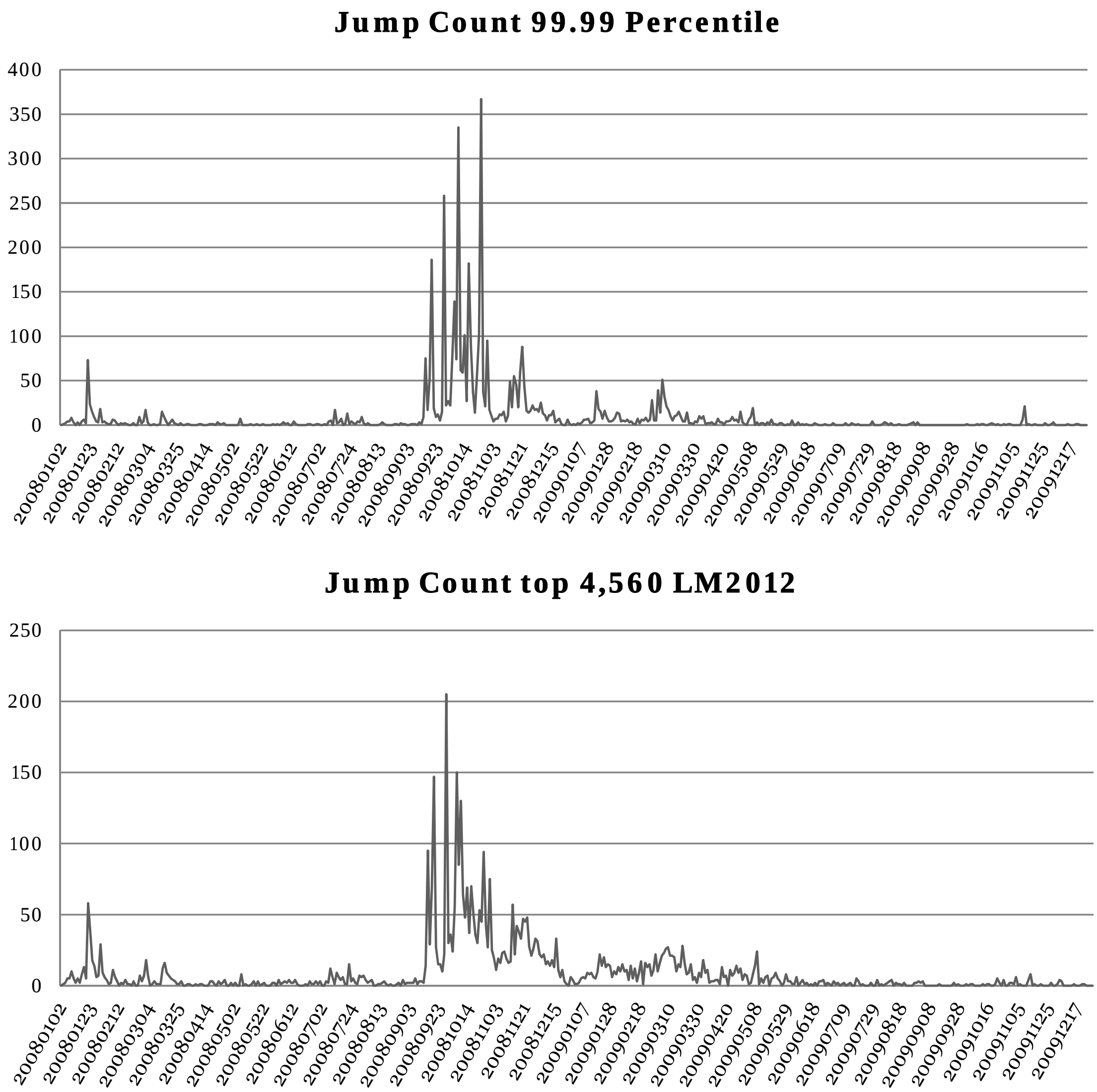
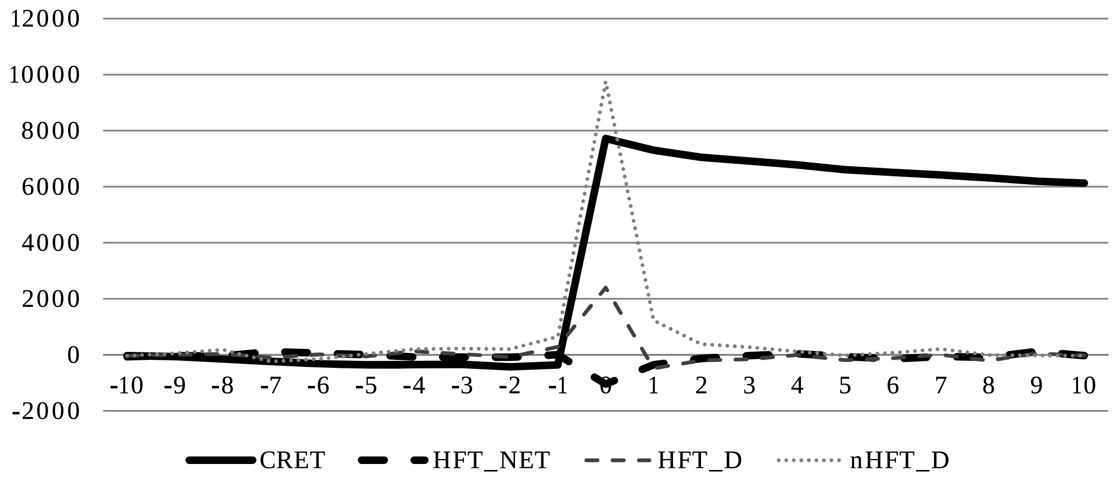


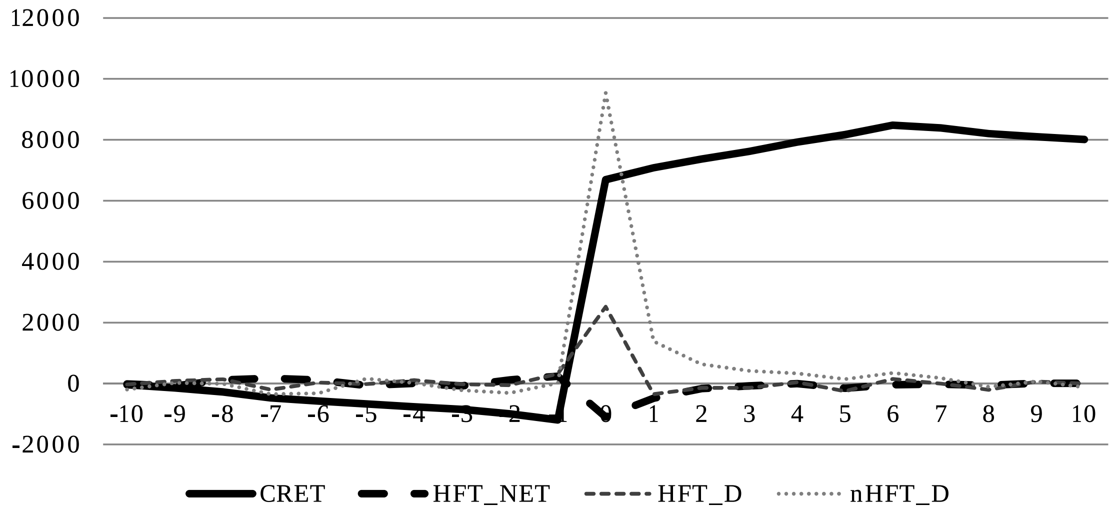
Figure 2: Daily Distribution of Extreme Price Changes

The horizontal axis contains the daily time line through 2008-2009. The vertical axis reflects the number of extreme price movements (EPMs) on a given day. The upper chart contains EPMs estimated as absolute returns above the 99.99 percentile; the bottom chart contains EPMs estimated as the 4,560 largest-magnitude jumps detected with the Lee and Mykland (2012) methodology.

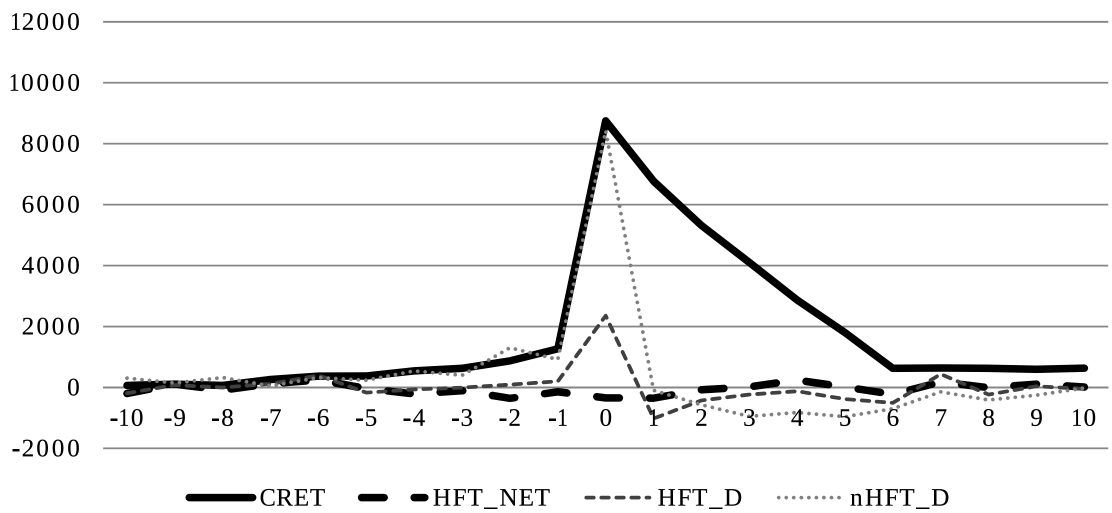
(a) Full sample



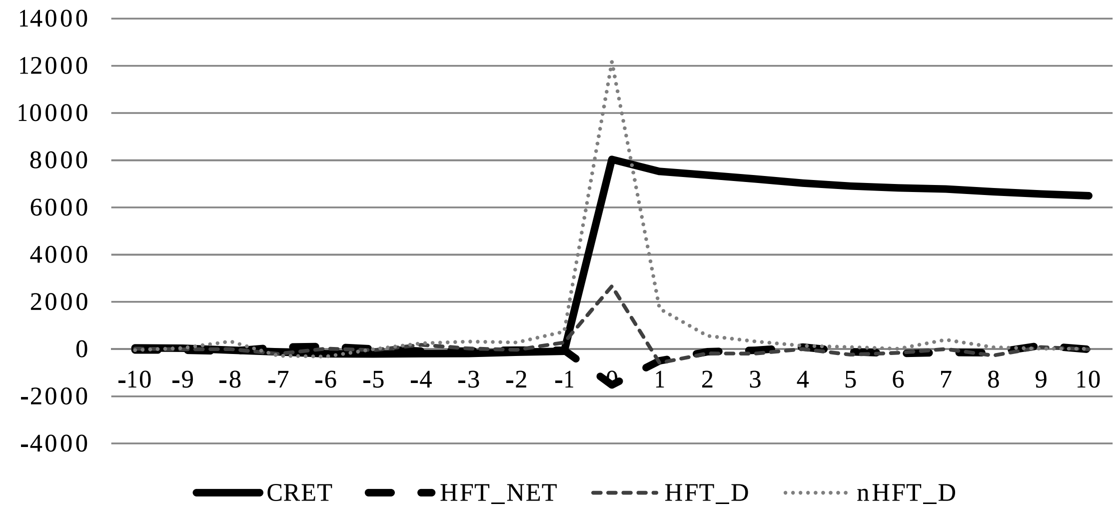
(b) Permanent



(c) Transitory



(d) Idiosyncratic



(e) Systematic

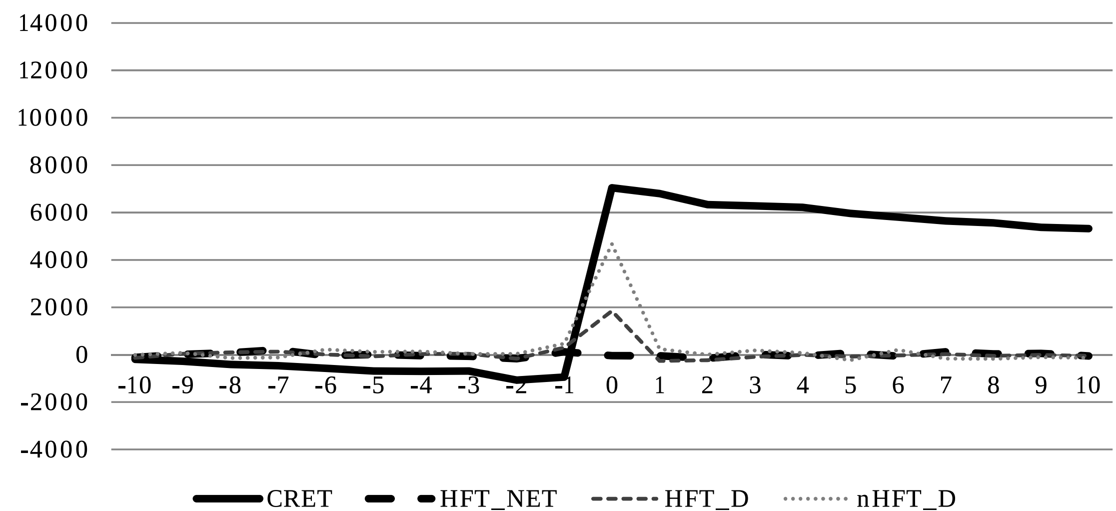
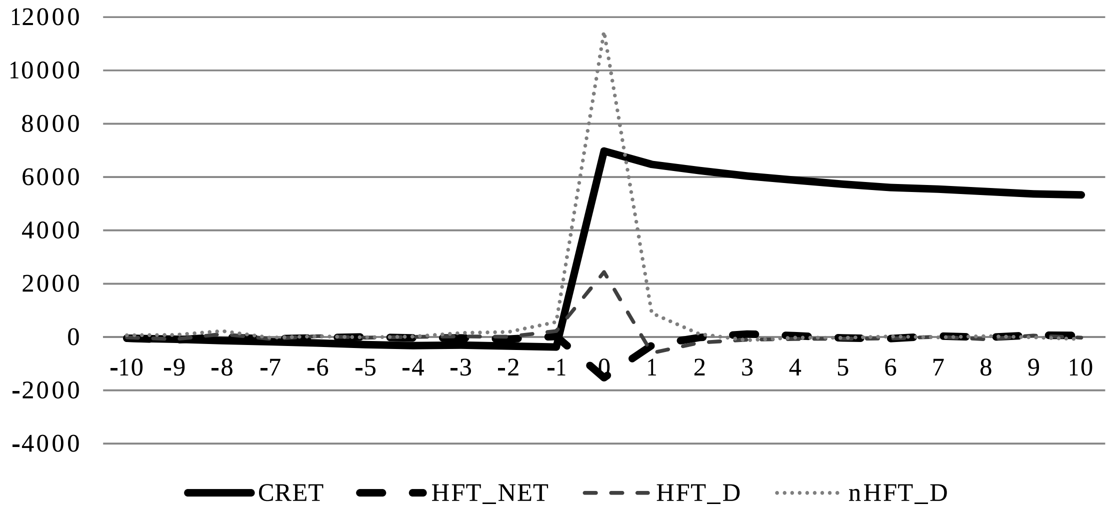


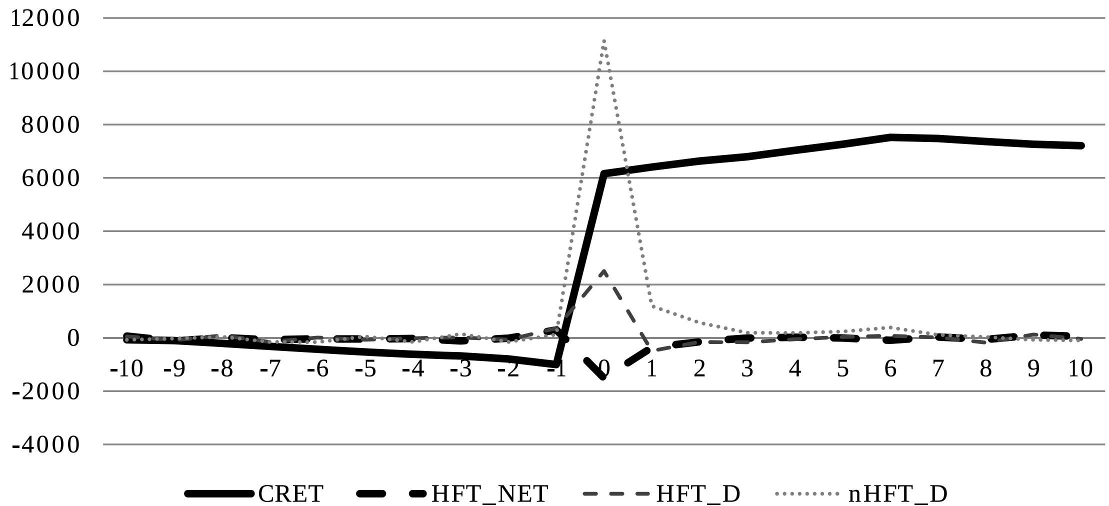
Figure 3: HFT and nHFT activity around EPMs (99.99 sample)

The figure contains EPMs estimated using the 99.99% technique. Figure (a) contains the results for all jumps, figures (b) and (c) divide jumps into permanent and transitory, figures (d) and (e) divide jumps into systematic and idiosyncratic. The horizontal axis outlines the event window that spans 10 intervals prior to and 10 intervals following a price jump. The vertical axis reflects HFT/nHFT imbalances and cumulative returns. We scale returns by a factor of 10,000 for display purposes.

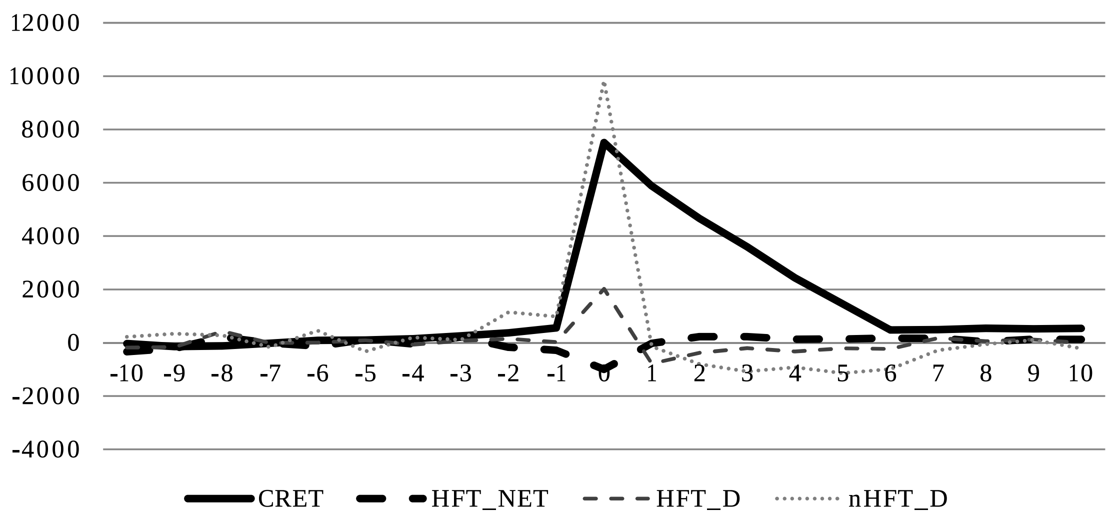
(a) Full sample

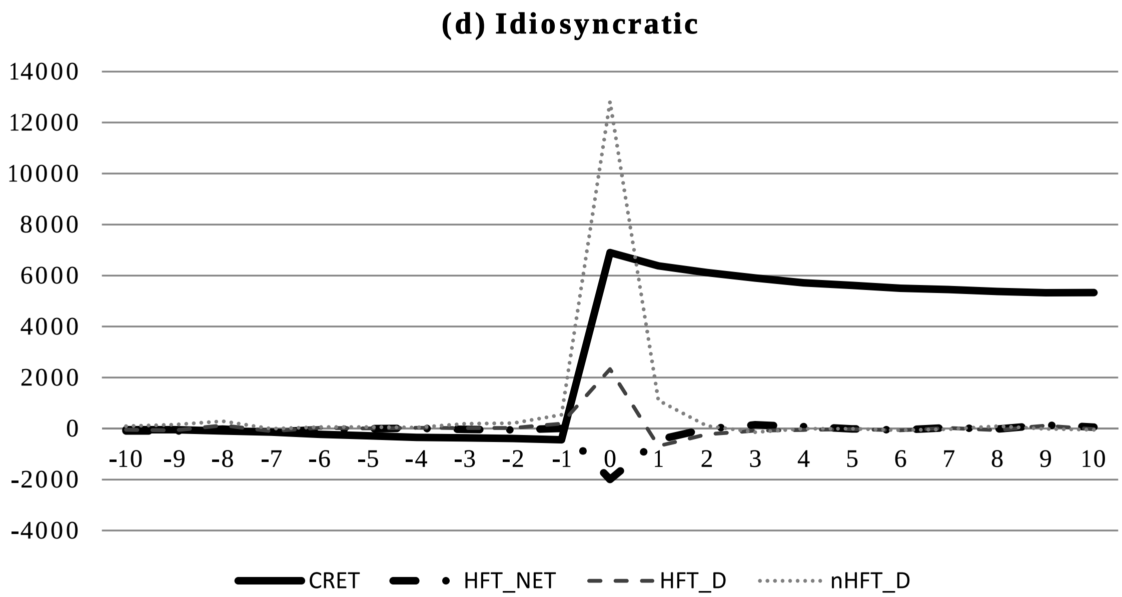


(b) Permanent



(c) Transitory





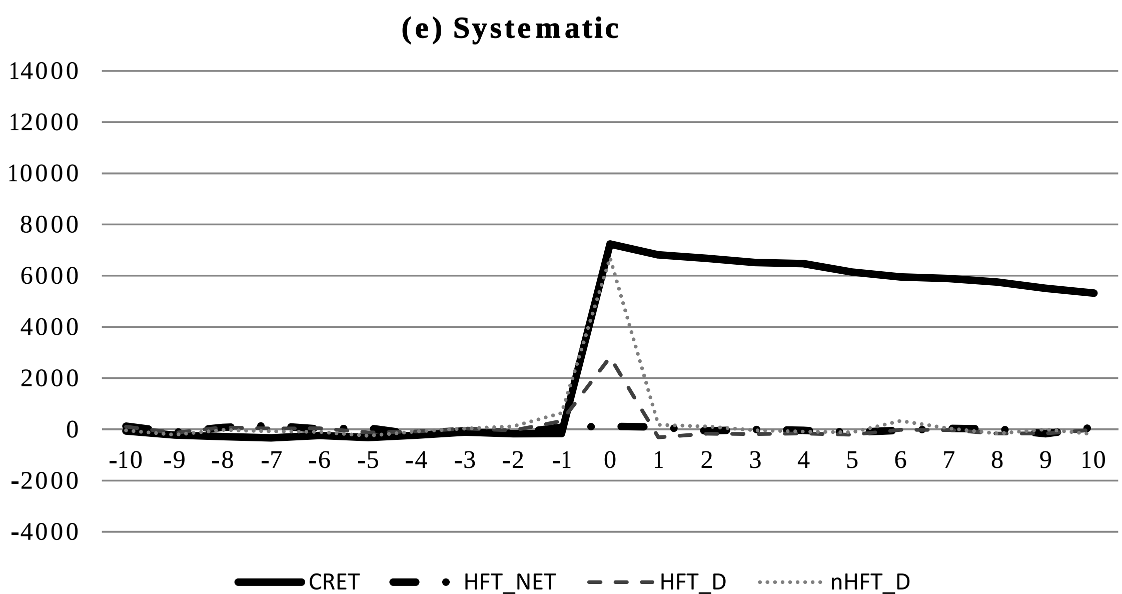


Figure 4: HFT and nHFT activity around EPMs (LM sample)
The figure contains EPMs estimated using the LM technique. Figure (a) contains the results for all jumps, figures (b) and (c) divide jumps into permanent and transitory, figures (d) and (e) divide jumps into systematic and idiosyncratic. The horizontal axis outlines the event window that spans 10 intervals prior to and 10 intervals following a price jump. The vertical axis reflects HFT/nHFT imbalances and cumulative returns. We scale returns by a factor of 10,000 for display purposes.

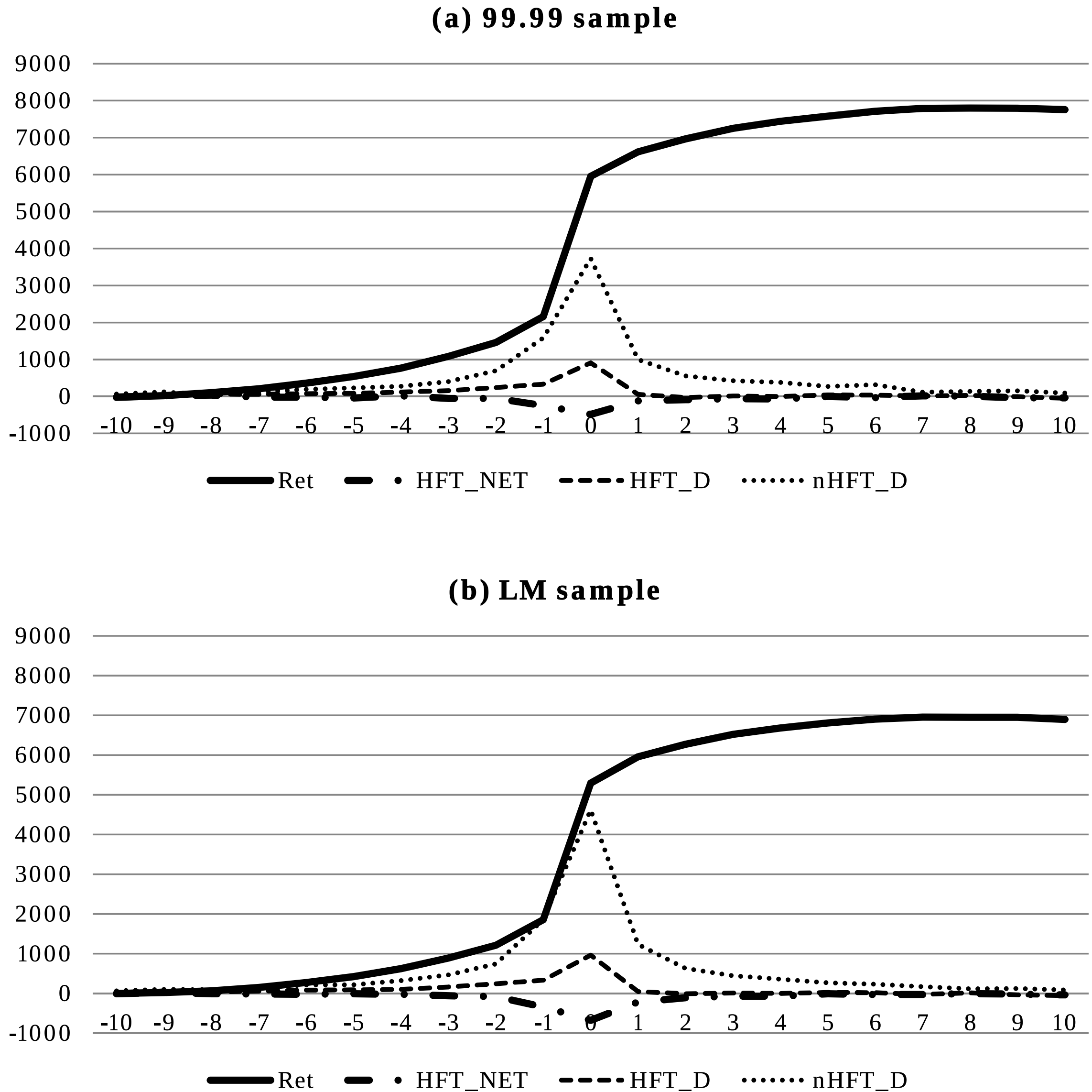


Figure 5: HFT and nHFT activity at the time of EPMs, a second-by-second view
The figure outlines HFT and nHFT activity during the 21-second window centered on the largest one-second return during a jump interval. The vertical axis reflects HFT/nHFT imbalances and cumulative returns. We scale returns by a factor of 10,000 for display purposes. Figure (a) contains the 99.99 sample, and figure (b) contains the LM sample.

Appendix

Lee and Mykland (2012) jump identification algorithm

The Lee and Mykland (2012) algorithm (LM) identifies the intervals with discrete price changes using the non-parametric approach based on realized volatility. First, the optimal sampling frequency is identified as k for the $(k-1)$-dependent noise. In our sample, the second-by-second midpoint return observations tend to follow an MA process with many statistically significant dependent AR lags. However, the magnitude of the lag coefficients tends to drop sharply after 6-8 lags. To make the estimated results comparable across stocks, we select $k = 10$. The algorithm suggests that a researcher pre-averages over M k-sampled observations before computing the jump statistics as follows: $M = C\sqrt{(n/k)}$, where C is a parameter defined by the noise variance, and n is the number of observations in the jump estimation period. Recognizing that in a high-frequency sample the realized variation of the log-prices $P(t)$ converges to noise variance, we estimate the volatility of noise as:

$$\hat{q} = \sqrt{\left(\sum_{m=1}^{n'}(P(t_m) - P(t_{m+k}))^2\right)/2n'} \qquad \text{(A1)}$$

Following LM, we split each trading day into seven intervals: 9:30-10:00, 10:00-11:00, 11:00-12:00, 12:00-13:00, 13:00-14:00, 14:00-15:00, and 15:00-16:00. The estimated noise variance for these intervals is reported in Table A1. Based on the estimates, we choose $C = 1/19$, and therefore the estimated M is close to one for all estimation periods.[20]

Next, the standardized statistic for jump detection is defined as follows:

$$\mathcal{X}(t_j) = \frac{\sqrt{M}}{\sqrt{V_n}}\mathcal{L}(t_j), \qquad \text{(A2)}$$

where $\mathcal{L}(t_j) = P(t_{j+k}) - P(t_j)$, and V_n is the estimate of the total variance. The total variance is a sum of the estimated noise variance $\hat{q}$ and price volatility. We use the noise- and outlier-

[20] Since we use midpoint prices, much of the noise coming from the bid-ask bounce is mitigated, and the remaining noise does not produce the estimate high enough to make pre-sampling useful.

robust bipower variation of Christensen, Oomen and Podolskij (2014) as the measure of price volatility.

From LM's Theorem 1, the null hypothesis of no jump in a given interval is rejected if:

$$\frac{|\mathcal{X}(t_j)|-A_n}{B_n} > \beta^*, \tag{A3}$$

where

$$A_n = \sqrt{2\log\frac{n}{kM}} - \frac{\log\pi+\log\left(\log\frac{n}{kM}\right)}{2\sqrt{2\log\frac{n}{kM}}} \tag{A4}$$

and

$$B_n = \frac{1}{\sqrt{2\log\frac{n}{kM}}} \tag{A5}$$

The rejection threshold is selected from the standard Gumbel distribution, which implies that $\beta^* = -\log(-\log(1-\alpha))$. We use the significance level of $\alpha = 5\%$, leading to $\beta^* = 2.97$. The above procedure results in rejecting the no-jump hypothesis for 0.54% of sample observations.

Table A1: Noise volatility

The table reports estimated noise volatility $\hat{q}$ as a percentage of price used for computation of the LM statistic. The noise variance is estimated by intraday period, day and stock.

period	$\hat{q}$	**max**	**st. dev.**
9:30-10:00	0.057%	0.095%	0.014%
10:00-11:00	0.040%	0.068%	0.010%
11:00-12:00	0.030%	0.051%	0.008%
12:00-13:00	0.025%	0.043%	0.006%
13:00-14:00	0.026%	0.042%	0.006%
14:00-15:00	0.030%	0.047%	0.007%
15:00-16:00	0.034%	0.054%	0.008%

Table A2. Volume imbalances around EPMs; early morning, mid-day, and prior-to-close EPMs

The table reports the direction of trading volume around the extreme price movements (EPMs), while separating EPMs into those occurring between 9:35 a.m. and 10:00 a.m. (Panel A), those that occur between 10:00 a.m. and 3:00 p.m. (Panel B), and those that occur during the rest of the day (Panel C). HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. HFT_NET (nHFT_NET) are the differences between HFT (nHFT) liquidity demand and supply. *p*-Values are in parentheses. Asterisks ** and * indicate significance at the 1% and 5% levels.

Panel A: 9:35 a.m. – 10:00 a.m.

	99.99 percentile					**Lee and Mykland 2012**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-87.1	64.9	-566.3**	-250.4*	-104.5	-5.9	82.6	-865.8***	-287.4***	-21.3
	(0.37)	(0.52)	(0.00)	(0.03)	(0.20)	(0.94)	(0.30)	(0.00)	(0.00)	(0.77)
HFT_D	39.1	276.7**	1620.2**	-406.3**	-136.7	59.2	116.2	1553.7***	-418.0***	-81.3
	(0.67)	(0.00)	(0.00)	(0.00)	(0.12)	(0.49)	(0.11)	(0.00)	(0.00)	(0.25)
HFT_S	-126.2	-211.7**	-2186.5**	155.8	32.2	-65.1	-33.6	-2419.4***	130.6*	59.9
	(0.06)	(0.01)	(0.00)	(0.06)	(0.70)	(0.26)	(0.57)	(0.00)	(0.04)	(0.32)
nHFT_NET	87.1	-64.9	566.3**	250.4*	104.5	5.9	-82.6	865.8***	287.4***	21.3
	(0.37)	(0.52)	(0.00)	(0.03)	(0.20)	(0.94)	(0.30)	(0.00)	(0.00)	(0.77)
nHFT_D	405.8	574.7**	6128.5**	1102.2**	165.2	245.1	239.5	6869.6***	778.2***	85.1
	(0.07)	(0.00)	(0.00)	(0.00)	(0.36)	(0.09)	(0.07)	(0.00)	(0.00)	(0.58)
nHFT_S	-318.7	-639.6**	-5562.3**	-851.7**	-60.7	-239.2	-322.1*	-6003.8***	-490.8***	-63.7
	(0.18)	(0.00)	(0.00)	(0.00)	(0.73)	(0.10)	(0.02)	(0.00)	(0.00)	(0.68)
N	2,422					2,011				

Panel B: 10:00 a.m. – 3:00 p.m.										
	99.99 percentile					**Lee and Mykland 2012**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	11.6	-176.3	-1365.3**	-710.0**	-91.0	-16.9	-137.8	-2182.8**	-638.6**	1.3
	(0.95)	(0.34)	(0.00)	(0.00)	(0.61)	(0.89)	(0.30)	(0.00)	(0.00)	(0.99)
HFT_D	-202.8	239.9	2839.9**	-352.4*	-137.5	-16.3	237.7	2371.9**	-664.3**	-263.8**
	(0.22)	(0.17)	(0.00)	(0.04)	(0.45)	(0.87)	(0.04)	(0.00)	(0.00)	(0.01)
HFT_S	214.4	-416.2*	-4205.2**	-357.6	46.5	-0.6	-375.5**	-4554.7**	25.7	265.1*
	(0.26)	(0.02)	(0.00)	(0.08)	(0.80)	(1.00)	(0.00)	(0.00)	(0.87)	(0.04)
nHFT_NET	-11.6	176.3	1365.3**	710.0**	91.0	16.9	137.8	2182.8**	638.6**	-1.3
	(0.95)	(0.34)	(0.00)	(0.00)	(0.61)	(0.89)	(0.30)	(0.00)	(0.00)	(0.99)
nHFT_D	-199.3	978.1**	12525.1**	2121.7**	759.9	-85.0	967.7**	13833.8**	1490.6**	99.3
	(0.53)	(0.01)	(0.00)	(0.00)	(0.07)	(0.71)	(0.00)	(0.00)	(0.00)	(0.67)
nHFT_S	187.7	-801.8**	-11159.8**	-1411.8**	-668.9	101.9	-829.9**	-11650.9**	-852.0**	-100.6
	(0.55)	(0.01)	(0.00)	(0.00)	(0.10)	(0.63)	(0.00)	(0.00)	(0.00)	(0.62)
N	1,734					2,068				

Panel C: 3:00 p.m. – 3:55 p.m.										
	99.99 percentile					**Lee and Mykland 2012**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-455.7	431.3	-2509.1**	568.2	-405.6	-619.0*	475.1	-1473.8	937.0*	-81.6
	(0.11)	(0.44)	(0.01)	(0.21)	(0.34)	(0.02)	(0.31)	(0.10)	(0.02)	(0.84)
HFT_D	-194.2	568.9	5196.3**	-1469.6**	-825.0	-95.4	598.5*	6439.2**	-1096.6**	-535.5
	(0.38)	(0.05)	(0.00)	(0.00)	(0.07)	(0.61)	(0.02)	(0.00)	(0.00)	(0.22)
HFT_S	-261.6	-137.6	-7705.4**	2037.8**	419.4	-523.6*	-123.4	-7913.0**	2033.6**	453.9
	(0.38)	(0.78)	(0.00)	(0.00)	(0.10)	(0.04)	(0.76)	(0.00)	(0.00)	(0.09)
nHFT_NET	455.7	-431.3	2509.1**	-568.2	405.6	619.0*	-475.1	1473.8	-937.0*	81.6
	(0.11)	(0.44)	(0.01)	(0.21)	(0.34)	(0.02)	(0.31)	(0.10)	(0.02)	(0.84)
nHFT_D	754.6	-254.8	19628.3**	-1799.8**	73.7	1178.5**	167.5	20468.1**	-1164.4	256.6
	(0.11)	(0.82)	(0.00)	(0.00)	(0.89)	(0.00)	(0.86)	(0.00)	(0.05)	(0.60)
nHFT_S	-298.9	-176.5	-17119.3**	1231.6*	331.9	-559.6	-642.6	-18994.3**	227.4	-175.0
	(0.43)	(0.81)	(0.00)	(0.03)	(0.45)	(0.08)	(0.32)	(0.00)	(0.67)	(0.67)
N	404					481				

Table A3. Volume imbalances around EPMs; non-crisis vs. crisis EPMs

The table reports the direction of trading volume around the extreme price movements (EPMs), while separating EPMs into those occurring in September-November 2008 from EPMs that occur during the rest of the sample period. HFT_D (nHFT_D) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement through HFT (non-HFT) liquidity demanding orders. HFT_S (nHFT_S) is the share volume traded against the direction of the price movement plus the share volume traded in the direction of the price movement through the HFT (non-HFT) liquidity providing orders. HFT_NET (nHFT_NET) are the differences between HFT (nHFT) liquidity demand and supply. *p*-Values are in parentheses. Asterisks ** and * indicate significance at the 1% and 5% levels.

Panel A: non-crisis

	99.99 percentile					**Lee and Mykland 2012**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	32.8	-149.1	-2506.4**	-825.0**	-177.4	-12.9	-81.5	-2576.0**	-621.1**	6.7
	(0.89)	(0.58)	(0.00)	(0.01)	(0.45)	(0.92)	(0.61)	(0.00)	(0.00)	(0.96)
HFT_D	-45.8	250.4	4249.4**	-862.0**	-420.7	13.4	193.2	3525.3**	-891.3**	-419.7**
	(0.84)	(0.26)	(0.00)	(0.00)	(0.10)	(0.91)	(0.10)	(0.00)	(0.00)	(0.00)
HFT_S	78.6	-399.5	-6755.8**	37.0	243.3	-26.3	-274.7	-6101.3**	270.2	426.4**
	(0.75)	(0.11)	(0.00)	(0.89)	(0.32)	(0.84)	(0.06)	(0.00)	(0.13)	(0.00)
nHFT_NET	-32.8	149.1	2506.4**	825.0**	177.4	12.9	81.5	2576.0**	621.1**	-6.7
	(0.89)	(0.58)	(0.00)	(0.01)	(0.45)	(0.92)	(0.61)	(0.00)	(0.00)	(0.96)
nHFT_D	296.4	746.3	18336.6**	2359.1**	979.1	64.5	765.5*	16862.8**	1281.0**	78.4
	(0.51)	(0.16)	(0.00)	(0.00)	(0.06)	(0.77)	(0.02)	(0.00)	(0.00)	(0.75)
nHFT_S	-329.2	-597.1	-15830.2**	-1534.1**	-801.7	-51.6	-684.0**	-14286.8**	-659.9**	-85.1
	(0.47)	(0.16)	(0.00)	(0.00)	(0.11)	(0.79)	(0.01)	(0.00)	(0.01)	(0.67)
N	1,443					2,068				

Panel B: crisis										
	99.99 percentile					**Lee and Mykland 2012**				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT_NET	-134.9	77.3	-363.9**	-134.2	-101.7	-129.0	111.7	-656.9**	-67.2	-37.2
	(0.06)	(0.33)	(0.00)	(0.09)	(0.16)	(0.05)	(0.18)	(0.00)	(0.45)	(0.63)
HFT_D	-88.6	306.2**	1544.2**	-302.5**	-93.4	3.4	246.2**	1539.5**	-359.4**	-38.1
	(0.16)	(0.00)	(0.00)	(0.00)	(0.15)	(0.96)	(0.00)	(0.00)	(0.00)	(0.56)
HFT_S	-46.3	-229.0**	-1908.0**	168.3**	-8.2	-132.4**	-134.6	-2196.4**	292.2**	0.8
	(0.38)	(0.00)	(0.00)	(0.00)	(0.88)	(0.01)	(0.05)	(0.00)	(0.00)	(0.99)
nHFT_NET	134.9	-77.3	363.9**	134.2	101.7	129.0	-111.7	656.9**	67.2	37.2
	(0.06)	(0.33)	(0.00)	(0.09)	(0.16)	(0.05)	(0.18)	(0.00)	(0.45)	(0.63)
nHFT_D	161.2	612.3**	5781.6**	712.2**	107.7	299.1*	393.4**	6980.7**	580.1**	135.1
	(0.27)	(0.00)	(0.00)	(0.00)	(0.41)	(0.04)	(0.01)	(0.00)	(0.00)	(0.34)
nHFT_S	-26.3	-689.6**	-5417.7**	-578.1**	-6.0	-170.1	-505.0**	-6323.8**	-512.8**	-97.8
	(0.86)	(0.00)	(0.00)	(0.00)	(0.97)	(0.26)	(0.00)	(0.00)	(0.00)	(0.52)
N	3,117					2,492				

Table A4. HFT and nHFT liquidity demand and supply around EPMs

The table reports statistics for the total liquidity supply and demand by HFTs and nHFTs around extreme price movements (EPMs). Unlike our main metrics in Tables 4-6, these statistics do not account for the direction of the price movement. *p*-Values are in parentheses. All estimated coefficients are statistically significant at the 1% level.

	99.99 percentile					Lee and Mykland 2012				
	t-2	t-1	t	t+1	t+2	t-2	t-1	t	t+1	t+2
HFT total demand	4,295	4,740	8,421	5,726	4,913	2,905	3,328	7,867	4,706	3,629
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFT total supply	6,376	7,155	13,234	8,948	7,273	4,342	5,000	12,662	7,433	5,457
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nHFT total demand	7,927	8,828	19,072	10,820	8,488	5,666	6,598	19,695	9,293	6,545
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nHFT total supply	5,846	6,413	14,259	7,597	6,128	4,230	4,925	14,900	6,566	4,717
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)