

High Frequency Trading and Market Stability*

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This paper investigates the relationship between high frequency traders (HFT) and price jumps in the stock market. Using the Nasdaq HFT dataset, we find that overall HFT trading activity is higher around and during price jumps. HFT liquidity taking activity is lower than normal while HFT liquidity supplying activity is higher. During extreme price jumps HFT liquidity providers accumulate an inventory position in the opposite direction of the jump. HFT liquidity takers take an inventory position in the direction of the jump. However, both positions appear unprofitable. The evidence is generally consistent with HFT dampening extreme market events.

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1. Introduction

In the aftermath of the 2008 financial crisis and the May 2010 flash crash the stability of financial markets has been debated. Market disruptions have numerous implications in terms of risk management (Duffie and Pan, 2001), derivative pricing (Bates, 2000; Eraker, Johannes, and Polson, 2003) and portfolio allocation with its influence on the optimal strategy (Jarrow and Rosenfield, 1984; Liu, Longstaff, and Pan, 2003). While overall market quality has improved lately (Castura, Litzenberger, and Gorelick, 2010), individual stock mini-crashes are prevalent (Golub et al., 2013). Those short-lived crashes could originate from several sources as outlined by Hendershott (2011): HFT activity, market structure changes, trading fragmentation and/or the disappearance of designed market makers.

In this paper, we analyze the relationship between HFT activity and high frequency market disruptions. We detect price jumps through the 99.99% percentile of ex-post observations. We made two cutoffs: idiosyncratic jumps and co-jumps; permanent and transitory jumps. Co-jumps are jumps that happen simultaneously in several individual stocks while idiosyncratic jumps are isolated individual stock jumps. A transitory jump is defined as a jump that reverses within thirty seconds of its inception while a permanent jump does not reverse in the same time period.

The mechanism of price jumps are not well understood. Farmer, Gillemot, Lillo, Mike, and Sen (2004) outline that large price fluctuations in a short period of time are driven by time-varying liquidity supply. On the other hand, Jiang, Lo, and Verdelhan (2010) and Miao, Ramchander, and Zumwalt (2012) find that most jumps appear at pre-scheduled macroeconomic news in the US treasury bond market and in the stock index futures market. High frequency trading (HFT) activities are often accused of triggering or enhancing these events. In response to these concerns exchanges and regulators have already taken action. The Euronext stock exchange now imposes a cancellation fee to avoid the implementation of

some HFT strategies. Several regulators are discussing the implementation of minimum liquidity provision by HFT firms.

Price jumps could be affected by HFT in several ways. In times of heightened market instability, when price jumps are more likely to occur, HFT firms may exit the market or could add to one-sided order imbalance, which could ignite or enhance a jump in prices. If so, the observation that HFT firms provide liquidity on average may hide that in times of market instability they switch from liquidity provision to liquidity taking.

We use the Nasdaq HFT dataset used in other research (e.g. Brogaard, Hendershott, and Riordan, 2013). The data divides market participants into two types, HFT and non-HFT (nHFT). The data also disclose which type of participant is taking and providing liquidity for each trade.

We find HFT do not cease their trading activity during or around price jumps. Moreover the increase in HFT activity is on their passive trading activity. Then, we investigate HFT/nHFT net volume around jumps. HFT and nHFT trade on average aggressively when in direction of the price jump and passively when against the price jump direction. In net, we find that neither HFT nor nHFT exhibit a significant net position for supply-driven jumps (midquote jumps) while demand-driven jumps (transaction jumps) unveil that HFT holds a significant contrarian net position during jumps.

The likelihood of a permanent price jump to occur is higher when lagged HFT net volume is in the direction of the price jump. At the opposite, transitory price jumps go along with HFT net volume against the price jump direction. It reflects that HFT activity can be related to a quicker adjustment of prices to information which in turn may explain the prevalence of stock specific price jumps.

The remainder of the paper proceeds as follows. Section 2 provides a review of the existing literature. Section 3 describes the data set used in this paper. Section 4 presents the applied methodology. Section 5 reports the empirical results. Section 6 concludes.

2. Literature Review

High frequency trading (henceforth HFT) is one of the latest major development in financial markets. The investigation of its externalities in the market is of utmost importance given its prominence. Indeed, several papers (Zhang, 2010; Brogaard, 2011) estimate that HFT accounts for about 70% of trading volume in the U.S. capital market as from 2009.

A comprehensive definition of what HFT activities include remains elusive. According to Castura, Litzenberger, and Gorelick (2010), it encompasses professional market participants that present some characteristics: high-speed algorithmic trading, the use of exchange co-location services along with individual data feeds, very short investment horizon and the submission of a large number of orders during the continuous trading session that are often cancelled shortly after submission.

The existing literature outlines overall that HFT activity improves market quality. Indeed, the rising of HFT activity went along with a reduction of the spread, a liquidity improvement and a reduction of intraday volatility (Castura, Litzenberger, and Gorelick, 2010; Angel, Harris, and Spatt, 2010; Hasbrouck, and Sarr, 2011). Hanson (2011) and Menkveld (2012) even describe HFT as the new market makers in U.S. financial markets. Indeed, HFT acts mostly as liquidity providers and engages in price reversal strategies (Brogaard, 2011).

Lately HFT activity was under the spotlight following the liquidity-induced flash crash on May 6th, 2010 that casts doubt on the soundness of HFT activity and its externalities on market stability and price efficiency.

Golub, Keane and Poon (2013) document that along with a market quality improvement, individual stock mini-crashes are prominent as well. Hendershott (2011) puts forward several potential origins of those liquidity-driven crashes such as high frequency trading activity, market structure changes, trading fragmentation and/or the disappearance of designed market makers.

In this paper, we document the relationship between HFT and market stability. We isolate period of instability by looking at high frequency market disruptions and investigate the behavior of HFT from a microstructure viewpoint during those periods. Our focus straddles two literatures. First, we briefly review the literature on the link between price movements and liquidity provision. Second, we summarize the expanding literature on HFT and market stability.

Several papers document the relationship between order book imbalances and price movements. Chordia and Subramanyam (2004) report a positive correlation between daily order book imbalance, stock returns and volatility. Chordia, Roll, and Subramanyam (2008) also highlight that return predictability is lower when the spread is tight. Cao, Hansch, and Wang (2009) investigate the informational content of the order book and show it fosters price discovery in the market.

On higher frequency aggregation sampling, Harris and Panchapagesan (2005) confirm a relationship between the limit order book and future price movements. Hellström and Simonsen (2009) point out that the information content of the order book is short-lived. Indeed, they find some predictability at a 1 and 2-minute aggregation sampling on the Stockholm stock exchange while it vanishes quickly on lower frequency sampling.

The relationship between market disruptions and liquidity provision is not straightforward and depends on the market.

The consensus is that the jump frequency observed in the stock market is not fully explained by news, whether macroeconomic or firm specific. Indeed, Farmer, Gillemot, Lillo, Mike, and Sen (2004) show that the trigger of large price fluctuations on the London Stock Exchange is time-varying liquidity supply. Hence, jump risks is stock specific. Illiquid stocks tend to suffer from jumps more often than liquid ones. Consistent results are found on US market data. Joulin, Lefevre, Grunberg, and Bouchaud (2008) and Weber and Rosenov (2005) document that the root of price jumps is a lower density of the order book in spite of

the surge of significant trading volume underlying the arrival of information. Lately, Boudt, Ghys, and Petitjean (2012) estimate that around 70% of jumps are liquidity-related on the DJIA index. They emphasize that the effective spread and the number of trades is informative of forthcoming jumps.

Recent papers (Jiang, Lo, and Verdelhan, 2010; Miao, Ramchander, and Zumwalt, 2012) on the US treasury bond market and in the stock index futures market contrast those results. They show that the majority of price jumps appear at pre-scheduled macroeconomic news.

Market instability is by definition a rarely occurring event which makes it a challenging issue to investigate. The behavior of HFT during those periods of instability remains broadly unexplored. The flash crash on May 6, 2010 is often given as an example of HFT deteriorating market stability. However, it relies on the strong assumption that the market would behave in a given way in the absence of HFT. Furthermore, the potential impact of a trader is related to its position. In this view, non-HFT who could attempt to buy/sell a large position quickly are more of a threat to market stability than HFT who typically limit their positions in a market.

Brogaard, Hendershott, and Riordan (2013) show that HFT activity is positively correlated to public information, market-wide movements and limit order book imbalances. This higher HFT activity doesn't seem to prevent from market overreaction. Indeed, Kirilenko, Kyle, Samadi, and Tuzun (2011) highlight that while the flash crash was originated by a bad execution of a large order initiated by a non-HFT trader, HFT exhibits abnormal behaviors and exacerbates market volatility that day.

Several papers outline a tight relationship between high frequency activity and stock specific volatility (Brogaard, 2012; Zhang, 2010; Kirilenko, Kyle, Samadi, and Tuzun, 2011). This higher stock price volatility could be the results of the interaction between HFT traders and fundamentals traders (Zhang, 2010).

Theoretically, Biais, Foucault, and Moinas (2012) develop a framework where they show that HFT traders increase adverse selection costs for non-HFT traders. Jovanovic and Menkveld (2011) found similar results. This additional adverse selection cost comes from the higher speed of information processing by HFT. Foucault, Hombert, and Rosu (2012) show that this speed advantage leads to a higher fraction of trading volume that is made by informed traders, it increases trading volume, decreases liquidity, induces price changes that are more correlated with fundamental value movements, and reduces informed order flow autocorrelations.

Bernales (2013) outlines that HFT traders are more profitable in high volatile periods (volatility shocks), which suggests they may have an incentive to manipulate market volatility. In a theoretical framework, Goettler, Parlour, and Rajan (2009) found that the limit order market acts as a "volatility multiplier" in that prices are more volatile than the fundamental value of the asset. This is all the more true when the fundamental volatility of the asset is higher or when there is information asymmetry across traders.

In this framework, market stability could be affected by HFT controversial strategies that could indirectly generate volatility in the market. Hendershott, Jones, and Menkveld (2011) outline that over 90% of the orders submitted by HFT are either cancelled or modified (cancelled and resubmitted) before being filled. Lately, Gai, Yao, and Ye (2012) show that HFT increases the order cancellation/execution ratio, which supports the significant implementation of quote stuffing¹, and layering² strategies in the market. Finally, Egginton, Van Ness, and Van Ness (2013) show that quote stuffing is ubiquitous in the US stock market. They find that stocks that experience quote stuffing display lower liquidity, higher trading costs, and higher short term volatility. Lately some regulators consider imposing a cancellation fee to prevent HFT potential detrimental externalities on the stock market. There is also talks to impose obligations on HFT to provide a minimum amount of liquidity and

¹ Quote stuffing consists in submitting a large number of orders followed immediately by a cancellation to generate order congestion.

² Layering consists in submitting a large number of orders in one side of the book that are not meant to be filled to facilitate the entry on the other side of the book.

prevent in such a way monetary drying up of liquidity, a role that was ensured previously by designed market makers.

On the other hand, market quality improves mainly as from 2006 and is tough to relate directly to the emergence of HFT activity (Castura, Litzenberger, and Gorelick, 2010). Indeed, almost at the same time, the market structure acknowledges major changes both in the U.S. and in Europe with respectively the implementation of RegNMS and MiFID. Furthermore, Golub et al. (2013) document that individual stock mini-crashes are prominent along with overall market quality improvement. Hendershott (2011) puts forward several potential origins of those liquidity-driven crashes; among them high frequency trading activity.

Some papers report a tight relationship between high frequency activity and stock specific volatility (Kirilenko, Kyle, Samadi, and Tuzun, 2011; Zhang, 2010; Brogaard, 2012). Indeed, HFT generates the majority of order flow while it displays periodicity in order submission and a high rate of order cancellations and modifications. Significant changes in their market activity from liquidity providers to liquidity takers suggest HFT may emphasize volatility/price movements and cause overreaction in the market.

3. Data

The database consists in 40 large market capitalization stocks that are listed half-and-half on NASDAQ and the New York Stock Exchange (NYSE).³ It is the same data used in other academic studies including Brogaard, Hendershott, and Riordan (2013) and O'hara, Yao, and Ye (2013).

The data spans two years from January 1, 2008 to December 31, 2009. NASDAQ categorizes market participants as a high-frequency trading firm or non-high-frequency trading (nHFT) firm, which allows us to identify investor types. A limitation of using market participant identifiers (MPIDs) is that NASDAQ is unable to disentangle HFT activity by large integrated firms that also engage in low-frequency trading strategies. Our data covers trading activity on the NASDAQ trading venue, other trading venues activity is thus not accounted for in this paper.

The dataset identifies 26 HFT firms that act as independent HFT proprietary trading firms.⁴ The dataset includes whether the buyer or seller initiated the trade and identifies the type of trader on both sides of the trade.

We supplement the NASDAQ HFT dataset with the National Best Bid and Offer (NBBO) from TAQ. The NBBO measures the best prices prevailing across all markets to focus on market-wide price discovery.

We remove trades that occur before 9:30 and after 16:00 as well as trades that take place during the opening and closing auction to focus on the stock market continuous trading hours. The filtered database consists in 41,342,013 10-second intervals.

³ NASDAQ OMX provides us the HFT database to academics under a non-disclosure agreement. Our data covers stocks such as Apple and GE.

⁴ Some HFT firms were consulted by NASDAQ in the decision to make data available. No HFT firm played any role in which firms were identified as HFT and no firms that NASDAQ considers HFT are excluded. While these 26 firms represent a significant amount of trading activity and according to NASDAQ fit the characteristics of HFT, determining the representativeness of these firms regarding total HFT activity is not possible.

4. Methodology

From the millisecond time-second trades we arrange the database into 10-second intervals to detect market disruptions.⁵

We consider the 99.99% percentile of ex-post observations as a threshold for a price jump. This straightforward methodology assumes static volatility which makes it a questionable proxy. Nevertheless, it offers a good compromise at very high frequency sampling scheme as more robust jump tests accuracy tends to be affected by microstructure noise. We investigate several jump cutoffs in the paper.⁶

First, midquote versus transaction jumps. Midquote jumps are extreme midquote changes during a 10-second interval while transaction jumps are extreme transaction price changes during the same interval. Both jumps offer insights since it can be seen as a liquidity supply jump (midquote jump) or a liquidity demande jump (transaction jump). For the sake of simplicity, we focus on midquote jumps in the core of the text and refer to transaction jumps when it holds additional insight compared to misquote jumps.

Second, permanent versus transitory jumps. A transitory jump is defined as a jump that fully reverses within 30 seconds of its inception while a permanent jump does not fully reverse in the short run.

Finally, we disentangle idiosyncratic versus co-jumps. Co-jumps are jumps that occur in several stocks within a small period of time. In the core of the paper, we set the definition to jumps that occur in at least 10% of our sample stocks within the same minute. By contrast, idiosyncratic jumps are “isolated” individual stock jumps.

⁵ We repeat the analysis with 1 minute, and 5-minute intervals to control for the robustness of our results. Those results are available upon request.

⁶ We carry out several robustness checks on our initial cutoffs that are not reported in the paper. Those results are available upon request.

Table 1 reports descriptive statistics of some microstructure variables during and around jumps.

INSERT TABLE 1 ABOUT HERE

Panel A reports all jumps descriptive statistics while Panel B and C highlights respectively the permanent and transitory cutoffs. Price dynamics unsurprisingly unveil a spike during the jump interval. Transitory jumps exhibit a wider scope than permanent jumps on average. The $t+1$ return shows the interval following jump inception is a pullback on average for transitory jumps while permanent jumps acknowledge no pullback. The trading volume both in shares and in US dollar is higher during the jump interval. Again transitory jumps go along with more trading activity than permanent jumps both during and around the jump interval. As expected, the net overall volume (in shares and in US dollar) is in the price jump direction. Net overall volume reverses after the jump inception for transitory price disruptions while it only moderates for permanent price jumps. Overall, we find that transitory price disruptions happen in a lower liquidity market context than permanent price disruptions. Indeed, the spread is wider and the depth lower for transitory jumps compared to permanent ones. Liquidity conditions (spread and depth) tend to improve for both permanent and transitory jumps.

Using the 99.99% percentile methodology and a 10-second window we isolate 3,431 jumps. Most of those jumps are permanent (2,669) with transitory jumps (762) that yields only for about a fifth of all price jumps. By definition the percentile definition is roughly evenly distributed among stocks, small differences arise from no trading intervals.

Table 2 displays the Pearson correlation coefficients for all the variables of interest in this paper. Overall we mention a correlation especially between price dynamics, volume in shares and in US dollar, net volume in shares and in US dollar. Net volume is positive correlated with HFT and nHFT demand while negatively correlated with HFT and nHFT

supply. It suggests that imbalance in trading activity comes mainly from aggressive trading for both HFT and nHFT. HFT Net volume demand/supply and nHFT net volume demand/supply are positively related. At the opposite, net HFT demand is higher when there is less nHFT net volume supply and vice versa.

INSERT TABLE 2 ABOUT HERE

5. Trading Behavior

a. Summary

We find HFT do not cease their trading activity during or around price jumps. Instead HFT trading activity significantly increases in such market condition. Looking more into details, we show that it is passive HFT trading activity that spike while aggressive trading activity remains broadly unchanged.

To investigate the one-sided of the order book activity, we report HFT/nHFT net volume around jumps. HFT and nHFT trade on average aggressively when in direction of the price jump and passively when against the price jump direction. In all, we find that neither HFT nor nHFT exhibit a significant net volume pattern for supply-driven jumps (midquote jumps) while demand-driven jumps (transaction jumps) unveil that HFT are price reversal during such market disruptions. The permanent/transitory cutoff supports our initial finding.

The likelihood of a permanent price jump to occur is higher when lagged HFT net volume is in the direction of the price jump. At the opposite, transitory price jumps go along with HFT net volume against the price jump direction. It reflects that HFT activity can be related to a quicker adjustment of prices to information which in turn may explain the prominence of stock specific price jumps outlined in Golub et al. (2013).

The size of the jump is mostly due to market condition. Volatile market environment (low depth and wide spread) as well as the sudden surge of trading volume are positively correlated to the jump size.

To evaluate whether HFT firms may have an incentive to try and trigger market disruptions, we evaluate their trading profits around price jumps. The results suggest that HFT firms have no obvious incentives to foster the inception of disruptions. Overall, nHFT make profit on their aggressive trading activity while HFT lose money on their passive trading activity during the jump interval. In all, we find no significant profit patterns during price jumps whether for HFT or nHFT.

b. HFT trading volume around jumps

A first concern that is often mentioned when market acknowledges unstable period is that HFT may withdraw the market. In this first table we investigate the HFT trading activity in share in the market and consider three cutoffs: All trading activity, Aggressive trading activity and passive trading activity.

Table 3 outlines HFT do not cease or even decrease its activity during and around jumps. Indeed, HFT activity is 18% higher during jump interval compared to non-jump interval. This higher HFT trading activity is also true 10-second prior and after the jump interval with an increase HFT activity of 30%. nHFT display similar patterns with a 50+% increase in trading volume for both passive and aggressive trading activity.

INSERT TABLE 3 ABOUT HERE

Looking at the splitting HFT aggressive/passive trading activity, it shows the spike of HFT trading activity is mainly due to the increase of HFT passive activity with an abnormal activity level of more than 30% while HFT aggressive activity is close to its normal market condition level and even below during the jump interval. It suggests that HFT increase their liquidity provision in times of market instability.

c. HFT net volume around jumps

Table 4 depicts HFT and nHFT net volume during and around price jumps as well as for the idiosyncratic/cojumps cutoff. All in all, HFT and nHFT exhibit similar behavior. They trade aggressively in the direction of the jump and against the direction of the jump, they trade passively. HFT net all volume is on average in the direction of the jump but not significant. It is also worthwhile to mention that HFT tend to become significantly aggressive the interval prior to a jump inception while nHFT are still net liquidity provider. Focusing on the cojumps/idiosyncratic cutoff, HFT are only more aggressive during the cojump interval while HFT already start their aggressive activity in the prior interval to jump occurrence.

Table 5 is a robustness check on transaction jumps instead of midquote jumps. It confirms the trading behaviors of both HFT and nHFT. The overall net volume of HFT and nHFT yields interesting insights. It supports the idea that HFT exhibit a significant price reversal behavior during price jumps. The idiosyncratic/cojumps cutoff draws the same conclusion even though HFT net volume is more pronounced for idiosyncratic jumps than for cojumps. It is in line with more trading activity and net volume position in the case of transitory jumps compared to permanent ones.

INSERT TABLES 4 AND 5 ABOUT HERE

All our results suggest neither HFT nor nHFT have a significant net volume position during the jump interval for midquote jumps. At the opposite, transaction jumps confirm HFT acts as market makers while nHFT display net volume in the jump direction. It is also worthwhile to outline that the scope of the imbalance is much more sizeable for nHFT than for HFT which supports that HFT does not hold a significant inventory during the continuous trading day.

d. HFT net volume around permanent/transitory jumps

Tables 6 and 7 report HFT and nHFT net volume during and around permanent/transitory price jumps. It support our initial finding in that HFT and nHFT exhibit similar behavior on average with aggressive trading in the jump direction and passive trading in the opposite jump direction. The size of net volume activity is more pronounced in the case of permanent jumps than transitory ones. Again, we point out to HFT as being market makers in the case of transaction jumps while midquote jumps unveil no significant patterns whether from HFT or nHFT.

INSERT TABLES 6 AND 7 ABOUT HERE

e. Drivers of price jumps occurrence

In Table 8, we investigate the drivers of price jumps in the stock market. For this purpose, we first control for a series of microstructure variables. Price jumps tend to happen in a low liquidity time period. Indeed, we find that a wide spread and a lower depth increase the likelihood of price jump occurrence. To the same extend, we outline that higher lagged trading volume both in shares and in US dollar goes along with more jumps. Price dynamics also outline a more volatile market environment.

Looking at the permanent/transitory cutoff, we show that lagged HFT net volume in the jump direction increase the probability of a jump to occur. During permanent price jumps, nHFT are aggressive against the jump direction while HFT net passive volume is in the jump direction during and prior the jump occurrence. At the opposite, HFT net volume is against the jump direction during transitory jumps. Prior to the jump, we outline that HFT net aggressive volume is significant and in the jump direction while nHFT provide liquidity in the jump direction.

INSERT TABLE 8 ABOUT HERE

f. Drivers of price jumps size

Table 9 points out to the positive relation between the size of permanent jumps and lagged volatility measure (High Low and Squared return). A sudden surge of trading volume (significantly lower prior to jump and significantly higher during the price jump) is another driver of permanent jump size. The depth at the best quote is also informative for a large jump size. HFT net trading activity shows that the size of permanent jump is larger when HFT trade aggressively in the jump direction. At the opposite the size of transitory jumps seem to be related to dollar trading volume during the jump interval. There are also bigger when lagged return is small. HFT and nHFT trading behavior seem to have no effect on the size of transitory jumps.

INSERT TABLE 9 ABOUT HERE

g. Profitability

To more accurately discern HFT firms' interest and anticipation of price jumps, we analyze HFT profits during market dislocations.

Table 10 shows HFT and nHFT profit around jumps as well as profit for the cutoff permanent/transitory. All in all, we find that HFT tend to incur losses on average during market disruptions while nHFT make profit on average. Nevertheless, few significant patterns appear in a 10-second interval. Overall nHFT make profit on their aggressive trading activity during jumps while HFT lose money on their liquidity supply activity. At a 90% confidence interval, we confirm this finding on all trading activity with HFT losing money at the expense of nHFT during price jumps.

We cannot associate permanent price jumps with any significant profit patterns for whether HFT or nHFT. Still on average, we find that HFT exhibit a negative PnL at the opposite of nHFT.

Finally, HFT profits are statistically insignificantly different from zero for transitory jumps. The splitting of aggressive and passive trading activity unveils that HFT incur a loss on their liquidity provision while nHFT make profit on their aggressive trading activity at a 90% confidence interval. This behavior is consistent with HFT firms acting as market makers.

INSERT TABLE 10 ABOUT HERE

6. Conclusion

In this paper, we take advantage of a NASDAQ HFT dataset that identifies investor types (HFT and non-HFT) to investigate the relationship between HFT activity and market disruptions. Market disruptions are detected using a straightforward 99.99% percentile. We cutoff idiosyncratic jumps (isolated individual stock jumps) and co-jumps (jumps that occur simultaneously in several individual stocks).

We find HFT are more active during market disruptions. It suggests that HFT process information quicker than nHFT and act as the main liquidity providers in time of higher information asymmetry.

We investigate the one-sided order book activity for HFT/nHFT around jumps. On average, they trade aggressively when in direction of the price jump and passively when against the price jump direction. In all, we find that neither HFT nor HFT exhibit a significant net volume pattern for midquote jumps while transaction jumps confirm that HFT are implementing price reversal strategies during such market disruptions.

The likelihood of a permanent price jump to occur is higher when lagged HFT net volume is in the direction of the price jump. It reflects that the higher HFT activity leads to a quicker adjustment of price to information, which in turn may explain the prominence of stock specific price jumps outlined in Golub et al. (2013). At the opposite, transitory price jumps go along with HFT net volume against the price jump direction.

The size of the jump is mostly due to market condition. Volatile market environment (low depth and wide spread) as well as the sudden surge of trading volume are positively correlated to the jump size.

To evaluate whether HFT firms may have an incentive to try and trigger market disruptions, we evaluate their trading profits around price jumps. The results suggest that HFT firms have no obvious incentives to foster the inception of disruptions. Overall, nHFT make profit on their aggressive trading activity while HFT lose money on their passive trading activity during the jump interval. In all, we find no significant profit patterns during price jumps whether for HFT or nHFT.

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Table 2 Pearson Correlation Coefficients

The Table displays the Pearson correlation coefficients between our considered variables. The variables are the High Low (High minus Low), return (relative close to close, positive if in the jump direction and vice versa), squared return, \$ volume (in US dollar), share volume (in shares), share OIB (net volume in shares, positive if in the jump direction and vice versa), \$ OIB (net volume in US dollar, positive if in the jump direction and vice versa), spread (relative bid-ask spread) and depth (depth in the jump direction at the best quote).

	High Low	Return	Squared Return	Share Volume	\$ Volume	Share OIB	\$ OIB	Spread	Depth	OIB HFT Demand	OIB HFT Supply	OIB nHFT Demand	OIB nHFT Supply
High Low	1.00	0.79	0.73	-0.01	0.00	0.00	0.00	0.00	-0.03	0.00	0.00	0.00	0.00
Return	0.79	1.00	0.94	-0.01	0.00	0.00	0.00	0.00	-0.03	0.00	0.00	0.00	0.00
Squared Return	0.73	0.94	1.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	0.01	-0.01	0.01
Share Volume	-0.01	-0.01	-0.01	1.00	0.59	0.49	0.32	0.00	0.17	0.29	-0.37	0.45	-0.44
\$ Volume	0.00	0.00	-0.01	0.59	1.00	0.28	0.53	-0.01	0.04	0.16	-0.19	0.26	-0.28
Share OIB	0.00	0.00	-0.01	0.49	0.28	1.00	0.65	0.00	0.07	0.63	-0.76	0.89	-0.90
\$ OIB	0.00	0.00	-0.01	0.32	0.53	0.65	1.00	0.00	0.01	0.41	-0.43	0.58	-0.63
Spread	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	1.00	-0.01	0.00	0.00	0.00	0.00
Depth	-0.03	-0.03	-0.02	0.17	0.04	0.07	0.01	-0.01	1.00	0.06	-0.08	0.05	-0.04
OIB HFT Demand	0.00	0.00	-0.01	0.29	0.16	0.63	0.41	0.00	0.06	1.00	-0.46	0.20	-0.59
OIB HFT Supply	0.00	0.00	0.01	-0.37	-0.19	-0.76	-0.43	0.00	-0.08	-0.46	1.00	-0.68	0.40
OIB nHFT Demand	0.00	0.00	-0.01	0.45	0.26	0.89	0.58	0.00	0.05	0.20	-0.68	1.00	-0.79
OIB nHFT Supply	0.00	0.00	0.01	-0.44	-0.28	-0.90	-0.63	0.00	-0.04	-0.59	0.40	-0.79	1.00

Table 3 HFT trading activity around jumps

The table reports the ratio of the average HFT (nHFT) trading volume (in shares) during and around jump intervals over the average HFT (nHFT) trading volume (in shares) during non-jump intervals. HFT (nHFT) All sums up aggressive and passive HFT (nHFT) volume, HFT (nHFT) Supply is passive HFT (nHFT) volume and HFT (nHFT) Demand is aggressive HFT (nHFT) volume.

	t-2		t-1		T		t+1		t+2	
HFT All	90.5%	***	127.0%	***	118.0%	***	130.6%	***	110.2%	***
	(5.13)		(5.36)		(6.18)		(7.1)		(6.74)	
HFT Demand	66.8%	***	104.5%	***	85.3%	***	107.2%	***	89.8%	***
	(4.38)		(5.57)		(5.47)		(6.83)		(6.43)	
HFT Supply	107.0%	***	138.6%	***	134.5%	***	147.1%	***	126.8%	***
	(5.13)		(4.83)		(5.81)		(6.64)		(6.44)	
<hr/>										
	t-2		t-1		T		t+1		t+2	
nHFT All	113.6%	***	146.7%	***	158.5%	***	142.2%	***	115.0%	***
	(5.22)		(4.81)		(7)		(7.3)		(6.9)	
nHFT Demand	135.3%	***	163.2%	***	186.7%	***	159.7%	***	130.2%	***
	(5.26)		(4.38)		(6.8)		(7.01)		(6.69)	
nHFT Supply	110.3%	***	142.2%	***	159.7%	***	131.7%	***	102.5%	***
	(4.62)		(4.41)		(6.63)		(6.69)		(6.45)	

Table 4 HFT net volume around jumps

Panel A, B and C report respectively all jumps, co-jumps and idiosyncratic midquote jumps cutoffs. The tables display net trading volume for HFT and non-HFT (nHFT). Trading activity statistics are All (Demand and Supply), Demand (Aggressive trading) and Supply (Passive trading). The variables are positive if in the jump direction and vice versa. The Table shows mean trading activity as well as its t-value. ***, **, * mean respectively that the mean trading activity is significant at 99%, 95% and 90%.

Panel A: All	t-2	t-1	T	t+1	t+2
HFT All	152.10 (1.18)	276.48 (1.58)	107.85 (0.88)	-3.61 (0.03)	32.80 (0.32)
HFT Demand	-29.64 (0.27)	460.27 (3.6)	*** 571.16 (5.93)	*** -43.63 (0.41)	-10.77 (12)
HFT Supply	181.74 (2.36)	** -183.79 (1.18)	-463.30 (5.53)	*** 40.02 (0.52)	43.57 (0.59)
nHFT All	-152.10 (1.18)	-276.48 (1.58)	-107.85 (0.88)	3.61 (0.03)	-32.80 (0.32)
nHFT Demand	-606.21 (2.1)	** 564.97 (1.17)	1949.33 (5.96)	*** 473.58 (2.17)	** 284.00 (1.81)
nHFT Supply	454.10 (1.59)	-841.45 (2)	** -2057.19 (6.67)	*** -469.97 (1.98)	** -316.80 (2.07)
Panel B: Cojumps	t-2	t-1	T	t+1	t+2
HFT All	-1021.29 (1.28)	418.78 (0.67)	299.64 (0.49)	384.12 (0.69)	265.14 (0.52)
HFT Demand	-1092.91 (1.41)	683.71 (1.25)	823.88 (1.93)	* 132.91 (0.33)	216.19 (0.62)
HFT Supply	71.62 (0.24)	-264.93 (0.63)	-524.24 (1.32)	251.21 (0.53)	48.95 (0.14)
nHFT All	1021.29 (1.28)	-418.78 (0.67)	-299.64 (0.49)	-384.12 (0.69)	-265.14 (0.52)
nHFT Demand	-1977.60 (1.37)	3174.35 (1.96)	** 6084.38 (2.17)	** 646.81 (0.96)	741.73 (0.96)
nHFT Supply	2998.89 (1.61)	-3593.12 (2.25)	** -6384.02 (2.46)	** -1030.93 (1.45)	-1006.87 (1.27)

Panel C: Idiosyncratic jumps	t-2		t-1		T		t+1		t+2
HFT All	281.48	**	260.86		87.69		-46.09		7.21
	(2.51)		(1.43)		(0.73)		(0.42)		(0.07)
HFT Demand	87.60		435.74	***	544.58	***	-62.98		-35.76
	(1.04)		(3.39)		(5.65)		(0.58)		(0.41)
HFT Supply	193.88	**	-174.88		-456.90	***	16.89		42.98
	(2.46)		(1.05)		(5.53)		(0.25)		(0.58)
nHFT All	-281.48		-260.86		-87.69		46.09		-7.21
	(2.51)		(1.43)		(0.73)		(0.42)		(0.07)
nHFT Demand	-455.00		278.47		1514.56	***	454.60	**	233.58
	(1.63)		(0.55)		(7.3)		(1.97)		(1.54)
nHFT Supply	173.52		-539.33		-1602.25	***	-408.51		-240.80
	(0.72)		(1.24)		(7.89)		(1.62)		(1.65)

Table 5 HFT net volume around jumps

Panel A, B and C report respectively all jumps, co-jumps and idiosyncratic transaction jumps cutoffs. The tables display net trading volume for HFT and non-HFT (nHFT). Trading activity statistics are All (Demand and Supply), Demand (Aggressive trading) and Supply (Passive trading). The variables are positive if in the jump direction and vice versa. The Table shows mean trading activity as well as its t-value. ***, **, * mean respectively that the mean trading activity is significant at 99%, 95% and 90%.

Panel A: All	t-2	t-1	t		t+1	t+2
HFT All	-140.61 (0.40)	-279.44 (0.77)	-2082.14 (4.68)	***	-633.94 (1.68)	* 97.90 (0.28)
HFT Demand	-437.82 (1.2)	425.76 (1.62)	2146.95 (5.18)	***	-665.65 (1.8)	* 59.37 (0.18)
HFT Supply	297.21 (0.69)	-705.20 (1.62)	-4229.09 (8.55)	***	31.71 (0.07)	38.53 (0.11)
nHFT All	140.61 (0.4)	279.44 (0.77)	2082.14 (4.68)	***	633.94 (1.68)	* -97.90 (0.28)
nHFT Demand	-328.23 (0.38)	2091.15 (2.38)	** 14395.93 (13.79)	***	2239.19 (2.92)	*** 1794.74 (2.38)
nHFT Supply	468.84 (0.59)	-1811.71 (2.44)	** -12313.8 (14.02)	***	-1605.25 (2.29)	** -1892.65 (2.63)
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Panel B: Cojumps	t-2	t-1	t		t+1	t+2
HFT All	-518.33 * (1.65)	499.02 (1.41)	-1477.63 (3.66)	***	-155.91 (0.56)	-0.55 (0.002)
HFT Demand	-465.04 (1.27)	685.37 (1.94)	* 545.48 (2.19)	**	-62.62 (0.3)	58.00 (0.31)
HFT Supply	-53.29 (0.22)	-186.35 (0.84)	-2023.11 (5.52)	***	-93.29 (0.57)	-58.55 (0.4)
nHFT All	518.33 * (1.65)	-499.02 (1.41)	1477.64 (3.66)	***	155.91 (0.56)	0.55 (0.002)
nHFT Demand	-626.28 (0.64)	1406.65 (1.45)	6877.27 (6.79)	***	1242.96 (1.3)	2313.56 (2.19)
nHFT Supply	1144.62 (1.08)	-1905.67 (1.78)	* -5399.63 (6.24)	***	-1087.05 (1.03)	-2313.02 (2.08)

Panel C: Idiosyncratic jumps	t-2	t-1	t		t+1	t+2
HFT All	108.65 (0.2)	-793.14 (1.42)	-2481.05 (3.6)	***	-949.39 (1.58)	162.87 (0.29)
HFT Demand	-419.86 (0.75)	254.44 (0.69)	3203.75 (4.8)	***	-1063.58 (1.78)	* 60.28 (0.11)
HFT Supply	528.50 (0.76)	-1047.59 (1.48)	-6584.80 (7.26)	***	114.19 (0.16)	102.59 (0.17)
nHFT All	-108.65 (0.19)	793.14 (1.43)	2481.05 (3.6)	***	949.39 (1.58)	-162.87 (0.29)
nHFT Demand	-131.55 (0.1)	2542.85 (1.94)	* 19357.44 (12.18)	***	2896.60 (2.62)	*** 1452.37 (1.39)
nHFT Supply	22.89 (0.02)	-1749.71 (1.73)	* -16876 (12.67)	***	-1947.21 (2.09)	** -1615.24 (1.71)

Table 6 HFT net volume around permanent and transitory jumps

Panel A and B report respectively permanent jumps and transitory midquote jumps cutoffs. The tables display net trading volume for HFT and non-HFT (nHFT). Trading activity statistics are All (Demand and Supply), Demand (Aggressive trading) and Supply (Passive trading). The variables are positive if in the jump direction and vice versa. The Table shows mean trading activity as well as its t-value. ***, **, * mean respectively that the mean trading activity is significant at 99%, 95% and 90%.

Panel A: Permanent Jumps	t-2		t-1		T		t+1		t+2
HFT All	356.80	*	417.38		206.68		49.49		53.71
	(1.87)		(1.46)		(0.94)		(0.27)		(0.3)
HFT Demand	56.53		985.80	***	820.71	***	-118.05		-55.57
	(0.39)		(4.33)		(4.8)		(0.68)		(0.38)
HFT Supply	300.27	**	-568.42	**	-614.03	***	167.54		109.28
	(2.24)		(2.25)		(4.22)		(1.23)		(0.85)
nHFT All	-356.80		-417.38		-206.68		-49.49		-53.71
	(1.87)		(1.46)		(0.94)		(0.27)		(0.3)
nHFT Demand	-965.93	*	1459.08	*	3163.70	***	495.70		402.38
	(1.95)		(1.75)		(5.22)		(1.33)		(1.51)
nHFT Supply	609.13		-1876.46	**	-3370.38	***	-545.19		-456.09
	(1.37)		(2.49)		(5.87)		(1.41)		(1.77)
									*
Panel B: Transitory Jumps	t-2		t-1		T		t+1		t+2
HFT All	-87.63		112.35		-1.07		-65.79		8.35
	(0.52)		(0.62)		(0.012)		(0.56)		(0.11)
HFT Demand	-130.56		-151.89	**	296.11	***	43.52		41.65
	(0.81)		(1.96)		(4.05)		(0.41)		(0.56)
HFT Supply	42.93		264.24		-297.18	***	-109.32	**	-33.30
	(0.75)		(1.62)		(4.09)		(2)		(0.59)
nHFT All	87.63		-112.35		1.07		65.79		-8.35
	(0.52)		(0.62)		(0.012)		(0.56)		(0.11)
nHFT Demand	-184.91		-476.55		610.91	***	447.68	**	145.50
	(0.77)		(1.23)		(3.87)		(2.42)		(1.05)
nHFT Supply	272.54		364.20		-609.85	***	-381.88		-153.85
	(0.8)		(1.47)		(4.55)		(1.53)		(1.1)

Table 7 HFT net volume around permanent and transitory jumps

Panel A and B report respectively permanent jumps and transitory transaction jumps cutoffs. The tables display net trading volume for HFT and non-HFT (nHFT). Trading activity statistics are All (Demand and Supply), Demand (Aggressive trading) and Supply (Passive trading). The variables are positive if in the jump direction and vice versa. The Table shows mean trading activity as well as its t-value. ***, **, * mean respectively that the mean trading activity is significant at 99%, 95% and 90%.

Panel A: Permanent Jumps	t-2	t-1	T		t+1	t+2
HFT All	-283.31 (0.8)	38.64 (0.096)	-2223.63 (4.67)	***	-258.60 (0.67)	21.27 (0.053)
HFT Demand	-256.36 (0.61)	388.33 (1.37)	2328.40 (6.01)	***	61.55 (0.21)	369.34 (0.96)
HFT Supply	-26.95 (0.065)	-349.69 (0.75)	-4452.03 (7.76)	***	-320.15 (0.64)	-348.07 (0.84)
nHFT All	283.31 (0.8)	-38.64 (0.096)	2223.63 (4.67)	***	258.60 (0.67)	-21.27 (0.053)
nHFT Demand	-662.92 (0.74)	1342.21 (1.29)	15438.46 (12.62)	***	3194.38 (3.85)	3250.57 (3.63)
nHFT Supply	946.23 (1.09)	-1380.85 (1.64)	-13214.83 (13.30)	***	-2935.78 (4.52)	-3271.84 (3.77)
Panel B: Transitory Jumps	t-2	t-1	T		t+1	t+2
HFT All	359.21 (0.36)	-1393.55 (1.64)	-1586.56 (1.43)		-1948.62 (1.88)	366.31 (0.48)
HFT Demand	-1073.40 (1.43)	556.87 (0.86)	1511.37 (1.18)		-3212.75 (2.44)	-1026.35 (1.46)
HFT Supply	1432.61 (1.14)	-1950.42 (1.78)	-3097.93 (3.61)	***	1264.13 (1.51)	1392.66 (2)
nHFT All	-359.21 (0.36)	1393.55 (1.64)	1586.56 (1.43)		1948.62 (1.88)	-366.31 (0.48)
nHFT Demand	844.08 (0.37)	4714.39 (3.04)	10744.34 (5.58)	***	-1106.49 (0.59)	-3304.48 (2.55)
nHFT Supply	-1203.28 (0.65)	-3320.84 (2.1)	-9157.77 (4.89)	***	3055.11 (1.4)	2938.16 (2.68)

Table 8 Drivers of price jumps occurrence

The table is a probit regression with fixed effects. The dependent variable takes 1 when a jump occurs and 0 otherwise. The independent variables are defined such as in Table 1. We report the results for the permanent / transitory cutoff. The Table shows the parameter estimates as well as their wald chi-square. ***, **, * mean respectively that the parameter is significant at 99%, 95% and 90%. The marginal effect (ME) of each explanatory variable is also reported.

Panel A: Permanent Jumps	Scaling	Coef.	ME	Coef.	ME	Coef.	ME
High Low (t-1)	1.E+03	2623.80 *** (192.69)	0.50	2622.90 *** (192.56)	0.50	2622.60 *** (192.52)	0.50
Return (t-1)	1.E+03	3254 *** (12.81)	0.62	3287 *** (12.95)	0.63	3220 *** (12.24)	0.61
Squared Return (t-1)	1.E+03	-23699 *** (21.42)	-4.53	-23880 *** (21.50)	-4.57	-23483 *** (20.56)	-4.48
Share Volume (t-1)	1.E+08	247.00 *** (535.45)	0.05	248.70 *** (517.82)	0.05	256.40 *** (548.39)	0.05
\$ Volume (t-1)	1.E+09	28.15 *** (46.14)	0.01	27.95 *** (47.28)	0.01	26.37 *** (39.28)	0.01
\$ Volume (t)	1.E+09	0.32 (0.01)	0.00	1.70 (0.17)	0.00	2.01 (0.22)	0.00
Spread (t-1)	1.E+01	210.00 *** (182.32)	0.04	210.20 *** (183.15)	0.04	210.00 *** (182.21)	0.04
Depth (t-1)	1.E+06	-1228.80 *** (154.73)	-0.23	-1224.90 *** (153.69)	-0.23	-1230.10 *** (155.23)	-0.23
OIB HFT (t)	1.E+08	82.80 (1.44)	0.02				
OIB HFT Demand (t)	1.E+08			-12.06 (0.02)	0.00		
OIB HFT Supply (t)	1.E+08					112.40 * (1.87)	0.02
OIB nHFT Demand (t)	1.E+08			-52.74 *** (4.69)	-0.01		
OIB nHFT Supply (t)	1.E+08					35.02 ** (2.17)	0.01
OIB HFT (t-1)	1.E+08	103.00 *** (6.52)	0.02				
OIB HFT Demand (t-1)	1.E+08			29.63 (0.47)	0.01		
OIB HFT Supply (t-1)	1.E+08					142.60 *** (8.29)	0.03
OIB nHFT Demand (t-1)	1.E+08			-11.45 (0.38)	0.00		
OIB nHFT Supply (t-1)	1.E+08					-27.83 * (1.87)	-0.01
Pseudo R^2		4.89%		4.88%		4.91%	

Panel B:										
Transitory Jumps	Scaling	Coef.		ME	Coef.		ME	Coef.		ME
High Low (t-1)	1.E+03	2551.80 ***		0.03	2548.90 ***		0.03	2554.10 ***		0.03
		(26.38)			(26.32)			(26.50)		
Return (t-1)	1.E+03	-37711 ***		-0.49	-37134 ***		-0.48	-36132 ***		-0.48
		(42.04)			(45.10)			(46.56)		
Squared Return (t-1)	1.E+03	-434769 ***		-5.67	-426111 ***		-5.52	-408942 ***		-5.39
		(18.50)			(20.16)			(21.04)		
Share Volume (t-1)	1.E+08	106.80 ***		0.00	112.80 ***		0.00	118.60 ***		0.00
		(34.79)			(32.25)			(35.97)		
\$ Volume (t-1)	1.E+09	30.66 ***		0.00	28.36 ***		0.00	27.79 ***		0.00
		(26.55)			(18.95)			(20.26)		
\$ Volume (t)	1.E+09	10.36 ***		0.00	11.56 ***		0.00	12.11 ***		0.00
		(3.81)			(3.48)			(4.77)		
Spread (t-1)	1.E+01	218.20 ***		0.00	217.90 ***		0.00	217.90 ***		0.00
		(62.81)			(62.52)			(62.37)		
Depth (t-1)	1.E+06	-775.10 ***		-0.01	-818.50 ***		-0.01	-821.80 ***		-0.01
		(10.26)			(10.95)			(10.88)		
OIB HFT (t)	1.E+08	-232.70 ***		0.00						
		(5.34)								
OIB HFT Demand (t)	1.E+08				-113.80		0.00			
					(0.76)					
OIB HFT Supply (t)	1.E+08							-101.90		0.00
								(0.52)		
OIB nHFT Demand (t)	1.E+08				21.73		0.00			
					(0.24)					
OIB nHFT Supply (t)	1.E+08							26.57		0.00
								(0.82)		
OIB HFT (t-1)	1.E+08	-15.44		0.00						
		(0.02)								
OIB HFT Demand (t-1)	1.E+08				-257.90 ***		0.00			
					(6.87)					
OIB HFT Supply (t-1)	1.E+08							275.90 ***		0.00
								(6.81)		
OIB nHFT Demand (t-1)	1.E+08				5.25		0.00			
					(0.02)					
OIB nHFT Supply (t-1)	1.E+08							-17.23		0.00
								(0.23)		
Pseudo R ²		6.33%			6.39%			6.43%		

Table 9 Drivers of price jumps size

The table is a panel regression with fixed effects on jump intervals. The dependent variable is the High Low during the 10-second jump interval. The independent variables are defined such as in Table 1. We report the results for the permanent / transitory cutoff. The Table shows the parameter estimates as well as their t-stat. ***, **, * mean respectively that the parameter is significant at 99%, 95% and 90%.

Panel A: Permanent Jumps	Scaling	Coef.	Coef.	Coef.
High Low (t-1)	1.E+03	249.43 *** (8.35)	253.80 *** (8.49)	253.84 *** (8.47)
Return (t-1)	1.E+03	9.20 (0.59)	17.61 (1.05)	18.59 (1.12)
Squared Return (t-1)	1.E+03	277.34 *** (4.08)	250.16 *** (3.54)	245.40 *** (3.49)
Share Volume (t-1)	1.E+08	0.40 (1.51)	0.29 (1.07)	0.25 (0.91)
\$ Volume (t-1)	1.E+09	-0.45 *** (2.73)	-0.44 *** (2.57)	-0.42 ** (2.47)
\$ Volume (t)	1.E+09	0.47 *** (3.29)	0.46 *** (3.10)	0.46 *** (3.10)
Spread (t-1)	1.E+01	-0.27 (0.32)	-0.27 (0.32)	-0.27 (0.32)
Depth (t-1)	1.E+06	-2.73 *** (2.81)	-2.91 *** (2.97)	-2.71 *** (2.83)
OIB HFT (t)	1.E+08	0.58 (0.64)		
OIB HFT Demand (t)	1.E+08		1.94 * (1.70)	
OIB HFT Supply (t)	1.E+08			-0.67 (0.56)
OIB nHFT Demand (t)	1.E+08		0.40 (0.67)	
OIB nHFT Supply (t)	1.E+08			-0.41 (0.53)
OIB HFT (t-1)	1.E+08	0.79 (1.49)		
OIB HFT Demand (t-1)	1.E+08		0.10 (0.15)	
OIB HFT Supply (t-1)	1.E+08			0.37 (0.60)
OIB nHFT Demand (t-1)	1.E+08		-0.55 *** (3.17)	
OIB nHFT Supply (t-1)	1.E+08			0.54 ** (2.08)
Adjusted R ²		76.03%	76.17%	76.12%

Panel B: Transitory Jumps	Scaling	Coef.	Coef.	Coef.
High Low (t-1)	1.E+03	248.64 (1.22)	261.09 (1.18)	255.90 (1.16)
Return (t-1)	1.E+03	-404.83 *** (2.73)	-414.54 ** (2.41)	-413.21 ** (2.50)
Squared Return (t-1)	1.E+03	7142.05 (0.71)	5900.05 (0.51)	6542.70 (0.60)
Share Volume (t-1)	1.E+08	0.13 (0.11)	-0.22 (0.13)	-0.33 (0.19)
\$ Volume (t-1)	1.E+09	-0.34 (0.73)	-0.25 (0.44)	-0.21 (0.46)
\$ Volume (t)	1.E+09	1.02 ** (2.16)	0.96 ** (2.08)	0.88 * (1.90)
Spread (t-1)	1.E+01	-1.20 (1.19)	-1.21 (1.21)	-1.22 (1.21)
Depth (t-1)	1.E+06	-2.75 (0.87)	-1.44 (0.41)	-2.73 (0.80)
OIB HFT (t)	1.E+08	-0.45 (0.13)		
OIB HFT Demand (t)	1.E+08		0.26 (0.11)	
OIB HFT Supply (t)	1.E+08			-20.68 (0.99)
OIB nHFT Demand (t)	1.E+08		2.88 (0.77)	
OIB nHFT Supply (t)	1.E+08			-0.24 (0.08)
OIB HFT (t-1)	1.E+08	-0.13 (0.06)		
OIB HFT Demand (t-1)	1.E+08		-1.37 (0.28)	
OIB HFT Supply (t-1)	1.E+08			-8.60 (1.12)
OIB nHFT Demand (t-1)	1.E+08		-0.03 (0.02)	
OIB nHFT Supply (t-1)	1.E+08			1.86 (0.76)
Adjusted R ²		81.84%	81.94%	82.47%

Table 10 HFT profits jumps (in dollars)

The Table exhibits the mean US dollar HFT profit around all jumps, permanent and transitory jumps. The profit is computed as the realized profit during the interval plus the flattening of the net position valued at the mid-quote at the end of the 10-second interval. The amount reported are the means and their t-value. ***, **, * mean respectively that the profit is significant at 99%, 95% and 90%.

Panel A: All Jumps	t-2	t-1	T	t+1	t+2
HFT All	-1371.69 (0.66)	-1390.30 (1.49)	-1655.59 * (1.9)	-826.69 (0.96)	112.33 (0.16)
HFT Demand	1081.96 (0.92)	-23.26 (0.1)	-537.51 (0.79)	-333.14 (0.57)	67.28 (0.13)
HFT Supply	-2453.64 (1.6)	-1367.04 (1.77)	* -1118.08 (2.27)	** -493.55 (0.88)	45.05 (0.1)
nHFT All	1371.69 (0.66)	1390.30 (1.49)	1655.59 * (1.90)	826.69 (0.96)	-112.33 (0.16)
nHFT Demand	2453.64 (1.60)	1367.04 (1.77)	* 1118.08 (2.27)	** 493.55 (0.88)	-45.05 (0.10)
nHFT Supply	-1081.96 (0.92)	23.26 (0.10)	537.51 (0.79)	333.14 (0.57)	-67.28 (0.13)
Panel B: Permanent Jumps	t-2	t-1	T	t+1	t+2
HFT All	-3310.44 (1.18)	-637.16 (0.8)	-988.84 (1.27)	-981.63 (1.53)	405.15 (0.74)
HFT Demand	-408.04 (0.76)	10.92 (0.04)	-189.39 (0.6)	-280.35 (0.74)	108.75 (0.39)
HFT Supply	-2902.40 (1.2)	-648.08 (1.08)	-809.45 (1.34)	-701.28 (1.44)	296.41 (0.58)
nHFT All	3310.44 (1.18)	637.16 (0.80)	988.84 (1.27)	981.63 (1.53)	-405.15 (0.74)
nHFT Demand	2902.40 (1.20)	648.08 (1.08)	809.45 (1.34)	701.28 (1.44)	-296.41 (0.58)
nHFT Supply	480.04 (0.76)	-10.92 (0.04)	189.39 (0.60)	280.35 (0.74)	-108.75 (0.39)

Panel C: Transitory Jumps	t-2	t-1	T	t+1	t+2
HFT All	1708.18 (0.56)	-10787.94 (1.4)	-2477.69 (1.46)	-576.28 (0.29)	-376.99 (0.23)
HFT Demand	3448.93 (1.17)	-449.73 (0.84)	-973.27 (0.65)	-418.46 (0.3)	-2.01 (0.001)
HFT Supply	-1740.75 * (1.79)	-10338.20 (1.43)	-1504.42 * (1.86)	-157.82 (0.13)	-374.98 (0.42)
nHFT All	-1708.18 (0.56)	10787.94 (1.40)	2477.69 (1.46)	576.28 (0.29)	376.99 (0.23)
nHFT Demand	1740.75 (1.79)	10338.20 (1.43)	1504.42 * (1.86)	157.82 (0.13)	374.98 (0.42)
nHFT Supply	-3448.93 (1.17)	449.73 (0.84)	973.27 (0.65)	418.46 (0.30)	2.01 (0.00)