High Frequency Trading and Extreme Price Movements*

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Abstract: Endogenous liquidity providers (ELPs) are often viewed as unreliable in times of stress. We examine the activity of a common ELP type – high frequency traders (HFTs) – around extreme price movements (EPMs). We find that HFTs provide liquidity during EPMs and absorb imbalances created by non-high frequency traders (nHFTs). This relation is observed for various types of EPMs, including those resulting in permanent price changes and those that occur during the 2008 financial crisis. There is little evidence of HFTs causing EPMs; most EPMs are triggered by nHFTs. Despite the highly unusual circumstances, HFTs are profitable during the average EPM.

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1. Introduction

Since the 2008-09 financial crisis, the fragility of financial markets has been widely debated. The May 2010 Flash Crash amplified one of the aspects of this debate: the relation between extreme price movements (EPMs) and certain forms of electronic trading, namely 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). Given the importance of EPMs and the ubiquity of HFT in modern markets, we examine in detail the relation between EPMs and HFT.

Research generally finds that high frequency traders (HFTs) act as liquidity providers (Hasbrouck and Saar, 2013; Menkveld, 2013; Malinova, Park, and Riordan, 2014, Conrad, Wahal, and Xiang, 2015). Generally, the rise of HFT has been accompanied by a reduction in trading costs (Angel, Harris, and Spatt, 2011; Jones, 2013; Harris, 2013) and an increase in price efficiency (Brogaard, Hendershott, and Riordan, 2014; Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014). Despite these findings, many investors are concerned that HFT liquidity provision is selective and limited to periods of low stress. 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 seek to understand if there is any ground for such concerns.

Our main finding is that, on balance, HFTs lean against the wind by trading in the opposite direction of rapid extreme price movements and supplying liquidity to non-HFTs (hereafter nHFTs). This result is observed for a wide variety of market conditions: the 2008 financial crisis and the non-crisis periods, morning hours and the remaining hours of the day, and instances when EPMs occur in a single stock or simultaneously in several stocks. Furthermore, HFTs continue to supply liquidity even during the largest EPMs. Finally, HFTs supply liquidity both to the EPMs that eventually reverse and the EPMs that result in permanent price changes. As such, an average HFT trade during extreme price movements provides liquidity to aggressive, occasionally informed traders. It is important to note that HFTs do not act in a purely benevolent fashion during these events; we find that HFT liquidity demand also increases. Yet, the increase in liquidity supply is of a higher magnitude, resulting in a net increase in liquidity.

Although the data suggest that HFTs provide liquidity during the EPMs, it is possible (and often alleged) that HFTs trigger EPMs. To test this possibility, we examine the association between HFT activity and future EPMs. We find no positive relation between the two. In fact, in most settings HFT activity is associated with a lower probability of an EPM in the subsequent period. The instances when this relation does not hold are relatively rare episodes when HFTs contribute to development of EPMs that correct pricing errors.

About 57% of EPMs in our sample occur simultaneously in several stocks. For such EPMs (co-EPMs), capital constraints and reduced hedging opportunities may inhibit HFT liquidity provision. Kirilenko, Kyle, Samadi, and Tuzun (2015) show that during the 2010 Flash Crash – an event characterized by concurrent EPMs in a large number of assets – HFTs withdrew from liquidity provision. Our results also point to reduced HFT liquidity provision when EPMs occur in multiple stocks. Still, even during such episodes, HFTs often act as net providers of liquidity and rarely as net liquidity demanders.

Relatedly, capital constraints may make it more difficult for HFTs to trigger EPMs in a group of stocks rather than in one stock. As such, the abovementioned absence of a link between HFT and subsequent EPMs may be due to the fact that co-EPMs dominate the sample. However, we find no evidence that HFTs trigger either future single stock EPMs or co-EPMs.

Christensen, Oomen, and Podolskij (2014) show that large price movements usually develop over sequences of many trades. Our data corroborate this notion; an average EPM in our sample occurs over a sequence of 73 trades, about 58 of which involve HFT. If HFT algorithms were not designed to lean against the wind, technology would allow them to withdraw limit orders as EPMs develop. Given sufficient opportunities to withdraw and no obligation to stabilize prices (e.g., Bessembinder, Hao, and Lemmon, 2011), it may not be immediately clear why HFTs provide liquidity during EPMs.[1]

To better understand why HFTs supply liquidity to nHFTs during EPMs, we rely on the literature that examines arbitrage and contrarian liquidity provision strategies. Gromb and Vayanos (2002) show that by exploiting price discrepancies arbitrageurs may often act as intermediaries, in effect providing liquidity to other investors. In a recent model, Colliard (2015) studies arbitrageurs, who follow non-fundamental trading strategies. He shows that traders who invest significant resources in acquiring order flow information – a common HFT investment strategy – improve market resiliency by trading against large transitory price movements caused by order flow pressure. Nagel (2012) and So and Wang (2014) find that providing liquidity against transitory price movements that eventually reverse (contrarian liquidity provision) is a profitable strategy.

Two thirds of EPMs in our sample occur during large intraday price reversals (Figures 4a and 4b contain two stylized examples). Consistent with research on contrarian liquidity provision, we find that HFT profits are higher than usual on days when EPMs are related to

[1] See also N. Mehta, "SEC Questions Trading Crusade as Market Makers Disappear," Bloomberg, September 12, 2010 (http://goo.gl/IXdhbj).

reversals. Since such days dominate the sample, and since HFTs are likely unable to determine whether a developing EPM will reverse, HFT strategies appear to be optimally designed to provide liquidity to all EPMs. Consistent with this intuition, HFT profits are higher on the average EPM stock-day (even including the EPMs that bring permanent price changes) than on the average stock-day with no EPMs.

Our analysis generalizes the results of studies that examine the 2010 Flash Crash (e.g., Easley, Lopez de Prado, and O'Hara, 2012; Kirilenko, Kyle, Samadi, and Tuzun, 2015; and Menkveld and Yueshen, 2015). Rather than focusing on this single event, we examine more than 45,000 instances of EPMs in a number of stocks during a two year period. Importantly, our data include the 2008 financial crisis and non-crisis periods. As such, we capture the height of intraday volatility in financial markets as well as relatively normal market conditions.

We contribute to a growing literature that examines the behavior of HFTs and, more generally, endogenous liquidity providers (ELPs) – firms that engage in liquidity provision but have no market making obligations. On the one hand, many recent studies show that HFT is associated with improved liquidity (e.g., Menkveld, 2013; Hasbrouck and Saar, 2013; Brogaard and Garriott, 2015). On the other hand, a growing number of studies report that HFTs, and more generally ELPs, stop making markets during stressful periods when liquidity is most needed. Specifically, Raman, Robe, and Yadav (2014), Anand and Venkataraman (2015) and Korajczyk and Murphy (2015) report that HFTs and ELPs pull back when market conditions become unfavorable.

Kirilenko, Kyle, Samadi, and Tuzun (2015) show that during the 2010 Flash Crash, HFTs first provided liquidity but withdrew after prices across multiple assets declined precipitously. In a more general setting, van Kervel and Menkveld (2015) report that HFTs switch from liquidity provision to demand when they recognize trading patterns of large institutions, the trading behavior that Yang and Zhu (2015) call *back-running*. Our results alleviate some concerns with ELP liquidity provision; however, our analysis lacks a counterfactual. Specifically, we are unable to examine if a different kind of liquidity provider, such as a designated market maker, would be more beneficial during EPMs. We leave this issue to future research.

While the abovementioned studies question the reliability of HFT liquidity provision during the EPMs, other studies draw a more direct link from HFT activity to EPM occurrence. Golub, Keane, and Poon (2013) report that individual stock mini-crashes have increased in recent years and suggest a link between these crashes and HFT. Leal, Napoletano, Roventini, and Fagiolo (2014) model a market, in which HFT play a fundamental role in generating flash crashes. Media reports and industry commentary also often draw a causal link between HFT and EPMs. In October 2015, Timothy Massad, chair of the U.S. Commodities Futures Trading Commission (CFTC), expressed concern over sudden large price movements and linked them to high-speed computerized trading.[2] Commentary on the market disruption that occurred on August 24, 2015 also point to HFT involvement.[3] Although our sample does not contain this disruption, our results provide a counterargument to claims that HFTs are involved in generating and exacerbating extreme price movements.

[2] "US regulator signals bid to curb high-speed trading," by Gregory Meyer and Joe Rennison, Financial Times, October 21, 2015.

[3] "Human traders can still beat computers," by Henny Sender, Financial Times, September 14, 2015; "Aggressive HFT and institutional trading activity – Who leads market crashes?" by Steve Krawciw and Irene Aldridge, Traders Magazine Online News, October 1, 2015.

2. Data, EPM detection and summary statistics

2.1. HFT data

The HFT data come from NASDAQ and span two years: 2008 and 2009. These data have been previously used by Carrion (2013), Brogaard, Hendershott, and Riordan (2014), and O'Hara, Yao, and Ye (2014), among others. For each trade, the dataset contains an indicator for whether an HFT or an nHFT participates on the liquidity-supplying or the liquidity-demanding side of a trade. When preparing the data, NASDAQ identified 26 firms that act as independent HFT proprietary trading firms based on its knowledge of the firm's activity. A firm is identified by NASDAQ as an HFT if it trades frequently, holds small intraday inventory positions, and ends the day with a near zero inventory.

The data are well-suited to answer our research question in that they allow us to directly observe HFT liquidity provision and demand. This said, the data have some limitations, and as such our results should be interpreted with caution. First, large firms, such as investment banks, may use the same accounts for both high- and low-frequency activity. Such accounts are conservatively labelled nHFT by NASDAQ. Consequently, HFT flags observed in the data identify firms, for which high frequency trading is the only (or the primary) line of business. Second, the dataset is limited to trades occurring on NASDAQ. Although trades on NASDAQ make up 30-40% of all trading activity in our sample, there is a possibility that during EPMs HFTs provide liquidity on NASDAQ while taking it from the other markets. We are unable to refute this possibility. Nonetheless, we believe that such liquidity transfer is unlikely as it implies that liquidity provision on NASDAQ is systematically more attractive than it is on other venues, which is not likely to be the case during our sample period.

Our data cover a relatively remote time period; however, this period is unique as it includes several months of exceptionally high volatility during the 2008 financial crisis. As such, the data allow us to examine HFT behavior during times of considerable market stress as well as during more normal times. Furthermore, by 2008 the HFT industry had largely matured, therefore our results are applicable to today's market.

Finally, we note that our data do not allow us to observe activities of individual firms. Some of these firms may primarily demand liquidity during EPMs, while others may supply it. Although we are unable to shed light on individual HFT behavior, our data are uniquely useful to understand the net effects of HFT.

2.2. EPM identification

We identify EPMs as extreme changes in the National Best Bid and Offer (NBBO) midquotes. We derive the midquotes from the NYSE Trade and Quote database (TAQ) after adjusting the data according Holden and Jacobsen's (2014) recommendations. Specifically, we (i) interpolate the times of trades and the times of NBBO quotes within a second, (ii) adjust for withdrawn quotes, and (iii) delete locked and crossed NBBO quotes as well as trades reported while the NBBO is locked or crossed. To avoid focusing on price dislocations that may be caused by market opening and closing procedures, we only consider trading activity between 9:35 a.m. and 3:55 p.m.

Using the filtered TAQ midquotes, we compute 10-second absolute midquote returns. The choice of the 10-second sampling frequency is based on two offsetting considerations. On the one hand, detecting EPMs that result from brief liquidity dislocations requires a relatively short sampling interval. On the other hand, a sampling interval that is too short may split an EPM into several moderate price changes not large enough to be captured by our identification procedure. The choice of 10-second intervals is a compromise between these two considerations. As a robustness check, the main analyses are repeated for several alternative interval lengths: 1 second, 5 seconds, 30 seconds, and 1 minute. The results are similar.

The NASDAQ HFT dataset contains 120 stocks divided into three size categories: large, medium, and small, with 40 stocks in each category. Medium and small stocks trade rather infrequently, and there are usually insufficient observations to draw statistically robust conclusions about HFT and nHFT activity during our relatively short sampling intervals. The analysis therefore focuses on the 40 largest stocks. In a similar application, and driven by similar considerations, Andersen, Bollerslev, Diebold, and Ebens (2001) also focus on the largest stocks when detecting EPMs. The sample of 40 largest stocks contains over 45.4 million 10-second intervals.

We use two techniques to identify EPMs. The main technique defines an EPM as an interval that belongs to the 99.9th percentile of 10-second absolute midpoint returns for each stock. That is, out of 45.4 million 10-second intervals, we label 45,406 intervals with the largest returns as EPMs. The intuitive nature of the 99.9 technique is appealing, but the technique has two limitations. First, the 99.9 cutoffs are stock-specific and as such implicitly assume that each stock is equally likely to undergo an EPM. As such, the 99.9 technique may (over-) under-sample stocks that are (less) more prone to EPMs. The second limitation is that the technique evaluates price changes regardless of volatility conditions. As such, the technique tends to oversample periods of high volatility. We note that understanding HFT behavior around EPMs is relevant regardless of whether the EPM is accompanied by high volatility. Nevertheless, to formally address this limitation, we repeat the analysis using a second EPM detection technique, the Lee and Mykland's (2012) (LM) methodology. The results obtained using this methodology are similar to those from the 99.9 technique.[4]

2.3. Summary Statistics

Table 1 reports the descriptive statistics for the sample of 45,406 EPMs in Panel A and, for comparison, the full sample of 10-second intervals in Panel B. The statistics expectedly show that returns, trading activity, and spreads are considerably larger during the EPMs than during an average 10-second period. The average absolute EPM return is 0.484%, which is more than 17 times (or more than 10 standard deviations) larger than the full-sample return. Trading activity is also substantially higher; increasing from 18 trades per 10 seconds to 73 trades. Dollar trading volume increases from $76,285 to $473,232, and share volume increases by a similar magnitude. Finally, the quoted and relative spreads nearly double during EPMs.

In both the 99.9 and LM samples, the number of positive EPMs is approximately equal to the number of negative EPMs. In untabulated results, we find that EPM characteristics such as the absolute return magnitude, trading volume, and quoted spreads are similar for positive and negative EPMs. HFT and nHFT behavior is also similar. As such, results reported in the remainder of this manuscript combine positive and negative EPMs.

INSERT TABLE 1 ABOUT HERE

Figures 1 and 2 report the time series EPM distributions. Figure 1 reports the intraday frequency of EPMs, with 53.8% of the events occurring in the first hour of trading. This pattern is consistent with studies that document relatively high price volatility and information

[4] In unreported results, we find that returns in the 99.9th percentile closely correspond to the 99.9th percentile of trade imbalances. As such, EPM identification that focuses on the largest trade imbalances rather than the largest returns produces a very similar sample.

uncertainly in the morning hours (Chan, Christie, and Schultz, 1995; Egginton, 2014). The remaining EPMs are distributed relatively evenly throughout the day, with a moderate spike near the end of the day. Figure 2 plots the daily frequency of EPMs during the 2008-2009 sample period. Most of the EPMs in our sample (65.1%) occur during the months of September, October, and November of 2008, the height of the financial crisis.

INSERT FIGURES 1 AND 2 ABOUT HERE

3. HFT and nHFT activity around EPMs

3.1. A typical EPM

To measure HFT activity during EPMs, we use directional trade imbalances computed as the difference between trading activity in the direction of the EPM and trading activity in the opposite direction: $HFT^{D} = HFT^{D+} - HFT^{D-}$ and $HFT^{S} = HFT^{S+} - HFT^{S-}$, where HFT^{D} is HFT liquidity demand, HFT^{S} is HFT liquidity supply, and the superscripts + (-) indicate activity in the same (opposite) direction of the EPM return. For example, if HFTs demand liquidity in 20 shares in the direction of the price movement and demand 1 share in the opposite direction, HFT^{D} is +19 (=20-1). Similarly, if HFTs supply liquidity in 20 shares against the direction of the EPM and supply 4 shares in the direction of the price movement, HFT^{S} is -16 (=-20+4). For nHFTs, we compute similar metrics.

In addition, we introduce two imbalance metrics, HFT^{NET} ($nHFT^{NET}$) computed as the sum of HFT^{D} and HFT^{S} ($nHFT^{D}$ and $nHFT^{S}$) in each period. Since liquidity is typically provided against the direction of return, $(n)HFT^{S}$ usually has a negative value, and the sum of $(n)HFT^{D}$ and $(n)HFT^{S}$ is in effect the difference between liquidity demanding and liquidity providing volume. Net imbalances indicate the direction in which net trading activity by a particular trader type is occurring relative to the EPM direction. For example, a positive (negative) net HFT imbalance indicates overall trading in the direction (opposite) of the EPM.

We begin the discussion of HFT and nHFT activity around EPMs using graphical evidence. Figure 3 reports cumulative returns, CRET, as well as HFT^{D}, $nHFT^{D}$, and HFT^{NET} patterns starting 100 seconds prior to an average EPM and up to 100 seconds afterwards. We make the following expositional choices. First, the figure includes both positive and negative EPMs, and we invert the statistics for the latter. Second, we benchmark the signs for HFT and nHFT activity against the EPM return. For example, if the EPM return is positive, a negative HFT^{D} ten seconds after the EPM, as in Figure 3, means that HFTs sell the stock via liquidity demanding orders, effectively counteracting the effects of the positive extreme price movement that occurred ten seconds earlier.

Prices are generally flat prior to an EPM, then change significantly during the EPM interval, and then revert somewhat during the remaining 100 seconds (10 intervals). There is a small increase in $nHFT^{D}$ in the intervals prior to the EPM, followed by a large increase during the EPM interval with a share imbalance of more than 5,500. The increase is in the direction of the EPM. In the meantime, HFT^{D} increases considerably less prior to the EPM. During the EPM, HFT^{D} is a little over 2,000 shares. As such, nHFTs demand considerably more liquidity than HFTs during EPMs, suggesting that HFTs are unlikely to be the main culprit.

INSERT FIGURE 3 ABOUT HERE

HFT^{NET} is negative during EPMs, suggesting that increased HFT liquidity supply more than offsets the increased HFT liquidity demand noted above and that HFTs partly absorb the trade imbalances created by nHFTs.[5] We note that although HFT^{NET} dampens EPMs, HFT^{D} is

[5] The net imbalance metrics are designed so that HFT^{NET}=-$nHFT^{NET}$.

in the direction of the price movement. Put differently, just like nHFTs, HFTs execute trades in the direction of EPMs and demand liquidity while doing so. On balance however, HFT activity is liquidity providing and counteracts the net activity of nHFTs, who execute substantial volume in the direction of EPMs.

The results in Figure 3 provide suggestive evidence on trading activity of HFTs and nHFTs around EPMs, but they lack detail on liquidity supply and are silent on issues of statistical significance. To shed more light on these issues, in Table 2 we examine the time windows around EPMs in more detail. We find that HFT^{NET} is statistically significant in the opposite direction of return during interval t (the EPM interval) and the two following intervals. Further, upon splitting HFT activity into demand and supply, we observe that HFTs trade in the direction of the EPM with their liquidity demanding trades (HFT^{D} is 2,215 shares) and in the opposite direction with their liquidity supplying trades (HFT^{S} is 2,515 shares). As such, HFTs provide about 300 shares of net liquidity against the direction of an average EPM. This finding is contrary to the widely held belief that HFTs trade large amounts in the direction of EPMs.

In the meantime, $nHFT^{NET}$ is statistically significant in the direction of the EPM, as nHFTs take the 300 shares of liquidity provided by HFTs. As in the case with HFTs, nHFTs both demand and provide liquidity, but their demand is relatively stronger. Overall, the results are consistent with the notion that, on balance, HFTs stabilize the markets during EPMs, whereas nHFTs exacerbate EPMs.

INSERT TABLE 2 ABOUT HERE

HFT and nHFT activity prior to and following the EPM intervals requires a separate discussion. In the 10-second interval starting 20 seconds prior to the EPM interval, HFT and nHFT trades do not show any directionality. However, during the 10 seconds prior to an EPM, HFTs trade in the direction of the future EPM return and demand 46 shares more than they supply.[6] Although the t-10 return is rather unremarkable (Figure 3), it appears that HFTs may play a role in triggering subsequent EPMs. In the following section, we show that this result comes from relatively rare instances when EPMs represent rapid pricing error corrections. For the majority of EPMs however, there is no evidence of price pressure from HFTs prior to the EPM.

Following the EPM, HFTs continue to trade in the opposite direction of the EPM return, but, unlike in interval t, they primarily use liquidity demanding trades. Specifically, HFTs demand a net of 122.5 shares and 42.7 shares against the direction of the preceding EPM return in intervals t+10 and t+20. From Figure 3, we know that on average the EPM return reverses in intervals t+10 and t+20, and as such the negative sign of HFT^{NET} means that HFTs speed up the reversal.

3.2. EPM types: reversals and permanent price changes

We divide the sample EPMs into three distinct types. Two of these are related to transitory price dislocations, and the third captures permanent price movements. The first type includes EPMs characterized by significant, yet temporary, price changes followed by reversals (Figure 4a). We refer to such EPMs as *transitory* and identify them as EPMs that revert by more than 2/3 of their original return by the end of the trading day. Transitory EPMs are the most commonly observed and represent 48% of the sample, yet they are perhaps the least desirable and arise from episodes of insufficient liquidity supply, the arrival of false news, or overreaction.

[6] In this table, as in Figure 3, we benchmark the signs of HFT and nHFT volume against the EPM return.

INSERT FIGURE 4 ABOUT HERE

The second type includes EPMs that are themselves reversals of the earlier price movements and therefore may be viewed as corrections of pricing errors (Figure 4b). We refer to such EPMs as *corrective* and identify them as those that revert the return cumulated since the market open by more than 2/3. This type is the least common, representing 19% of EPMs.

Finally, the third EPM type includes price movements that likely result from the arrival of new information (Figure 4c). We refer to such EPMs as *permanent* and identify them as extreme price movements that do not reverse by more than 1/3 by the end of the day. Permanent EPMs represent 33% of all EPMs, and rapid information incorporation during such price movements is a characteristic of an efficient market. We note that our identification procedure excludes EPMs that revert by the amount between 1/3 and 2/3 of the EPM return to allow for a clean separation between permanent and transitory EPMs. This exclusion reduces the number of EPMs by 2.74% compared to the number reported in Panel A of Table 1. The results are unchanged when we include the omitted EPMs. The results are also robust to using alternative reversal thresholds and alternative intraday time periods.

Separating EPMs into those related to price reversals and those related to permanent price changes is important to understand HFT behavior. Providing liquidity during price reversals is often profitable, especially if such activity is well-timed (Hendershott and Seasholes, 2007; Nagel, 2012; So and Wang, 2014). In the meantime, providing liquidity during permanent price movements may not be in the traders' best interests as the adverse price impacts are likely to be higher than the spread revenue, especially for the large permanent EPMs. If HFTs can distinguish between transitory and permanent EPMs, they should provide liquidity during the former and withdraw during the latter. Alternatively, if HFTs are unable to recognize the EPM type at the outset, their behavior for both types should be similar. In this case, whether they provide liquidity to an average EPM will depend on the expected profitability of doing so. Given that only 33% of EPMs are permanent, it is possible that providing liquidity to an average EPM is profitable. We address this issue in detail in a subsequent section.

In Tables 3 and 4, we examine the characteristics of the three EPM types as well as HFT and nHFT activity around them. Despite a significant difference in price patterns described in Figure 4, returns, trading activity, HFT participation, and spreads are notably similar across the three EPM types. For instance, the average absolute return is 0.486% during a transitory EPM, 0.479% during a corrective EPM, and 0.483% during a permanent EPM. The dollar volumes and spreads are also quite similar; dollar volumes do not vary by more than 1.5%, and realized spreads do not vary by more than 3.9% across the three EPM types. In untabulated results, we also show that the three EPM types look similar in intervals t-20 and t-10, reinforcing our earlier suggestion that EPM types are not easily distinguishable in real time.

Table 4 shows that HFT and nHFT activity is often similar during different EPM types, with some noteworthy exceptions. First, for each EPM type, we find evidence that HFTs provide liquidity to nHFTs in period t, and that on balance HFT activity is opposite to the EPM direction. Second, HFTs continue to trade against the direction of both transitory (Panel A) and permanent (Panel C) EPMs in period t+10, consistent with the notion that they are unable to distinguish between permanent and transitory price movements even over time horizons of 10-20 seconds. Finally, as we mention in the previous section, there is evidence that in period t-10 HFTs aggressively trade in the direction of corrective EPMs (Panel B). Consistent with Brogaard, Hendershott, and Riordan (2014), such trading should improve price efficiency. This said, despite demanding liquidity in the direction of the future corrective EPMs, HFTs supply liquidity to these EPMs during interval t. This result is likely attributable to the fact that our

HFT sample contains different types of algorithms, some of which may execute arbitrage strategies, while others follow market making strategies.

INSERT TABLES 3 and 4 ABOUT HERE

3.3. EPM types: standalone and co-EPMs

In addition to the three EPM types identified in the previous section, we categorize EPMs into two types according to the timing of their occurrence relative to EPMs in other stocks. Specifically, we define *co-EPMs* as those that occur in two or more stocks during the same 10-second time interval. The remaining EPMs are defined as *standalone*. As we mention previously, given capital constraints and hedging considerations, we expect that HFTs may provide less liquidity during co-EPMs.

Table 5 reports that the sample consists of 43% standalone EPMs and 57% co-EPMs. The prevalence of co-EPMs should not be surprising given the exceptionally high EPM frequencies during the 2008 financial crisis when prices of multiple assets experienced large simultaneous movements (Figure 2). An average co-EPM contains 3.5 stocks. The average return is 0.491% during a standalone EPM and 0.479% during a co-EPM. Trading activity metrics are noticeably different between the two types, with dollar volume during the standalone EPMs about 75% higher than during the co-EPMs. The relative spreads are also somewhat higher during the standalone EPMs; 0.085 bps vs. 0.076 bps for the co-EPMs.

INSERT TABLE 5 ABOUT HERE

3.4. Regression analysis

The univariate results discussed in the previous sections suggest that HFT behavior has a stabilizing effect on prices during EPMs. Next, we test this notion in a multivariate setting that takes into account different EPM types, magnitudes, and times of occurrence as well as firm fixed-effects, contemporaneous and lagged returns, volume, and spreads:

$$HFT^{NET}{}_{it} = \alpha + \beta_1 1_{EMP_{it}} + \beta_2 Ret_{it} + \beta_3 Vol_{it} + \beta_4 Spr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (1)$$

where HFT^{NET} is the difference between HFT^D and HFT^S as discussed earlier; $1_{EPM\,it}$ is a dummy variable equal to one if the 10-second interval t in stock i is identified as an EPM and is equal to zero otherwise, Ret_{it} is the absolute return, Vol_{it} is the traded share volume, Spr_{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 $\sigma \in \{1, 2, \ldots, 10\}$ and the variables indexed with a subscript k. All variables are standardized at the stock level to allow for comparability across stocks.

The estimated coefficients confirm the univariate results. In column 1 of Table 6, the estimated coefficient on the 1_{EPM} dummy suggests that HFTs trade in the opposite direction of extreme price movements, with the net liquidity provision by HFTs being 0.818 standard deviations higher during the EPM episodes. The coefficients of the control variables are consistent with earlier studies and indicate that, in normal times, HFTs demand liquidity in the direction of contemporaneous return and demand more liquidity when volume is high. Furthermore, HFT liquidity provision increases when spreads widen, as indicated by the negative coefficient of the Spr variable.

INSERT TABLE 6 ABOUT HERE

Having established the basic result, we next turn to examining HFT activity during the previously identified EPM types. The results in column 2 confirm that HFTs provide liquidity during all three EPM types: transitory, corrective, and permanent. More specifically, HFTs provide similar amounts of liquidity to transitory and permanent EPMs (HFT^{NET} is -0.851 and -0.833 standard deviations away from the norm), corroborating the notion that they are unable to distinguish between these EPM types in real time. The magnitude of liquidity provision to the corrective EPMs is lower, the estimated coefficient on $1_{EPM\text{-}CORRECTIVE}$ is -0.688. Given that our univariate results suggest that HFTs may occasionally trigger corrective EPMs, lower liquidity provision to these EPMs is not surprising.

In column 3, we examine liquidity provision to standalone and co-EPMs. Here again, we find that HFTs provide liquidity to both EPM types, although more liquidity is provided to the standalone EPMs; the coefficient on $1_{EPM\text{-}STANDALONE}$ is -1.441, while the coefficient on $1_{CO\text{-}EPM}$ is only -0.328. These results are expected since HFT capital constraints and reduced hedging opportunities are more pronounced when correlations between individual stock returns are high.

The notion of lower liquidity provision during the times when return commonality is high is also supported in column 4, where we examine HFT behavior during the financial crisis. We find that HFTs provide liquidity to both the EPMs that happened during the crisis and those that happened during the non-crisis months. Still, the liquidity provision during the crisis is notably lower; the coefficient on $1_{EPM\text{-}CRISIS}$ is only -0.538, whereas the coefficient on $1_{EPM\text{-}NON\text{-}CRISIS}$ is -1.371.

In column 5, we ask if HFTs provide less liquidity to the EPMs that happen during the morning hours. Since information asymmetries are often high in the morning, HFTs' willingness to intermediate may be reduced. The results do not support this notion; HFT liquidity provision is similar for the EPMs that occur in the first hour of trading and during the rest of the day; the coefficient on $1_{EPM\text{-}MORNING}$ is -0.832, whereas the coefficient on $1_{EPM\text{-}day}$ is -0.805.

Although the EPMs in our sample represent the 99.9th percentile of all price movements, some readers may be concerned that our setup may obscure the effects for largest EPMs, for which HFT activity may differ from what has been discussed so far. After all, Kirilenko et al. (2015) show that when prices reached extraordinary low values during the Flash Crash, HFTs withdrew liquidity. We address this concern in column 6 by separating EPMs into quartiles by magnitude, where Q1 represents the smallest EPMs and Q4 – the largest. The data show that HFTs trade consistently in the opposite direction of EPMs across all magnitude quartiles. Furthermore, the coefficient on HFT^{NET} for the largest EPMs is twice the coefficient for the smallest.

In Panels B through D, we expand eq. 1 analysis to sub-samples of transitory, corrective, and permanent jumps. The results confirm our previous findings; HFTs provide liquidity to nHFTs during EPM episodes of all three types during both crisis and non-crisis periods, during all hours of the day, and for EPMs of all magnitudes. The only difference between the sub-sample results and those in Panel A is the lack of evidence of liquidity provision to corrective and permanent co-EPMs.

3.5. HFT-return relation

The results in the previous section suggest that HFTs provide liquidity during EPMs, but they do not provide much clarity on the effect of net HFT activity on EPM magnitude. To add clarity to this issue and to establish a baseline for the subsequent analyses of returns, we estimate the following fixed effects model:

$$Ret_{it} = \alpha + \beta_1 HFT^{NET}{}_{it} + \beta_2 HFT^{NET}{}_{it} * 1_{EPM_{it}} + \beta_3 1_{EPM_{it}} + \beta_4 Spr_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (2)$$

where all variables are as previously defined, and HFT^{NET} is interacted with the dummy variables that proxy for various EPM types to examine possible differences in return effects. The estimated coefficients are reported in Table 7.

INSERT TABLE 7 ABOUT HERE

The results show that during normal times returns are positively correlated with HFT^{NET}, consistent with the results of Brogaard, Hendershott, and Riordan (2014), who show that HFTs usually trade in the direction of prices. This said, during EPMs returns are negatively correlated with net HFT activity, consistent with the notion that HFTs dampen EPMs. This result holds for the full EPM sample as well as for most subsamples; transitory, corrective, and permanent; crisis and non-crisis; morning and day; and standalone and co-EPMs. The only instance where the relation between HFT^{NET} and return is insignificant is for the transitory co-EPMs. We also note that even though the earlier analysis finds no evidence of an increase in HFT liquidity provision during corrective and permanent EPMs, Table 7 reports a dampening effect on returns even during these EPM types.

3.6. HFT-return relation within the 10-second intervals

Some readers may be concerned that the 10-second event windows used thus far are too wide and therefore may conceal higher frequency HFT activity that exacerbates EPMs. Such concerns are worth examining, especially in light of the results of van Kervel and Menkveld (2015), who show that HFTs are able to recognize trading patterns after a period of time and switch from supplying liquidity to demanding it. As such, even though HFTs tend to supply liquidity during EPMs on average, they may exacerbate the tail ends of EPMs.

To examine this possibility, in Figure 5 we plot second by second cumulative returns, HFT, and nHFT activity centered on the largest one-second return during an average EPM. The figure shows that prices continue to move in the direction of the largest return for several seconds afterwards. As such, if HFT algorithms were designed to switch from liquidity supply to demand after observing large price changes, they would have sufficient time to do so. The figure however contains no evidence of HFT^{NET} switching to positive values. If anything, net HFT remains slightly negative for up to five seconds after the largest return, consistent with continuing liquidity provision.

INSERT FIGURE 5 ABOUT HERE

Figure 5 shows that both $nHFT^{D}$ and HFT^{D} increase several seconds prior to the largest return, with $nHFT^{D}$ increasing substantially more than HFT^{D}. Despite an increase in HFT^{D}, net HFT is either zero or negative, suggesting that HFTs do not trigger the largest returns. To examine this issue in a more rigorous setting, we expand the base regression model described in eq. 2 to the second by second setting as follows:

$$Ret_{it} = \alpha + \beta_1 HFT^{NET}{}_{it} + \beta_2 HFT^{NET}{}_{it-1} + \beta_3 HFT^{NET}{}_{it-2} + \beta_4 Spr_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it}, \quad (3)$$

where all variables are as previously defined, and the subscript t denotes the one-second with the highest return during an EPM. The model is estimated with ten lags of the dependent and independent variables and, by construction, examines the HFTs' role in triggering the largest return during the EPM episodes.

The results are reported in Table 8 and contain no evidence of HFT involvement in triggering or exacerbating the largest returns. In the full sample (Panel A), a one standard deviation increase in HFT^{NET} is associated with a return that is 0.097 standard deviations less extreme, suggesting a stabilizing effect. This result is consistent across all EPMs, although we observe some variation across the sub-types. Specifically, net HFT activity has a more stabilizing effect on returns during the non-crisis period, during non-morning hours, and for the standalone EPMs. We note that because $nHFT^{NET} = -HFT^{NET}$, these results imply that nHFT activity exacerbates the largest EPM returns.

Further, for most EPM sub-types (22 out of 28 specifications), there is evidence that HFT activity one second prior to the largest return reduces the magnitude of this return (by 0.035 standard deviations in the full sample). Nevertheless, this lagged relation quickly dissipates; HFT activity two seconds away from the largest return is only significant in 1 out of 28 specifications, and HFT activity three or more seconds away is never significant and therefore not tabulated.

INSERT TABLE 8 ABOUT HERE

3.7. HFT activity and future EPMs

Although the data do not support the notion that HFTs exacerbate the largest EPM returns, these returns often do not represent the entirety of the EPM. As such, some readers may remain concerned that HFTs trigger EPMs by applying pressure to prices. To shed some light on this issue, in Table 9 we return to 10-second intervals, which better capture EPMs in their entirety, and use probit regressions to model the probability of EPM occurrence.

The results show no evidence of HFT^{NET} being associated with a higher probability of future EPMs. Rather, the -0.008 value of the marginal effect of HFT^{NET} in the full sample (Panel A) suggests that the probability of an EPM decreases by 0.8% of the unconditional probability with every standard deviation increase in pre-EPM HFT^{NET}. As previously, this result is more pronounced during the non-crisis period, during the day, and for the standalone

EPMs. We note that the probit analysis does not confirm the earlier result that HFTs trigger corrective EPMs, although this EPM sub-type is the only one for which HFT is not a statistically significant EPM deterrent.

INSERT TABLE 9 ABOUT HERE

3.8. Profitability of liquidity provision during EPMs

The results in the earlier sections suggest that HFTs provide liquidity to aggressive, occasionally informed traders during extreme price movement episodes. Some of these episodes (transitory and corrective EPMs) are related to price movements that reverse by the end of the trading day. Providing liquidity during such episodes may be profitable, as the growing literature on contrarian liquidity provision (e.g., Hendershott and Seasholes, 2007; Nagel, 2012; So and Wang, 2014) suggests that a skillful market maker may earn larger profits on volatile days than on days when prices are relatively flat.

Although it may be possible to profit by providing liquidity to reversal-related EPMs, liquidity provision to permanent EPMs is likely to result in losses. Earlier, we note that HFTs are likely unable to differentiate between permanent and non-permanent EPMs; however, since permanent EPMs are relatively rare, and since liquidity provision to the non-permanent EPMs is likely profitable, HFT algorithms may be designed to lean against the wind for all EPMs.

To shed some light on this possibility, we estimate HFT trading revenues on days when EPMs occur and compare them to the days without EPMs. We follow the approach used by Sofianos (1995), Menkveld (2013), and Brogaard, Hendershott and Riordan (2014) and assume that for each sample stock and each day, HFTs start and end the day with zero inventories, and that all inventory accumulated by the end of the day is sold at the closing midpoint. We then compute the revenue from HFT for each stock and each day as:

$$\pi HFT = -\sum_{n=1}^{N} HFT_n \times I \times P_n + invHFT_N \times P_N, \tag{4}$$

where HFT_n is the number of shares traded by HFTs during the n^{th} transaction, I is the indicator equal to 1 for buy trades and -1 for sell trades, P_n is the trade price, $invHFT_N$ is the inventory accumulated through HFT trades by the end of the day, and P_N is the end of day midquote. We adjust transaction prices by the taker fee of 0.00295 and the maker rebate of 0.0028, although the results are robust to other levels of maker-taker fees and to omitting the fees. Overall, the first term of eq. 4 represents cash flows throughout the day, and the second term assigns a value to the end-of-day inventory.

To assess the impact of EPMs on daily HFT revenues, we estimate the following panel for each stock i on day t:

$$\pi HFT_{it} = \alpha + \beta_1 nTransitory_{it} + \beta_2 nCorrective + \beta_3 nPermanent + \varepsilon_{it}, \tag{5}$$

where $nTransitory$, $nCorrective$, and $nPermanent$ are count variables that capture the number of EPMs of each sub-type on day i. An additional specification replaces the count variables for the sub-types with a single count variable, $nEPM$, for all EPMs.

The results are reported in Table 10, with the intercept in Panel A showing that the average HFT revenue on days without EPMs is \$3,498. Consistent with contrarian liquidity provision, the average revenue is higher on days with transitory and corrective EPMs, by respectively \$2,084 and \$2,738. In the meantime, the revenue is lower by \$4,378 on days with permanent EPMs. Even though the losses on days with permanent EPMs are substantial, Panel

B shows that the incremental revenue from providing liquidity to an average EPM is $274. As such, HFT liquidity-providing behavior during EPMs is likely profitable.[7]

4. Conclusion

In this study, we show that high frequency traders (HFTs) provide liquidity to non-high frequency traders (nHFTs) during extreme price movement (EPM) episodes. During EPMs, returns are about 17 times larger than normal, accompanied by exceptionally high trading volume. Prices often revert to their previous levels after EPMs, following the so called *flash crash* patterns often mentioned in the popular press as a negative feature of modern markets.

By providing liquidity to EPMs, HFTs perform a stabilizing function, a behavior unexpected by industry participants and regulators, but hypothesized in the academic literature (e.g., Gromb and Vayanos, 2002; Colliard, 2015). HFT liquidity provision is observed for various types of price movements, including those resulting in permanent price changes, those occurring in the midst of the 2008 financial crisis, during the exchange opening hours, and occasionally even during periods when multiple stocks are undergoing simultaneous extreme price movements.

We find no evidence that HFTs cause or exacerbate EPM episodes. The data also contain no evidence of HFTs' withdrawing liquidity as EPMs develop or switching from liquidity provision to liquidity demand. These results somewhat alleviate concerns that arose after the 2010 Flash Crash, during which HFTs initially provided liquidity, but later began trading in the direction of the rapidly falling prices. Although the EPMs in our sample are not comparable to the magnitude and the systemic nature of the Flash Crash, the results suggest

[7] We note that the intercepts in Panels A and B are somewhat different due to a small difference in the samples sizes as discussed in 3.2.

that concerns about HFT liquidity provision should be limited to episodes of especially sizeable market-wide disruptions or crashes that are longer lived. Both of these features could cause HFTs to reach their inventory constraints and lead them to trade in the direction of EPMs to manage their overall level of risk.

At first glance, liquidity provision during EPMs may appear to be a losing strategy. After all, significant price movements associated with permanent EPMs carry significant adverse selection risk. We show however that permanent price movements comprise only 1/3 of all EPMs. The remaining 2/3 of EPMs exhibit price reversal patterns. A large literature on contrarian liquidity provision (e.g., Nagel, 2012; So and Wang, 2014) suggests that skillful market makers may benefit by providing liquidity to return reversals. Our results are consistent with this evidence. Specifically, we find that despite losing money on liquidity provision to the permanent EPMs, HFT make notably more on days when EPMs belong to reversal patterns. As such, a strategy that provides liquidity to all EPMs appears profitable.

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Table 1. Summary statistics

The table reports summary statistics for the sample of extreme price movements (EPMs) (Panel A) and for the full sample of 10-second intervals (Panel B). $Absolute\ Return$ is the absolute value of the 10-second midpoint return. $Total\ (HFT)\ Trades$ is the number of (HFT) trades during the interval. $Dollar\ Volume$ and $Share\ \ Volume$ are the total dollar and share volume traded during the interval. $Quoted\ Spread$ and $Relative\ Spread$ are quoted and relative quoted NBBO spreads, respectively in dollars and basis points. All statistics are averaged within the 10-second sampling intervals.

Panel A: Extreme price movements

	Mean	**Median**	**Std. Dev.**
Absolute Return, %	0.484	0.441	0.193
Total Trades	73.0	43.0	88.7
Total HFT Trades	57.6	33.0	73.2
Dollar Volume	473,232	171,158	1,024,504
Share Volume	15,595	5,431	31,734
Quoted Spread, $	0.046	0.016	0.147
Relative Spread, bps	0.080	0.065	0.148
N	45,406		

Panel B: Full sample

Absolute Return, %	0.028	0.009	0.048
Total Trades	18.1	11.0	18.7
Total HFT Trades	15.8	10.0	15.5
Dollar Volume	76,285	14,038	231,397
Share Volume	1,991	318	6,055
Quoted Spread, $	0.026	0.010	0.057
Relative Spread, bps	0.046	0.040	0.033
N	45.4 M		

Table 2. Liquidity supply and demand around EPMs

The table reports directional trading volume around extreme price movements. Time interval t is the 10-second interval, during which we observe an EPM. In addition, we report the results for the two time intervals preceding the EPM and two subsequent time intervals. HFT^{D} ($nHFT^{D}$) is the difference in liquidity-demanding HFT (nHFT) volume in the direction of the EPM and liquidity-demanding volume against the direction of the EPM. HFT^{S} ($nHFT^{S}$) is the difference in liquidity-providing volume against the direction of the EPM and liquidity-providing volume in the direction of the EPM. HFT^{NET} ($nHFT^{NET}$) is the difference between HFT^{D} and HFT^{S} ($nHFT^{D}$ and $nHFT^{S}$). p-values are in parentheses. *** and ** indicate statistical significance at the 1% and 5% levels.

	t-20	**t-10**	**t**	**t+10**	**t+20**
HFT^{NET}	1.5	45.7**	-299.3***	-122.5***	-42.7**
	(0.94)	(0.04)	(0.00)	(0.00)	(0.04)
HFT^{D}	30.6	163.4***	2215.2***	-279.0***	-99.1***
	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{S}	-29.1	-117.6***	-2514.6***	156.5***	56.4***
	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
$nHFT^{NET}$	-1.5	-45.7**	299.3***	122.5***	42.7**
	(0.94)	(0.04)	(0.00)	(0.00)	(0.04)
$nHFT^{D}$	75.3**	326.7***	5576.3***	672.4***	317.0***
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
$nHFT^{S}$	-76.8**	-372.5***	-5277.0***	-549.9***	-274.3***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3. Summary statistics; reversals and permanent price changes

The table reports summary statistics for three types of EPMs: transitory, corrective, and permanent. Transitory EPMs are those that revert by more than 2/3 of the EPM return by the end of the trading day. Corrective EPMs reverse the return cumulated since the market open by more than 2/3. Permanent EPMs are those that do not revert by more than 1/3 by the end of the trading day. Because we exclude EPMs that revert by the amount between 1/3 and 2/3, the total number of EPMs in this table is 2.74% lower than the number reported in Panel A of Table 1. The reported statistics are similar to those in Table 1.

Panel A: Extreme price movements – transitory

	Mean	Median	Std. Dev.
Absolute Return, %	0.486	0.442	0.195
Total Trades	72.81	43.0	89.07
Total HFT Trades	57.26	32.0	72.83
Dollar Volume	472,562	168,671	1,052,698
Share Volume	15,396	5,347	31,448
Quoted Spread, $	0.047	0.016	0.150
Relative Spread, bps	0.081	0.066	0.146
N	21,250		

Panel B: Extreme price movements – corrective

	Mean	Median	Std. Dev.
Absolute Return, %	0.479	0.440	0.188
Total Trades	76.49	45.0	95.09
Total HFT Trades	62.03	34.0	82.25
Dollar Volume	472,489	181,218	907,741
Share Volume	16,836	5,831	33,192
Quoted Spread, $	0.046	0.014	0.151
Relative Spread, bps	0.078	0.063	0.152
N	8,379		

Panel C: Extreme price movements - permanent

	Mean	Median	Std. Dev.
Absolute Return, %	0.483	0.439	0.193
Total Trades	70.64	42.0	82.63
Total HFT Trades	55.10	32.0	67.13
Dollar Volume	465,409	167,217	1,024,331
Share Volume	14,829	5,338	28,838
Quoted Spread, $	0.045	0.016	0.134
Relative Spread, bps	0.080	0.065	0.152
N	14,534		

Table 4. Liquidity supply and demand: transitory, corrective, and permanent EPMs

The table reports directional trading volume around three types of EPMs (transitory, corrective and permanent). HFT^{D} ($nHFT^{D}$) is the difference in liquidity-demanding HFT (nHFT) volume in the direction of the EPM and liquidity-demanding volume against the direction of the EPM. HFT^{S} ($nHFT^{S}$) is the difference in liquidity-providing volume against the direction of the EPM and liquidity-providing volume in the direction of the EPM. HFT^{NET} ($nHFT^{NET}$) is the difference between HFT^{D} and HFT^{S} ($nHFT^{D}$ and $nHFT^{S}$). *p*-values are in parentheses. *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Extreme price movements – transitory

	t-20	**t-10**	**t**	**t+10**	**t+20**
HFT^{NET}	-7.0	-30.1	-339.7***	-149.1***	-48.7
	(0.81)	(0.34)	(0.00)	(0.00)	(0.11)
HFT^{D}	36.8	115.7***	2117.0***	-347.6***	-158.8***
	(0.17)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{S}	-43.7	-145.7***	-2456.7***	198.5***	110.1***
	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
$nHFT^{NET}$	7.0	30.1	339.7***	149.1***	48.7
	(0.81)	(0.34)	(0.00)	(0.00)	(0.11)
$nHFT^{D}$	192.9***	449.1***	5572.7***	602.1***	264.9***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$nHFT^{S}$	-185.9***	-419.0***	-5233.0***	-453.0***	-216.3***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Extreme price movements – corrective

HFT^{NET}	20.8	240.7***	-207.5***	13.5	-65.9
	(0.72)	(0.00)	(0.00)	(0.82)	(0.27)
HFT^{D}	38.1	308.5***	2743.4***	-132.4**	-55.0
	(0.57)	(0.00)	(0.00)	(0.02)	(0.37)
HFT^{S}	-17.3	-67.8	-2950.9***	146.0**	-10.9
	(0.77)	(0.28)	(0.00)	(0.02)	(0.85)
$nHFT^{NET}$	-20.8	-240.7***	207.5***	-13.5	65.9
	(0.72)	(0.00)	(0.00)	(0.82)	(0.27)
$nHFT^{D}$	-437.9***	-241.5**	5323.4***	618.2***	241.9***
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)
$nHFT^{S}$	417.1***	0.9	-5115.9***	-631.7***	-175.9**
	(0.00)	(0.99)	(0.00)	(0.00)	(0.04)

Panel C: Extreme price movements - permanent

HFT^{NET}	-3.7	49.8	-287.9***	-158.5***	-16.1
	(0.91)	(0.14)	(0.00)	(0.00)	(0.64)
HFT^{D}	6.3	149.9***	2022.4***	-251.2***	-34.5
	(0.82)	(0.00)	(0.00)	(0.00)	(0.28)
HFT^{S}	-10.0	-100.1***	-2310.2***	92.7***	18.5
	(0.73)	(0.00)	(0.00)	(0.00)	(0.54)
$nHFT^{NET}$	3.7	-49.8	287.9***	158.5***	16.1
	(0.91)	(0.14)	(0.00)	(0.00)	(0.64)
$nHFT^{D}$	200.1***	472.1***	5519.8***	837.9***	435.9***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$nHFT^{S}$	-196.4***	-521.9***	-5231.9***	-679.5***	-419.9***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 5. Summary statistics; standalone and co-EPMs

Panel A reports summary statistics for the idiosyncratic EPMs, those not accompanied by EPMs in other stocks in the same time interval; Panel B reports statistics for co-EPMs, those happening in two or more stocks at the same time. The summary statistics are similar to those in Table 1. Panel B also contains a statistic for the number of stocks experiencing a co-EPM.

Panel A: Standalone EPMs

	Mean	**Median**	**Std. Dev.**
Absolute Return, %	0.491	0.448	0.198
Total Trades	89.30	53.0	107.05
Total HFT Trades	68.60	38.0	87.76
Dollar Volume	625,553	231,961	1,272,083
Share Volume	21,368	7,601	40,535
Quoted Spread, $	0.049	0.016	0.125
Relative Spread, bps	0.085	0.068	0.118
N	19,424		

Panel B: Co-EPMs

Absolute Return, %	0.479	0.435	0.190
Total Trades	60.83	38.0	69.54
Total HFT Trades	49.34	29.0	58.72
Dollar Volume	359,359	138,911	770,887
Share Volume	11,280	4,408	22,092
Quoted Spread, $	0.044	0.015	0.160
Relative Spread, bps	0.076	0.063	0.168
# Stocks	3.5	2	2.66
N	25,982		

Table 6. Net HFT activity and EPMs

The table reports estimated coefficients from the following regression:

$$HFT^{NET}{}_{it} = \alpha_i + \beta_1 1_{EMP_{it}} + \beta_2 Ret_{it} + \beta_3 Vol_{it} + \beta_4 Spr + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$

where HFT^{NET} is the difference between HFT^{D} and HFT^{S}; the dummy 1_{EPM} is equal to one if the interval is identified to contain an EPM and is equal to zero otherwise; $1_{EPM\text{-}TRANSITORY}$, $1_{EPM\text{-}CORRECTIVE,}$ and $1_{EPM\text{-}PERMANENT}$ are dummies that capture the three EPM types; $1_{EPM\text{-}STANDALONE}$ captures the standalone EPMs; $1_{CO\text{-}EPM}$ captures EPMs that occur simultaneously in several sample stocks; $1_{EPM\text{-}CRISIS}$ captures EPMs that occur during the period from September through November 2008; $1_{EPM\text{-}NON\text{-}CRISIS}$ captures the remaining EPMs; $1_{EPM\text{-}MORNING}$ captures EPMs that occur between 9:35 a.m. and 10:30 a.m.; $1_{EPM\text{-}DAY}$ captures EPMs that occur during the rest of the day; $1_{EPM\text{-}Q1}$ through $1_{EPM\text{-}Q4}$ identify four EPM quartiles by magnitude, from the smallest to the largest; Ret is the absolute return; Vol is the total trading volume; Spr is the percentage quoted spread; and $\boldsymbol{Lags_{kit-\sigma}}$ is a vector of σ lags of the dependent variable and each of the independent variables, with $\sigma \in \{1, 2, \dots, 10\}$ and the variables indexed with a subscript k. All non-dummy variables are standardized on the stock level. Regressions are estimated with stock fixed effects. p-Values associated with the double-clustered standard errors are in parentheses. *** and ** denote statistical significance at the 1% and 5% levels.

Panel A: Extreme price movements - all

	(1)	(2)	(3)	(4)	(5)	(6)
1_{EPM}	-0.818***					
	(0.00)					
$1_{EPM\text{-}TRANSITORY}$		-0.851***				
		(0.00)				
$1_{EPM\text{-}CORRECTIVE}$		-0.688***				
		(0.00)				
$1_{EPM\text{-}PERMANENT}$		-0.833***				
		(0.00)				
$1_{EPM\text{-}STANDALONE}$			-1.441***			
			(0.00)			
$1_{CO\text{-}EPM}$			-0.328***			
			(0.00)			
$1_{EPM\text{-}CRISIS}$				-0.538***		
				(0.00)		
$1_{EPM\text{-}NON\text{-}CRISIS}$				-1.371***		
				(0.00)		
$1_{EPM\text{-}MORNING}$					-0.832***	
					(0.00)	
$1_{EPM\text{-}DAY}$					-0.805***	
					(0.00)	
$1_{EPM\text{-}Q1}$						-0.490***
						(0.00)
$1_{EPM\text{-}Q2}$						-0.631***
						(0.00)
$1_{EPM\text{-}Q3}$						-0.807***
						(0.00)
$1_{EPM\text{-}Q4}$						-1.406***
						(0.00)
Ret	0.072***	0.072***	0.072***	0.072***	0.072***	0.073***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Vol	0.081***	0.081***	0.081***	0.081***	0.081***	0.081***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.02	0.02	0.02	0.02	0.02	0.02

Panel B: Extreme price movements – transitory

1_{EPM}	-0.812***				
	(0.00)				
$1_{EPM\text{-}STANDALONE}$		-1.303***			
		(0.00)			
$1_{CO\text{-}EPM}$		-0.251***			
		(0.00)			
$1_{EPM\text{-}CRISIS}$			-0.511***		
			(0.00)		
$1_{EPM\text{-}NON\text{-}CRISIS}$			-1.418***		
			(0.00)		
$1_{EPM\text{-}MORNING}$				-0.791***	
				(0.00)	
$1_{EPM\text{-}DAY}$				-0.833***	
				(0.00)	
$1_{EPM\text{-}Q1}$					-0.465***
					(0.00)
$1_{EPM\text{-}Q2}$					-0.600***
					(0.00)
$1_{EPM\text{-}Q3}$					-0.807***
					(0.00)
$1_{EPM\text{-}Q4}$					-1.407***
					(0.00)
Controls	Yes	Yes	Yes	Yes	Yes

Panel C: Extreme price movements – corrective

1_{EPM}	-0.624***				
	(0.00)				
$1_{EPM\text{-}STANDALONE}$		-0.975***			
		(0.00)			
$1_{CO\text{-}EPM}$		-0.002			
		(0.98)			
$1_{EPM\text{-}CRISIS}$			-0.415***		
			(0.00)		
$1_{EPM\text{-}NON\text{-}CRISIS}$			-1.131***		
			(0.00)		
$1_{EPM\text{-}MORNING}$				-0.715***	
				(0.00)	
$1_{EPM\text{-}DAY}$				-0.567***	
				(0.00)	
$1_{EPM\text{-}Q1}$					-0.464***
					(0.00)
$1_{EPM\text{-}Q2}$					-0.495***
					(0.00)
$1_{EPM\text{-}Q3}$					-0.567***
					(0.00)
$1_{EPM\text{-}Q4}$					-1.032***
					(0.00)
Controls	Yes	Yes	Yes	Yes	Yes

Panel D: Extreme price movements - permanent

1_{EPM}	-0.780***				
	(0.00)				
$1_{EPM\text{-}STANDALONE}$		-1.269***			
		(0.00)			
$1_{CO\text{-}EPM}$		-0.159			
		(0.09)			
$1_{EPM\text{-}CRISIS}$			-0.496***		
			(0.00)		
$1_{EPM\text{-}NON\text{-}CRISIS}$			-1.281***		
			(0.00)		
$1_{EPM\text{-}MORNING}$				-0.792***	
				(0.00)	
$1_{EPM\text{-}DAY}$				-0.764***	
				(0.00)	
$1_{EPM\text{-}Q1}$					-0.389***
					(0.00)
$1_{EPM\text{-}Q2}$					-0.626***
					(0.00)
$1_{EPM\text{-}Q3}$					-0.813***
					(0.00)
$1_{EPM\text{-}Q4}$					-1.317***
					(0.00)
Controls	Yes	Yes	Yes	Yes	Yes

Table 7. Returns, trading and EPMs at 10-second intervals

The table reports estimated coefficients from regressions of return sensitivity to HFT^{NET} during normal periods and during EPMs. The regression models are as follows:

$$Ret_{it} = \alpha_i + \beta_1 HFT^{NET}{}_{it} + \beta_2 HFT^{NET}{}_{it} * 1_{EPM_{it}} + \beta_3 1_{EPM_{it}} + \beta_4 Spr_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$

where the dependent variable is the standardized return. All other non-dummy variables are also standardized at the stock level. the dummy 1_{EPM} is equal to one if the interval is identified to contain an EPM and is equal to zero otherwise; $1_{EPM\text{-}TRANSITORY}$, $1_{EPM\text{-}CORRECTIVE,}$ and $1_{EPM\text{-}PERMANENT}$ are dummies that capture the three EPM types; $1_{EPM\text{-}STANDALONE}$ captures the standalone EPMs; $1_{CO\text{-}EPM}$ captures EPMs that occur simultaneously in several sample stocks; $1_{EPM\text{-}CRISIS}$ captures EPMs that occur during the period from September through November 2008; $1_{EPM\text{-}NON\text{-}CRISIS}$ captures the remaining EPMs; $1_{EPM\text{-}MORNING}$ captures EPMs that occur between 9:35 a.m. and 10:30 a.m.; $1_{EPM\text{-}DAY}$ captures EPMs that occur during the rest of the day; and Spr is the percentage quoted spread. Regressions are estimated with fixed effects. The 10 lags of return and the independent variables are included in each regression specification (not reported). p-Values associated with the double-clustered standard errors are in parentheses. *** and ** denote statistical significance at the 1% and 5% levels.

	All				Transitory			
HFT^{NET}	0.074***	0.074***	0.074***	0.074***	0.073***	0.073***	0.073***	0.073***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HFT^{NET}*1_{EPM}$	-0.106***				-0.111***			
	(0.00)				(0.00)			
$HFT^{NET}*1_{EPM\text{-}STANDALONE}$		-0.105***				-0.114***		
		(0.00)				(0.00)		
$HFT^{NET}*1_{CO\text{-}EPM}$		-0.110***				-0.103		
		(0.00)				(0.14)		
$HFT^{NET}*1_{EPM\text{-}CRISIS}$			-0.113***				-0.113***	
			(0.00)				(0.00)	
$HFT^{NET}*1_{EPM\text{-}NON\text{-}CRISIS}$			-0.103***				-0.111***	
			(0.00)				(0.00)	
$HFT^{NET}*1_{EPM\text{-}MORNING}$				-0.086***				-0.100***
				(0.00)				(0.00)
$HFT^{NET}*1_{EPM\text{-}DAY}$				-0.119***				-0.119***
				(0.00)				(0.00)
1_{EPM}	8.305***	8.306***	8.306***	8.306***	8.265***	8.265***	8.266***	8.262***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr	0.016	0.016	0.016	0.016	0.014	0.014	0.014	0.014
	(0.36)	(0.36)	(0.36)	(0.36)	(0.48)	(0.48)	(0.48)	(0.48)
Adj. R^2	0.28	0.28	0.28	0.28	0.24	0.24	0.24	0.24

	Corrective				Permanent			
HFT^{NET}	0.073***	0.073***	0.073***	0.073***	0.073***	0.073***	0.073***	0.073***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HFT^{NET}*1_{EPM}$	-0.089***				-0.094***			
	(0.00)				(0.00)			
$HFT^{NET}*1_{EPM\text{-}STANDALONE.}$		-0.098***				-0.101***		
		(0.00)				(0.00)		
$HFT^{NET}*1_{CO\text{-}EPM}$		-0.047				-0.068***		
		(0.11)				(0.00)		
$HFT^{NET}*1_{EPM\text{-}CRISIS}$			-0.118***				-0.083***	
			(0.00)				(0.00)	
$HFT^{NET}*1_{EPM\text{-}NON\text{-}CRISIS}$			-0.070**				-0.099***	
			(0.02)				(0.00)	
$HFT^{NET}*1_{EPM\text{-}MORNING}$				-0.041***				-0.074***
				(0.08)				(0.00)
$HFT^{NET}*1_{EPM\text{-}DAY}$				-0.106***				-0.106***
				(0.00)				(0.00)
1_{EPM}	7.971***	7.978***	7.974***	7.960***	8.120***	8.118***	8.121***	8.112***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr	0.014	0.014	0.014	0.014	0.015	0.015	0.015	0.015
	(0.49)	(0.49)	(0.49)	(0.49)	(0.44)	(0.44)	(0.44)	(0.44)
Adj. R^2	0.23	0.23	0.24	0.24	0.25	0.25	0.25	0.25

Table 8. Returns, trading and EPMs within 10-second intervals

The table reports estimated coefficients from second by second regressions of return sensitivity to HFT^{NET} prior to and during the largest return during EPM intervals. The regression models are as follows:

$$Ret_{it} = \alpha_i + \beta_1 HFT^{NET}{}_{it} + \beta_2 HFT^{NET}{}_{it-1} + \beta_3 HFT^{NET}{}_{it-2} + \beta_4 Spr_{it} + \boldsymbol{Lags_{kit-\sigma}\gamma_{k\sigma}} + \varepsilon_{it},$$

where the dependent variable is the maximum absolute 1-second return. All other non-dummy variables are standardized at the stock level. Ten lags of return and the independent variables are included in each regression specification (not reported beyond the second lag due to lack of significance). p-Values associated with the heteroscedasticity-robust standard errors are in parentheses. *** and ** denote statistical significance at the 1% and 5% levels.

Panel A: Extreme price movements - all

	All	**Crisis**	**Non-crisis**	**Morning**	**Day**	**Standalone**	**Co-EPMs**
HFT^{NET}	-0.097***	-0.081***	-0.121***	-0.064***	-0.147***	-0.137***	-0.048***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HFT^{NET}{}_{t-1}$	-0.035***	-0.057***	-0.015	-0.017**	-0.061***	-0.022**	-0.050***
	(0.00)	(0.00)	(0.13)	(0.02)	(0.00)	(0.02)	(0.00)
$HFT^{NET}{}_{t-2}$	-0.007	-0.005	-0.018	-0.006	-0.009	-0.002	-0.015**
	(0.23)	(0.43)	(0.06)	(0.41)	(0.29)	(0.80)	(0.03)
Ret_{t-1}	0.010	0.020	0.007	-0.008	0.015	0.034**	-0.000
	(0.54)	(0.35)	(0.61)	(0.59)	(0.38)	(0.02)	(0.99)
Spr	0.154***	0.135***	0.087***	0.001	0.124***	0.109***	0.149***
	(0.00)	(0.00)	(0.00)	(0.97)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.05	0.04	0.06	0.07	0.12	0.06	0.04

Panel B: Extreme price movements – transitory

	All	**Crisis**	**Non-crisis**	**Morning**	**Day**	**Standalone**	**Co-EPMs**
HFT^{NET}	-0.108***	-0.073***	-0.113***	-0.065***	-0.140***	-0.109***	-0.045***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HFT^{NET}{}_{t-1}$	-0.041***	-0.066***	-0.012	-0.030***	-0.053***	-0.041***	-0.036***
	(0.00)	(0.00)	(0.37)	(0.01)	(0.00)	(0.00)	(0.00)
$HFT^{NET}{}_{t-2}$	-0.003	0.006	-0.007	-0.006	0.002	-0.000	-0.009
	(0.71)	(0.52)	(0.58)	(0.52)	(0.86)	(0.99)	(0.29)
Ret_{t-1}	0.006	0.021	0.003	-0.008	0.024	0.023	0.010
	(0.75)	(0.37)	(0.86)	(0.60)	(0.33)	(0.22)	(0.66)
Spr	0.203***	0.186	0.111***	0.136***	0.175***	0.135	0.212***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.06	0.07	0.06	0.09	0.16	0.06	0.08

Panel C: Extreme price movements – corrective

	All	Crisis	Non-crisis	Morning	Day	Standalone	Co-EPMs
HFT^{NET}	-0.102***	-0.118***	-0.098***	-0.060***	-0.152***	-0.101***	-0.047
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.09)
HFT^{NET}_{t-1}	-0.038**	-0.059***	-0.015	-0.012	-0.057***	-0.018	-0.068***
	(0.02)	(0.00)	(0.53)	(0.54)	(0.01)	(0.32)	(0.00)
HFT^{NET}_{t-2}	-0.011	0.006	-0.021	0.032	-0.031	-0.014	-0.007
	(0.40)	(0.68)	(0.36)	(0.07)	(0.10)	(0.42)	(0.73)
Ret_{t-1}	0.031	0.019	-0.020	-0.003	0.036	0.025	0.007
	(0.22)	(0.51)	(0.46)	(0.90)	(0.10)	(0.34)	(0.82)
Spr	0.133***	0.163***	0.071**	0.073	0.130***	0.144	0.186***
	(0.00)	(0.00)	(0.02)	(0.07)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.06	0.07	0.07	0.08	0.08	0.06	0.05

Panel D: Extreme price movements - permanent

	All	Crisis	Non-crisis	Morning	Day	Standalone	Co-EPMs
HFT^{NET}	-0.100***	-0.058***	-0.143***	-0.070***	-0.135***	-0.137***	-0.017
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)
HFT^{NET}_{t-1}	-0.025**	-0.038***	-0.020	-0.016	-0.053***	-0.017***	-0.025
	(0.01)	(0.00)	(0.24)	(0.13)	(0.00)	(0.18)	(0.10)
HFT^{NET}_{t-2}	-0.009	-0.007	-0.007	-0.017	-0.005	-0.011	0.018
	(0.39)	(0.59)	(0.64)	(0.14)	(0.76)	(0.44)	(0.16)
Ret_{t-1}	0.010	0.023	0.018	0.022	0.017	-0.046***	0.002
	(0.61)	(0.33)	(0.35)	(0.27)	(0.45)	(0.01)	(0.98)
Spr	0.082***	0.068	0.075**	0.135***	0.008	0.046	0.090**
	(0.00)	(0.07)	(0.01)	(0.00)	(0.84)	(0.17)	(0.02)
Adj. R^2	0.04	0.03	0.06	0.07	0.07	0.06	0.03

Table 9. EPM determinants

The table reports the coefficients and the marginal effects from a probit model of EPM occurrence. The dependent variable is equal to one if an interval t contains an extreme price movement and zero otherwise. All independent variables are lagged by one 10-second interval. HFT^{NET} ($nHFT^{NET}$) is the share volume traded in the direction of the price movement minus the share volume traded against the direction of the price movement for all HFT (non-HFT) trades. Vol is total share traded volume. Spr is the percentage quoted spread. All variables are standardized on the stock level. The marginal effects are scaled by a factor of 1,000. p-Values are in parentheses. *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Extreme price movements - all

	All	Crisis	Non-crisis	Morning	Day	Standalone	Co-EPMs
Intercept	-3.232***	-3.348***	-3.486***	-3.411***	-3.410***	-3.438***	-3.380***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{NET}_{t-1}	-0.003***	0.000	-0.006***	-0.002	-0.005***	-0.006***	0.001
Marginal Effect	-0.008	0.000	-0.007	-0.003	-0.007	-0.009	0.001
	(0.00)	(0.99)	(0.00)	(0.10)	(0.00)	(0.00)	(0.42)
Ret_{t-1}	0.171***	0.171***	0.112***	0.148***	0.142***	0.123***	0.167***
Marginal Effect	0.494	0.335	0.126	0.236	0.213	0.168	0.290
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Vol_{t-1}	0.046***	0.024***	0.054***	0.035***	0.042***	0.054***	0.020***
Marginal Effect	0.134	0.047	0.061	0.055	0.064	0.073	0.035
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr_{t-1}	0.041***	0.026***	0.045***	0.071***	0.004***	0.045***	0.025***
Marginal Effect	0.119	0.051	0.051	0.114	0.006	0.061	0.043
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pseudo-R^2	0.14	0.14	0.10	0.15	0.11	0.11	0.13

Panel B: Extreme price movements – transitory

	All	Crisis	Non-crisis	Morning	Day	Standalone	Co-EPMs
Intercept	-3.423***	-3.531***	-3.676***	-3.591***	-3.599***	-3.578***	-3.610***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{NET}_{t-1}	-0.005***	-0.004***	-0.007***	-0.004***	-0.007***	-0.007***	-0.003**
Marginal Effect	-0.008	-0.004	-0.004	-0.003	-0.005	-0.006	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
Ret_{t-1}	0.146***	0.146***	0.101***	0.131***	0.122***	0.117***	0.104***
Marginal Effect	0.215	0.146	0.056	0.106	0.091	0.096	0.019
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Vol_{t-1}	0.036***	0.019***	0.044***	0.027***	0.034***	0.042***	0.012
Marginal Effect	0.053	0.019	0.024	0.022	0.026	0.032	0.009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr_{t-1}	0.029***	0.019***	0.029***	0.045***	0.013	0.024***	0.016***
Marginal Effect	0.042	0.019	0.016	0.036	0.000	0.032	0.012
	(0.00)	(0.00)	(0.00)	(0.00)	(0.99)	(0.00)	(0.00)
Pseudo-R^2	0.12	0.12	0.09	0.13	0.09	0.10	0.11

Panel C: Extreme price movements – corrective

	All	Crisis	Non-crisis	Morning	Day	Standalone	Co-EPMs
Intercept	-3.653***	-3.738***	-3.930***	-3.875***	-3.766***	-3.760***	-3.423***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{NET}_{t-1}	-0.001	-0.003	-0.003	-0.003	-0.002	-0.001	-0.005
Marginal Effect	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.56)	(0.08)	(0.08)	(0.13)	(0.24)	(0.31)	(0.05)
Ret_{t-1}	0.122***	0.123***	0.077***	0.101***	0.110***	0.108***	0.107***
Marginal Effect	0.077	0.056	0.016	0.027	0.044	0.045	0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Vol_{t-1}	0.035***	0.021***	0.042***	0.028***	0.032***	0.038***	0.014
Marginal Effect	0.022	0.010	0.009	0.007	0.013	0.016	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr_{t-1}	0.019***	0.012***	0.021***	0.027***	0.003**	0.021***	0.006***
Marginal Effect	0.012	0.005	0.004	0.007	0.001	0.09	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Pseudo-R^2	0.11	0.10	0.08	0.10	0.09	0.10	0.08

Panel D: Extreme price movements - permanent

	All	Crisis	Non-crisis	Morning	Day	Standalone	Co-EPMs
Intercept	-3.514***	-3.640***	-3.736***	-3.648***	-3.723***	-3.653***	-3.715***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{NET}_{t-1}	-0.004***	-0.001	-0.006***	-0.004**	-0.004***	-0.006***	-0.001
Marginal Effect	0.004	0.001	-0.003	-0.002	-0.002	-0.004	-0.000
	(0.00)	(0.34)	(0.00)	(0.01)	(0.00)	(0.00)	(0.61)
Ret_{t-1}	0.133***	0.134***	0.091***	0.123***	0.107***	0.107***	0.128***
Marginal Effect	0.138	0.090	0.039	0.079	0.049	0.065	0.064
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Vol_{t-1}	0.031***	0.016***	0.037***	0.024***	0.029***	0.036***	0.009***
Marginal Effect	0.032	0.011	0.016	0.015	0.013	0.022	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spr_{t-1}	0.031***	0.023***	0.024***	0.035***	0.005***	0.026***	0.020***
Marginal Effect	0.032	0.015	0.010	0.023	0.002	0.016	0.010
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pseudo-R^2	0.11	0.11	0.07	0.11	0.08	0.09	0.10

Table 10: HFT revenues on EPM days

Panel A reports coefficient estimates from the following regression model:

$$\pi HFT_{it} = \alpha + \beta_1 nTransitory_{it} + \beta_2 nCorrective + \beta_3 nPermanent + \varepsilon_{it},$$

where πHFT_{it} is the total revenue from net HFT activity in stock i on day t, and and $nTransitory$, $nCorrective$, and $nPermanent$ are count variables for the number of each of the three EPM types. Panel B reports coefficient estimates from a similar model that does not differentiate among the EPM types. Profits are computed as follows:

$$\pi HFT = -\sum_{n=1}^{N} HFT_n \times I \times P_n + invHFT_N \times P_N,$$

where HFT_n is the number of shares traded by HFTs during the n^{th} transaction, I is the indicator equal to 1 for buy trades and -1 for sell trades, P_n is the trade price, $invHFT_N$ is the inventory accumulated through HFT trades by the end of the day, and P_N is the end of day midquote. The regression is estimated without fixed effects, to maintain a meaningful intercept that captures average HFT^{NET} profits on days without EPMs.

Panel A: Profitability by EPM type

	estimate	**p-value**
Intercept	3497.74	(0.00)
nTransitory	2084.01	(0.00)
nCorrective	2737.79	(0.00)
nPermanent	-4377.70	(0.00)

Panel B: Overall EPM profitability

	estimate	**p-value**
Intercept	3718.09	(0.00)
nEPM	273.89	(0.01)

Figure 1: Intraday distribution of EPMs

The figure contains a minute-by-minute intraday distribution of sample EPMs identified using the 99.9 technique.

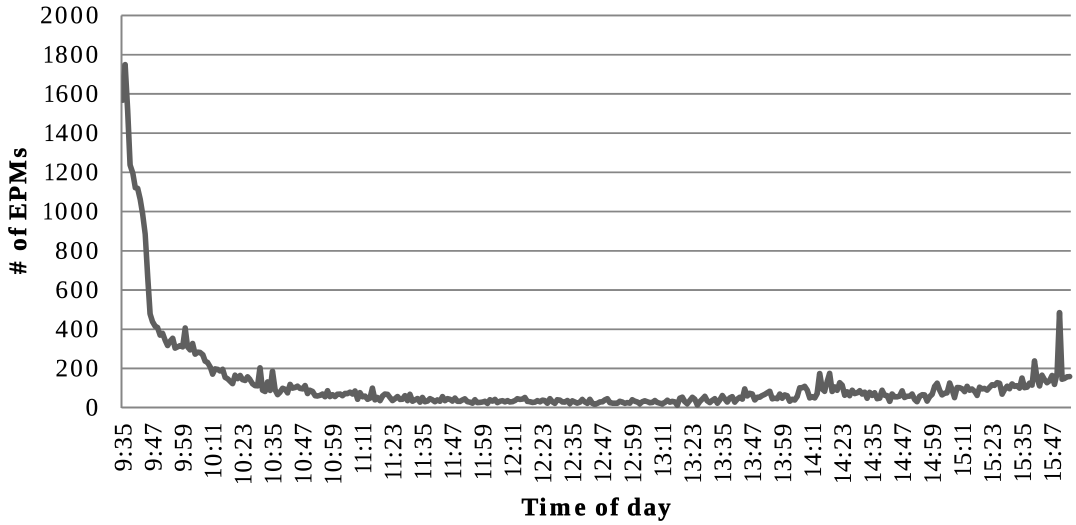

Figure 2: Daily distribution of EPMs

The figure contains the daily distribution of 45,406 sample EPMs identified during the 2008-2009 period using the 99.9 technique.

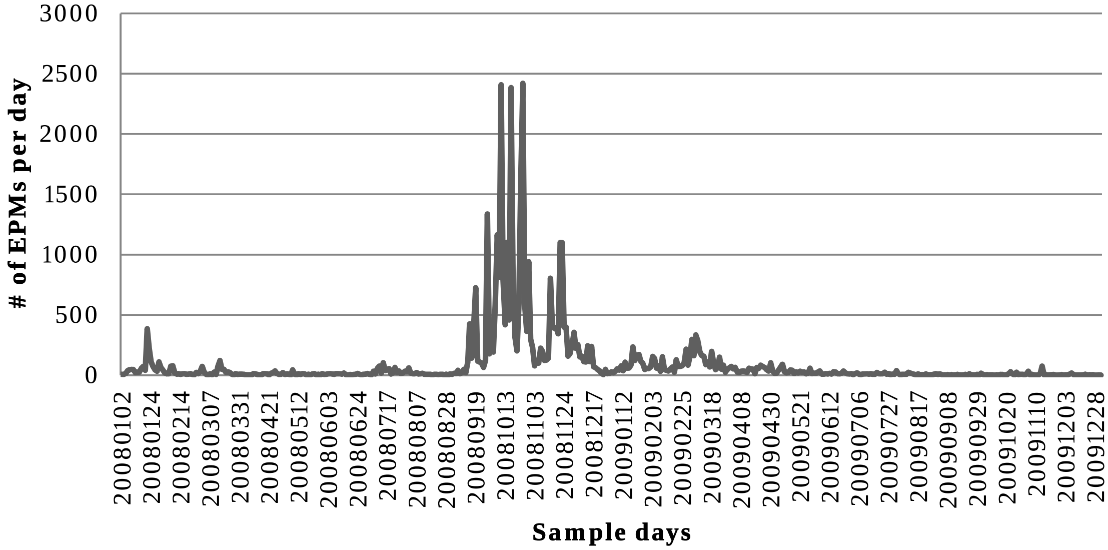

Figure 3: HFT and nHFT activity around EPMs

The figure displays the average return path and trading activity around 45,406 sample EPMs. HFT^D ($nHFT^D$) is liquidity demanded by HFTs (nHFTs) in the direction of the EPM (in # shares) minus liquidity demanded against the direction of the EPM. HFT^{NET} is the net effect of HFT liquidity demand and supply. CRET is the cumulative return. The figure includes both positive and negative EPMs, and for exposition purposes we invert the statistics for the latter.

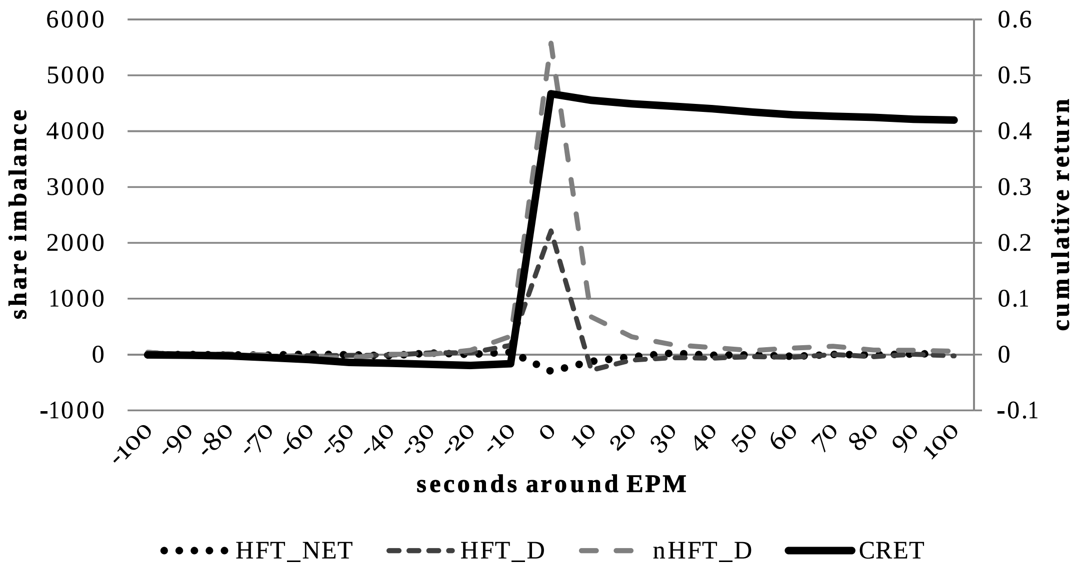

Figure 4: EPM types, an illustration

The figure describes three EPM types according to the permanence of the price change: (i) a transitory EPM that reverses by the end of the trading day (reversal1), (ii) an EPM that is a correction of a price movement that has occurred since the beginning of the day (reversal2), and (iii) a permanent EPM.

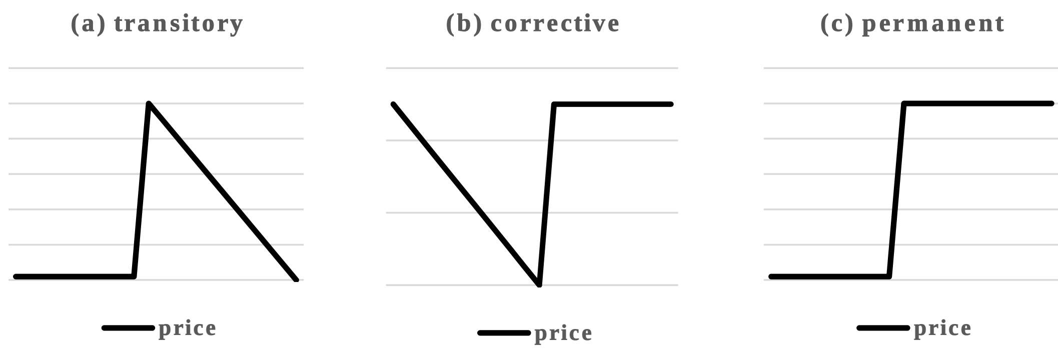

Figure 5: HFT and nHFT activity during EPMs, a second by second view

The figure displays the average second by second price path and trading activity during [-10; +10]-second windows centered on the largest one-second EPM return. HFT^{D} ($nHFT^{D}$) is liquidity demanded by HFTs (nHFTs) in the direction of the EPM (in # shares) minus liquidity demanded against the direction of the EPM. HFT^{NET} is the net effect of HFT liquidity demand and supply. CRET is the cumulative return. The figure includes both positive and negative EPMs, and for exposition purposes we invert the statistics for the latter.