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High frequency trading and extreme price movements☆

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Are endogenous liquidity providers (ELPs) reliable in times of market stress? We examine the activity of a common ELP type—high frequency traders (HFTs)—around extreme price movements (EPMs). We find that on average HFTs provide liquidity during EPMs by absorbing imbalances created by non-high frequency traders (nHFTs). Yet HFT liquidity provision is limited to EPMs in single stocks. When several stocks experience simultaneous EPMs, HFT liquidity demand dominates their supply. There is little evidence of HFTs causing EPMs.

1. Introduction

In modern markets, high frequency traders (HFTs) play an important role in providing liquidity (Hasbrouck and Saar, 2013; Menkveld, 2013; Malinova et al., 2014; Conrad et al., 2015). Generally, the rise of HFT has been accompanied by a reduction in trading costs (Angel et al., 2011; Jones, 2013; Harris, 2013) and an increase in price efficiency (Carrion, 2013; Brogaard et al., 2014; Chaboud et al., 2014). Nevertheless, liquidity provision by HFTs is endogenous as they are typically not obligated to stabilize markets in periods of stress. A growing literature finds that endogenous liquidity providers (ELPs) often withdraw from the market during such periods (Raman et al., 2014; Bongaerts and Van Achter, 2015; Cespa and Vives, 2015; Korajczyk and Murphy, 2015; Anand and Venkataraman, 2016). The focus of this study is HFT behavior during stressful conditions.

We define stressful periods as unexpected and rapidly developing extreme price movements (EPMs) that belong

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to the 99.9th percentile of the return distribution. While a growing body of work examines HFT activity during normal conditions, less attention has been given to periods of market stress such as EPMs. Our main finding is that, on average, HFTs trade in the opposite direction of EPMs and supply liquidity to non-high frequency traders (nHFTs) by absorbing their trade imbalances. This result holds even during the largest EPMs and during the times when nHFTs demand substantial amounts of liquidity. Notably, HFTs supply liquidity both to the EPMs that eventually reverse and the EPMs that result in permanent price changes. This means that an average HFT trade during extreme price movements provides liquidity to aggressive, occasionally informed, nHFTs.

Even though EPMs occur quickly, they consist of multiple sequential trades. If HFT algorithms are designed to stop providing liquidity during EPMs, technology would allow them to withdraw limit orders as EPMs develop. Yet the results imply that the algorithms are designed to remain in the market, likely because doing so is profitable. Although revenue estimates are noisy, we find evidence that the revenues are greater on days when EPMs occur. Despite the enhanced revenue potential, the data show that HFTs do not cause EPMs. Our results complement those of Bessembinder et al., (2016), who show that liquidity provision increases around large uninformed predictable trades. In our setting EPMs are generally unpredictable and are occasionally informed, yet the incentive to provide liquidity remains. Our findings expand the understanding of resiliency of modern markets in stressful times.

Although HFTs stabilize prices during an average EPM, we find clear limits to HFT liquidity provision. HFT liquidity supply is outstripped by their liquidity demand when more than one stock simultaneously undergoes an EPM (we refer to these instances as co-EPMs). We show that during such periods, HFTs accumulate substantial position risk, which likely triggers risk controls, particularly for their liquidity-supplying strategies. Focusing on one exceptionally large co-EPM, the 2010 Flash Crash, Kirilenko et al., (2017) find that HFTs withdrew from liquidity provision. Reflecting on the Crash, the regulators have expressed concern that incentives to provide liquidity are deficient during market-wide periods of stress (Commodity Futures Trading Commission-Securities and Exchange Commission (CFTC-SEC), 2011). Our findings generalize these results and deepen our understanding of market-wide liquidity shortages and offer evidence in support of the regulators' view.

Theory suggests that ELPs may choose several ways of reacting to order imbalances. Traders described by Grossman and Miller (1988) choose to supply liquidity during order imbalances. On the contrary, the predatory traders of Brunnermeier and Pedersen (2005) opt to demand liquidity. The back-runners of Yang and Zhu (2015) supply liquidity until they recognize an institutional trading pattern and then switch to demanding liquidity. In our setting, HFT behavior during an average EPM is more consistent with that described by Grossman and Miller (1988), although the data point to net HFT liquidity demand during co-EPMs and occasional back-running for long EPM sequences.

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 et al., (2014), and O'Hara et al., (2014), among others. For each trade the data set contains an indicator for whether an HFT or an nHFT participates on the liquidity-supplying or the liquidity-demanding side of the 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. HFTs on Nasdaq have no obligation to stabilize prices during stressful times (Bessembinder et al., 2011; Clark-Joseph et al., 2017) and so are ideal participants to study liquidity provision by ELPs.

The data allow us to directly observe HFT liquidity provision and demand. We are subject to the same limitations as the abovementioned studies, mainly that we cannot observe individual HFT activity and that we only observe trading on Nasdaq. Although trades on Nasdaq make up 30–40% of all trading activity in the sample stocks, it is possible 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 liquidity provision on Nasdaq is not systematically more attractive than it is on other venues during the sample period.

2.2. EPM identification

We identify EPMs as extreme changes in the National Best Bid and Offer (NBBO) midquotes. The use of midquotes instead of trade prices allows us to reduce the effect of the bid-ask bounce. In untabulated results we find similar effects when using trade prices. We obtain the midquotes from the NYSE Trade and Quote database (TAQ) after adjusting the data according to the recommendations of Holden and Jacobsen (2014). Specifically, we (i) interpolate the times of trades and the times of NBBO quotes within a second, (ii) adjust for withdrawn quotes, (iii) delete locked and crossed NBBO quotes, and (iv) delete 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 price changes that are not large enough to be captured by the identification procedure. The choice of 10-second intervals is a compromise between these two considerations. As a robustness check, we repeat the main analyses for several alternative interval lengths: one second, five seconds, 30 s, and one minute. The results are qualitatively similar.

The Nasdaq HFT data set contains 120 stocks divided into three size categories: large, medium, and small. There are 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. The main analysis therefore focuses on the 40 largest stocks. In a similar application, and driven by similar considerations, Andersen et al., (2001) also focus on the largest stocks when detecting EPMs. The sample of 40 largest stocks contains 45.2 million 10-second intervals.

We use three approaches to identify EPMs. The first approach is straightforward and simply labels all intervals that belong to the 99.9th percentile of 10-second absolute midpoint returns for each stock as EPMs. The second approach is more sophisticated and accounts for predictable return correlations in time and across firms. First, for each day we estimate a short-term market model of the following form:

$$Ret_{it} = p_{t-1}SPY_{t-1} + \cdots + p_{t-10}SPY_{t-10} + q_{t-1}Ret_{it-1} + \cdots + q_{t-10}Ret_{it-10} + \varepsilon_{it}, \quad (1)$$

where Ret_{it} is stock i's return over the 10-second interval t, and SPY_t is the return on the Standard & Poor's (S&P) 500 exchange-traded fund (ETF) (SPRD). Second, we use the coefficients from the previous day's regressions to compute residuals of the current day's model. Third, we label all intervals with residuals that belong to the 99.9th percentile as EPMs. As a robustness check, we use in-sample residuals, with the model estimated over the full sample. The results are similar.

Both approaches select intervals with the largest absolute returns out of 45.2 million 10-second intervals, and define them as EPMs. The intuitive nature of these techniques is appealing, yet they come with two limitations. First, the 99.9 cutoffs are stock-specific and therefore implicitly assume that each stock is equally likely to undergo an EPM. Consequently, the 99.9 technique may (over-) under-sample stocks that are (less) more prone to EPMs. The second limitation is that the techniques (especially the first one) are agnostic to volatility conditions and therefore tend to oversample periods of high volatility. We suggest that understanding HFT behavior is relevant regardless of accompanying volatility. Nevertheless, to formally address this limitation, we repeat the analysis using a third EPM detection technique, the Lee and Mykland (2012) methodology, which accounts for contemporaneous (local) volatility.

Throughout the main manuscript, we use the results obtained from the second identification technique where EPMs are based on the residuals from Eq. (1). A summary of results obtained using the first and the third techniques is reported in the robustness section. A comprehensive set of results from the first and third techniques is reported in the Internet Appendix. The results obtained from these techniques are in line with those reported in the paper.

Finally, in unreported results, we find that the 99.9th percentile returns closely correspond to the 99.9th percentile of trade imbalances. An EPM identification that focuses on the largest imbalances rather than the largest returns produces a similar sample.

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 percentage points. All statistics are averaged over the 10-second sampling intervals.

	Mean	Median	Std. dev.
Panel A: Extreme price movements			
Absolute return, %	0.478	0.436	0.188
Total trades	72.19	42.00	88.33
Total HFT trades	57.29	32.00	72.89
Dollar volume	462,950	166,929	998,832
Share volume	15,361	5,300	31,778
Quoted spread, $	0.044	0.015	0.138
Relative spread, %	0.076	0.063	0.154
N	45,200		
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	15.4
Dollar volume	76,076	11,701	230,661
Share volume	1,987	292	6,045
Quoted spread, $	0.026	0.010	0.057
Relative spread, %	0.046	0.041	0.032
N	45.2 M		

2.3. Summary statistics

Table 1 reports the descriptive statistics for the sample of 45,200 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 bid-ask spreads are considerably larger during the EPMs than during an average 10-second period. The average absolute EPM return is 0.478%, which is more than 17 times (or about ten standard deviations) larger than the full-sample return. Trading activity is also substantially higher; increasing from 18 trades per ten seconds to 72 trades. Dollar trading volume increases from $76,076 to $462,950, and share volume increases by a similar magnitude. Finally, the quoted and relative spreads nearly double during EPMs suggesting that liquidity is impaired during these events.

The number of positive EPMs is approximately equal to the number of negative EPMs. In unreported 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 across these different types of events. The results reported in the remainder of the paper report combined positive and negative EPMs.

Figs. 1 and 2 report the EPM time series. In both figures, the scale of the vertical axis is logarithmic. Fig. 1 reports the intraday frequency of EPMs, with 50.3% of the events occurring in the first hour of trading. This pattern is

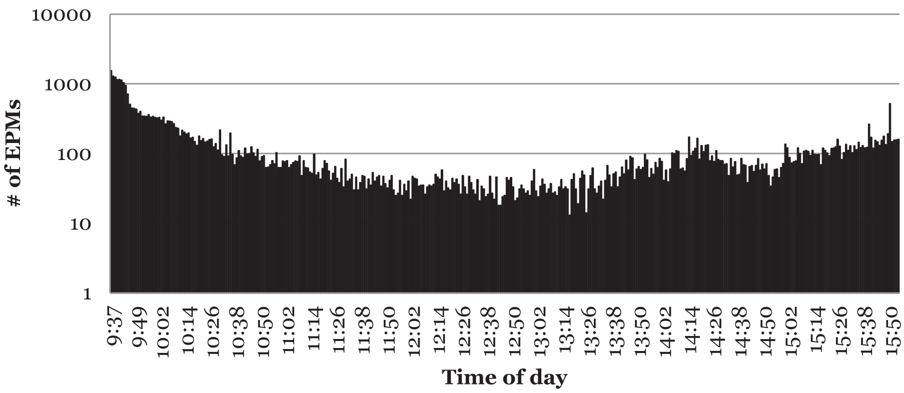

Fig. 1. Intraday distribution of EPMs. The figure contains a minute-by-minute intraday distribution of EPMs. The scale of the vertical axis is logarithmic.

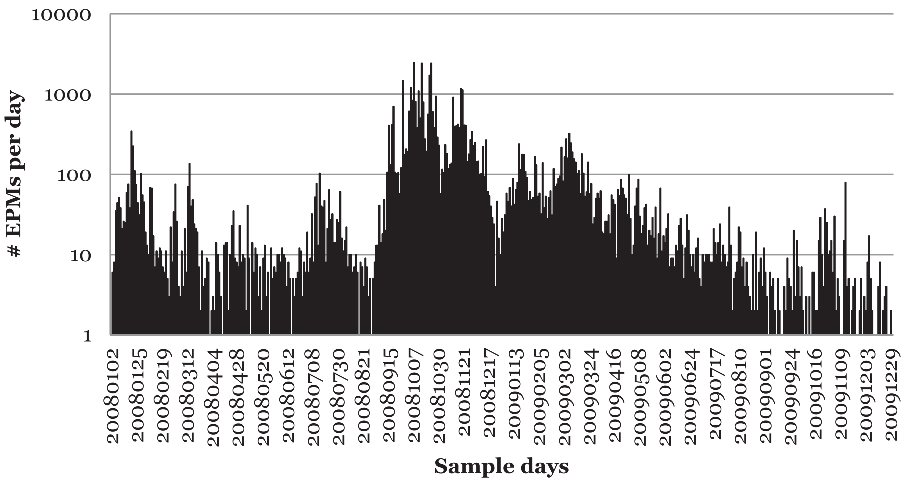

Fig. 2. Daily distribution of EPMs. The figure contains the daily distribution of sample EPMs identified during the 2008–2009 period. The scale of the vertical axis is logarithmic.

consistent with studies that show high price volatility and information uncertainly in the morning hours (Chan et al., 1995; Egginton, 2014). The remaining EPMs are distributed relatively evenly throughout the day, with a moderate increase near the end of the day.[1] Fig. 2 plots the daily frequency of EPMs during the 2008–2009 sample period. Most EPMs (66.3%) occur during the months of September, October, and November of 2008, the height of the financial crisis.

3. HFT and nHFT activity around EPMs

In this section, we show that HFTs provide liquidity to nHFTs during a typical EPM, even when the EPM is very large and even when the price change is permanent. We also show that HFT liquidity supply is overshadowed by their demand when several stocks undergo simultaneous EPMs and also during long sequences of EPMs. We also show that liquidity provision during an average EPM is profitable, yet we find no evidence that HFTs trigger EPMs to benefit from this profitability.

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 20 shares of liquidity in the direction of the price movement and demand one share in the opposite direction, $\mathrm{HFT^D}$ is $+19$. Similarly, if HFTs supply 20 shares of liquidity against the direction of the EPM and supply four shares in the direction of the EPM, $\mathrm{HFT^S}$ is -16. We compute similar metrics for nHFTs.

In addition, we introduce two net imbalance metrics, $\mathrm{HFT^{NET}}$ ($\mathrm{nHFT^{NET}}$) computed as the sum of $\mathrm{HFT^D}$ and $\mathrm{HFT^S}$ ($\mathrm{nHFT^D}$ and $\mathrm{nHFT^S}$). Since liquidity is typically provided against the direction of return, $\mathrm{(n)HFT^S}$ usually has a

[1] Aitken et al. (2015) find that proliferation of HFT has reduced instances of end-of-day price manipulation.

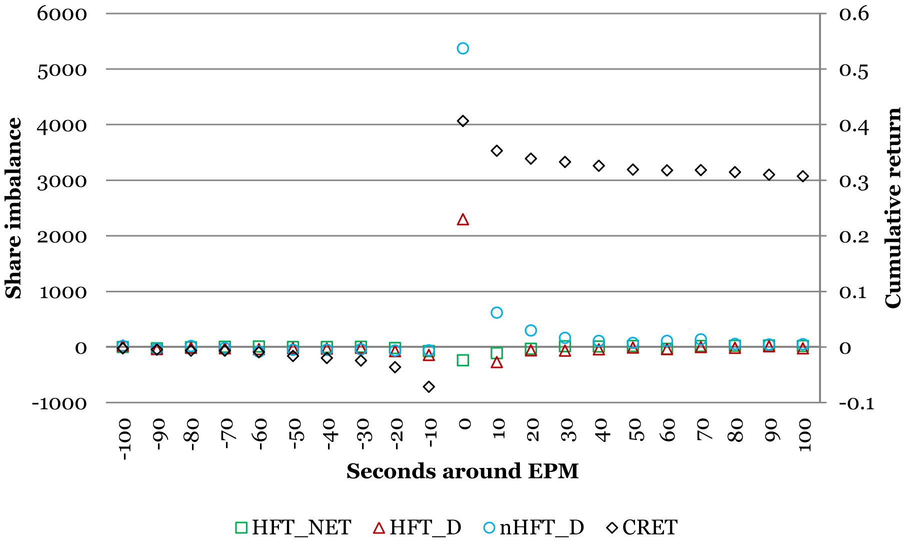

Fig. 3. HFT and nHFT activity around EPMs. The figure displays the average return path and trading activity around the sample EPMs. HFT^{D} (nHFT^{D}) is liquidity demanded by HFTs (nHFTs) in the direction of the EPM (in # shares) minus liquidity demanded against the direction of the EPM. HFT^{NET} is 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.

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.

To begin the discussion of HFT and nHFT activity around EPMs, Fig. 3 reports the cumulative return (CRET) as well as HFT^{D}, nHFT^{D}, and HFT^{NET} 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 to the EPM return. For example, if the EPM return is positive, a negative HFT^{D} ten seconds after the EPM means that HFTs sell the stock via liquidity-demanding orders, effectively counteracting the effects of the positive EPM that occurred ten seconds earlier.

Fig. 3 shows that prices change significantly during the EPM interval, and then revert somewhat during the remaining 100 seconds (ten intervals).[2] There is a large increase in nHFT^{D} during the EPM, with a share imbalance of more than 5,300. In the meantime, HFT^{D} is about 2,300 shares. More importantly, HFT^{NET} is negative, indicating that HFT liquidity supply offsets HFT liquidity demand and that HFTs absorb volume imbalances created by nHFTs.[3]

Table 2
Liquidity supply and demand around EPMs.

The table reports directional trading volume around extreme price movements (EPMs). Time interval t is the 10-second EPM interval. 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. Asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

	$t-20$	$t-10$	t	$t+10$	$t+20$
HFT^{NET}	−20.2	−73.9***	−242.7***	−112.8***	−33.7
	(0.32)	(0.00)	(0.00)	(0.00)	(0.11)
HFT^{D}	−76.5***	−143.5***	2296.3***	−273.6***	−63.1***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFT^{S}	56.3***	69.6***	−2539.0***	160.8***	29.4
	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)
nHFT^{NET}	20.2	73.9***	242.7***	112.8***	33.7
	(0.32)	(0.00)	(0.00)	(0.00)	(0.11)
nHFT^{D}	−64.6*	−63.6	5369.0***	613.6***	296.0***
	(0.05)	(0.13)	(0.00)	(0.00)	(0.00)
nHFT^{S}	84.8**	137.5***	−5126.4***	−500.8***	−262.3***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)

The results in Fig. 3 provide first evidence on HFT and nHFT behavior around EPMs. In Table 2, we examine EPM event windows in more detail. Specifically, we focus on event windows that span 20 seconds before and after the EPM interval and report liquidity demand and supply statistics for HFTs and nHFTs. We find that HFT^{NET} is statistically significant in the direction opposite of returns during interval t (the EPM interval) and the two following intervals. Our results are also statistically significant when we cluster standard errors in time. Further, upon splitting HFT activity into demand and supply, we observe that

[2] Our reliance on quote midpoints aims to focus the analysis, as much as possible, on the permanent component of the security price. Nevertheless, some transitory components remain. For instance, in Fig. 3, the return trends downward up to t=0, then jumps, and then partly reverses after the EPM. This process is best described as a combination of a random walk and a stationary noise process.

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

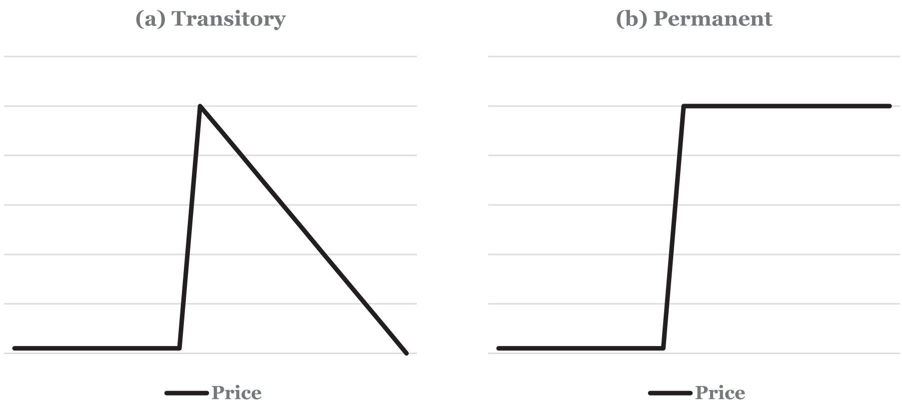

Fig. 4. EPM types, an illustration. The figure describes two EPM types according to the associated price patterns: (a) a transitory EPM that reverses after a period of time and (b) a permanent EPM that does not reverse.

HFTs trade in the direction of the EPM with their liquidity-demanding trades (HFT^D is 2,296 shares) and in the opposite direction with their liquidity-supplying trades (HFT^S is 2,539 shares). HFTs provide 243 shares of net liquidity against the direction of an average EPM. This finding is contrary to the belief held by some market observers that HFTs trade large amounts in the direction of EPMs.

Is 243 shares too small a quantity to claim that HFTs stabilize prices? The results in Table 2 are simple averages and therefore do not suggest that HFT liquidity provision is limited to 243 shares per EPM. Rather, 243 is the number of shares that nHFTs demand during an average EPM.

Beyond being liquidity providers during EPMs, do HFTs trigger EPMs? In the 10-second interval starting 20 s prior to an EPM (t-20), HFT^{NET} and $nHFT^{NET}$ do not show any directionality. However, in t-10, HFTs trade against the direction of the future EPM return.[4] As such, it appears that HFTs do not trigger EPMs. We examine this issue in more detail in a subsequent section.

Following an 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 113 shares against the direction of the preceding EPM return in interval $t+10$. This suggests that HFTs may speed up the reversal process. We study reversals in more detail in the following section.

3.2. EPM types: reversals and permanent price changes

The literature suggests that large price movements can be triggered by at least two types of events: information arrival and trade imbalances. A news arrival, for instance, often results in prices adjusting rapidly to incorporate information. In an efficient market, such price movements will be permanent. Alternatively, trade imbalances usually arise because impatient traders submit large volumes of buy or sell orders and push prices away from the fundamental values. Price movements arising from such pressures are transitory and are followed by reversals. Fig. 4 presents an illustration.

Do HFTs provide liquidity to both EPM types? To answer this question, we divide the sample into transitory and permanent EPMs. The former are characterized by significant, yet temporary, price changes followed by reversals. We identify these as EPMs that revert by more than 2/3 by the end of a 30-minute period. The latter, permanent, EPMs do not revert by more than 1/3 by the end of this period. To allow for a clean separation of the two EPM types, we exclude the EPMs that revert by more than 1/3 and less than 2/3; these are 14.2% of the sample. The results are robust to using alternative reversal thresholds (e.g., reversals of more than 1/2 of the EPM return), time thresholds of one, ten, and 20 minutes, and allowing reversals to occur by the end of the trading day.

In Table 3, we examine the characteristics of the two EPM types and HFT activity around them. Despite a significant difference in post-EPM price patterns, other EPM characteristics (i.e., returns, trading activity, HFT participation, and spreads) are similar across the two types (Panel A). For instance, the average absolute return is 0.481% during both a typical transitory and a typical permanent EPM. In Panel B, we describe HFT activity around the two EPM types. Consistent with the full-sample results, HFTs provide liquidity to both types during interval t.

3.3. EPM magnitude

Although the EPMs in the sample represent the 99.9th percentile of all price movements, the setup may obscure the picture for the largest EPMs, during which HFT activity may differ from what has been discussed so far. Kirilenko et al., (2017) show that when prices reached extraordinary lows during the 2010 Flash Crash, HFTs withdrew from liquidity provision. So far, the results suggest that EPMs are not accompanied by similar withdrawals. But what about the largest EPMs? In Table 4, we examine if HFT liquidity provision varies in EPM magnitude, and particularly if HFTs provide liquidity to the largest of the extreme price movements.

Table 4 reports summary statistics and HFT^{NET} results for EPMs divided into four magnitude quartiles, from the

[4] In Table 2, as in Fig. 3, we benchmark the signs of HFT and nHFT volume to the EPM return.

Table 3
Transitory and permanent EPMs.

The table reports summary statistics for transitory and permanent EPMs. Transitory EPMs revert by more than 2/3 of the EPM return in the following 30 min. Permanent EPMs do not revert by more than 1/3 in the same interval. Because we exclude EPMs that revert by the amount between 1/3 and 2/3, the total number of EPMs in this table is 85.8% of that reported in Panel A of Table 1. Panel B reports HFT^{NET} around the two EPM types. Asterisks *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Summary statistics

	Transitory		Permanent	
	Mean	Std. dev.	Mean	Std. dev.
Absolute return, %	0.481	0.188	0.481	0.187
Total trades	70.90	87.79	69.78	85.64
Total HFT trades	55.97	71.35	55.54	71.90
Dollar volume	456,326	1,022,813	434,572	947,261
Share volume	14,576	29,516	14,470	29,250
Quoted spread, $	0.047	0.147	0.046	0.140
Relative spr., %	0.079	0.144	0.080	0.157
N	17,915		20,848	

Panel B: HFT^{NET}

	t-20	t-10	t	t+10	t+20
Transitory	−72.0**	−144.2***	−363.0***	−121.6***	−92.5***
Permanent	35.5	−3.0	−303.5***	−110.8***	12.0

Table 4
EPM magnitude quartiles.

Panel A divides EPMs into quartiles by return magnitude, from smallest to largest. Panel B contains HFT^{NET} statistics. Asterisks *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Summary statistics

	Q1 (small)		Q2	
	Mean	Std. dev.	Mean	Std. dev.
Absolute return, %	0.385	0.094	0.415	0.102
Total trades	59.96	67.79	63.77	72.67
Total HFT trades	48.29	57.05	51.09	60.33
Dollar volume	365,702	764,091	390,139	819,044
Share volume	12,191	24,783	12,947	25,700
Quoted spread, $	0.040	0.114	0.041	0.118
Relative spr., %	0.071	0.090	0.073	0.095
N	11,280		11,320	

	Q3		Q4 (large)	
Absolute return, %	0.465	0.116	0.645	0.261
Total trades	70.69	81.24	94.28	118.37
Total HFT trades	56.08	67.08	73.67	97.28
Dollar volume	455,307	977,999	640,282	1,316,028
Share volume	14,806	29,864	21,488	42,633
Quoted spread, $	0.044	0.119	0.051	0.188
Relative spr., %	0.077	0.107	0.082	0.258
N	11,280		11,320	

Panel B: HFT^{NET}

	t-20	t-10	t	t+10	t+20
Q1	−4.9	−106.2**	−115.7**	−102.2**	−6.9
Q2	−8.5	−90.3**	−60.3	−108.4***	−7.1
Q3	−70.9**	−65.5	−248.7***	−89.8**	−44.7
Q4	3.4	−33.6	−545.5***	−150.6***	−76.0

Table 5
Standalone and co-EPMs.

Panel A divides EPMs into standalone and co-EPMs, with the latter group capturing EPMs that occur simultaneously in several stocks. Panel B contains HFTNET statistics. Asterisks *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Summary statistics

	Standalone		Co-EPMs	
	Mean	Std. dev.	Sean	Std. dev.
Absolute return, %	0.487	0.198	0.471	0.181
Total trades	88.34	106.18	60.04	69.64
Total HFT trades	68.13	87.24	49.15	58.58
Dollar volume	611,337	1,237,578	351,352	753,084
Share volume	21,109	40,462	11,038	22,238
Quoted spread, $	0.049	0.124	0.040	0.148
Relative spr., %	0.084	0.147	0.069	0.159
# Stocks			3.5	2.78
N	19,402		25,798	

Panel B: HFT^{NET}

	t-20	t-10	t	t+10	t+20
Standalone	25.5	−31.4	−1295.7***	−101.2**	−37.1
Co-EPMs	−54.5***	−105.8***	549.3***	−121.5***	−31.1

relatively small (Q1) to the largest (Q4). As expected, trading volume and spreads increase in return magnitude (Panel A). HFT liquidity provision also increases, going from 116 shares in Q1 to 546 shares in Q4 (Panel B). Insofar as these results are generalizable to events like the 2010 Flash Crash, they suggest that it was probably not the magnitude of the crash that triggered HFT withdrawal.

3.4. EPM types: standalone and co-EPMs

The 2010 Flash Crash was characterized not only by the magnitude of price movements, but also by the large number of stocks that were affected. It is possible that liquidity withdrawals during the crash were due to the HFT firms' risk controls that were triggered when accumulated inventories reached high levels. The Flash Crash was a uniquely large and rare event, and it is not clear if it should be viewed as typical of HFT behavior in instances of multi-stock price movements. To examine this issue, we define co-EPMs as those that occur in two or more stocks during the same 10-second time interval and repeat earlier analyses.

Panel A of Table 5 reports that co-EPMs comprise 57% of the sample. The prevalence of co-EPMs should not be surprising given the exceptionally high EPM occurrence during the 2008 financial crisis when prices of multiple assets experienced large simultaneous movements (Fig. 2). An average co-EPM includes 3.5 stocks. The average return is 0.487% during a standalone EPM and 0.471% during a co-EPM. Trading activity metrics are noticeably different between the two types, with dollar volume during the standalone EPMs being about 74% higher than that during the co-EPMs.

Panel B shows that HFTs supply 1,296 shares of net liquidity during the standalone EPMs. In the meantime, they demand 549 shares of net liquidity during the co-EPMs. This reversal in HFT behavior is striking. In Fig. 5,

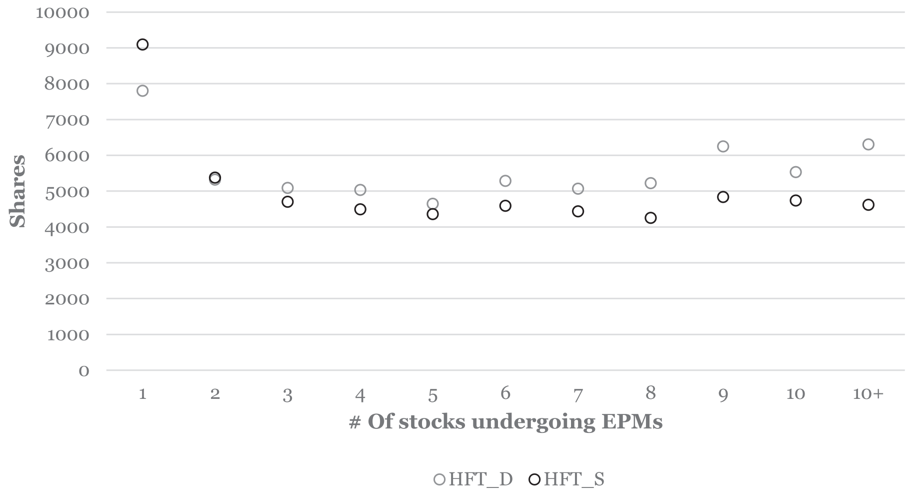

Fig. 5. HFT^D and HFT^S during co-EPMs. The figure reports per-stock HFT^D and HFT^S during the standalone EPMs and co-EPMs.

we examine its evolution. To do so, we plot HFT^D and HFT^S for standalone and co-EPMs. As previously, the metrics are computed on a per-stock basis. HFT^D and HFT^S decline rapidly when more than one stock undergoes simultaneous EPMs. Notably, the decline is more pronounced for supply than demand. As such, the risk controls triggered during co-EPMs appear to affect liquidity-supplying strategies more than they affect liquidity-demanding strategies, giving rise to positive HFT^{NET} during co-EPMs.

Note that even though HFT activity per stock declines, total inventory accumulated during co-EPMs may increase. For instance, inventory accumulated during the 10-stock co-EPM is 7,960 $(= 796 \times 10)$ shares, more than six times the inventory accumulated during the standalone EPMs. As such, even though HFTs reduce activity on the per-share basis, the risk of their total positions may increase. This risk may be further exacerbated if, in addition to the co-EPM stocks, other stocks in the HFT portfolios are experiencing large price movements. Such movements, even if they do not qualify as EPMs, may affect total HFT position risk. We examine this issue next.

3.5. Co-EPMs and position risk

To gain a better understanding of the risks assumed by HFTs during co-EPMs, we turn to the concept of value at risk (VaR). We caution that our data do not contain capital positions or inventories of individual HFTs, so we are unable to estimate the true VaR. Rather, we follow the general intuition of VaR analyses and refer to the results as quasi-VaR (QVaR). Specifically, we rely on the non-parametric method of Allen et al., (2012) and begin by estimating, on a daily basis, the 99th percentile of the 10-second absolute returns for the portfolio of 40 sample stocks. Then, to account for cross-correlation of individual stock returns in the portfolio tail returns, we estimate average stock returns for each sample stock i during the instances of portfolio tail returns on each day d, Ret_{id}^{tail}. The contribution of individual stocks to the portfolio tail return varies slowly. As such, the composition of portfolio tail returns on day $d-1$ is a sufficient proxy for the expected composition on day d. With this in mind, we compute intraday QVaR as follows:

$$QVaR_t = -\min\left(\sum_{i}^{40} Ret_{id-1}^{tail} \times DINV_{it}, \sum_{i}^{40} -Ret_{id-1}^{tail} \times DINV_{it}\right), \tag{2}$$

where $DINV_{it}$ is the dollar inventory in stock i accumulated by the HFTs during the interval t valued at the last midquote of the interval. The first term captures potential portfolio losses if the EPM is followed by a positive tail return, and the second term captures potential losses if the EPM is followed by a negative tail return. We then select the minimum of the two terms to estimate the maximum loss. In a nutshell, QVaR estimates the expected dollar loss during the following 10-second interval if the HFT portfolio experiences an unfavorable 99th percentile return.

Fig. 6 shows that QVaR increases steadily in the number of stocks experiencing a co-EPM. Specifically, it increases from \$287 during intervals without EPMs to \$936 for standalone EPMs, and further to over \$5,000 for intervals with more than ten EPMs. This increase is driven by the inventory accumulation in both the stocks undergoing EPMs and in the rest of the portfolio and likely explains the HFTs' tendency to reduce risk exposure on a per-stock basis.

3.6. EPM sequences

Earlier results show that HFTs provide substantial liquidity to the standalone EPMs, yet demand liquidity during co-EPMs. In Panel A of Table 6, which serves as a companion to Fig. 5, we examine HFT sensitivity to the number of stocks in a co-EPM. The sensitivity is high; HFT^{NET} switches from being negative during the standalone EPMs to zero for the two-stock co-EPMs and to being positive for co-EPMs that involve three and more stocks. The

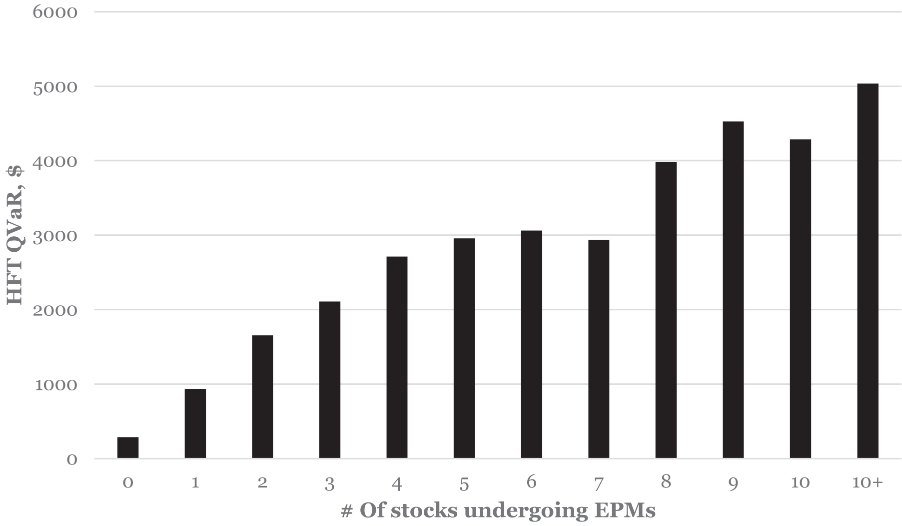

Fig. 6. QVaR. The figure reports the quasi-value at risk (QVaR) accumulated by HFTs during 0, 1, 2, ... and 10+ simultaneous EPMs. We begin by estimating the 99th percentile of the 10-second absolute return of the portfolio of sample stocks. Then, we estimate average returns for each stock i, Ret_i^{tail}, during the instances of portfolio tail returns. The contribution of individual stocks to the portfolio tail returns varies slowly. With this in mind, we use the previous day's composition of portfolio tail returns as a proxy for the expected composition on day d. We then compute intraday QVaR as follows:

$QVaR_t = -\min(\sum_i^N Ret_{id-1}^{tail} \times DINV_{it}, \sum_i^N -Ret_{id-1}^{tail} \times DINV_{it})$,

where $DINV_{it}$ is the dollar inventory in stock i accumulated by HFTs during the interval t valued at the last midquote of the interval.

Table 6
Standalone and co-EPMs, EPM sequences.

The table reports HFT^{NET} for standalone and co-EPMs (Panel A) and for EPM sequences (Panel B). EPM sequences are strings of same-directional EPMs during the trading day, with Column 4 identifying the position of a particular EPM in the sequence. p-Values are in parentheses. Asterisks *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Standalone and co-EPMs			*Panel B: EPM sequences*		
	HFT^{NET}	# Obs.		HFT^{NET}	# Obs.
(1)	(2)	(3)	(4)	(5)	(6)
1	−1,295***	19,402	1st	−717***	10,221
2	−55	7,326	2nd	−526***	5,679
3	389***	4,353	3rd	−419***	3,931
4	542***	2,980	4th	−315**	2,982
5	288***	2,210	5th	−209	2,379
6	698***	1,602	6th	−229	2,001
7	630***	1,274	7th	316	1,710
8	973***	888	8th	−21	1,483
9	1,411***	891	9th	91	1,303
10	796***	690	10th	69	1,145
11+	1,684***	3,584	11th+	177***	12,366

results suggest HFT liquidity supply is sensitive to inventory risk. This is consistent with Amihud and Mendelson (1980) and Comerton-Forde et al., (2010), who show that market maker strategies depend on inventories.

Given this fragility, it is possible that HFTs also remain on the sidelines on days with long sequences of EPMs, especially if these EPMs have the same return direction. In Panel B of Table 6, we examine if this occurs. The data show that HFTs usually provide net liquidity to the first four EPMs in the sequence and reduce net liquidity provision to zero if the sequence continues. There is some evidence of positive HFT^{NET} for very long sequences.

3.7. Does HFT activity during EPMs differ from their usual behavior?

Research shows that HFTs usually demand liquidity in the direction of returns (e.g., Brogaard et al., 2014). If this pattern persisted during EPMs, we would observe significantly positive and large HFT^{NET}. On the contrary, we find that the pattern reverses for standalone EPMs. Although the pattern does not reverse for co-EPMs, it is possible that the positive HFT-return relation is reduced even for these EPMs. Accounting for return magnitude, HFTs may demand less liquidity during the times when multiple stocks undergo EPMs than they normally would. To examine this issue, we turn to the following multivariate setting:

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

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 lags for the dependent and each of the independent variables, with $\sigma \in \{1, 2, \ldots, 10\}$. The variables in the vector are indexed with a subscript k. All variables are standardized at the stock level.

Because the coefficients on the 1_{EPM} dummy are related to returns, they should be interpreted jointly with those on the Ret variable. For example, in Column 1 of Table 7, the estimated coefficient on the Ret variable confirms that HFTs usually demand liquidity in the direction of return. In the meantime, the 1_{EPM} dummy shows that HFTs reduce liquidity demand during EPMs, with the incremental effect

Table 7
Net HFT activity and EPMs.
The table reports estimated coefficients from the following regression:

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

where HFT^{NET} is the difference between HFT^{D} and HFT^{S}; the dummy 1_{EPM} is equal to one if a 10-second interval t is identified to contain an EPM and is equal to zero otherwise; $1_{EPM\text{-}TRANSITORY}$ and $1_{EPM\text{-}PERMANENT}$ are dummies that capture the two EPM types; $1_{EPM\text{-}STANDALONE}$ captures the standalone EPMs; $1_{CO\text{-}EPM}$ captures EPMs that occur simultaneously in two or more sample stocks; $1_{EPM\text{-}Q1}$ 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 $\sigma \in \{1, 2, \ldots, 10\}$ 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.

	(1)	(2)	(3)	(4)
1_{EPM}	−0.798***			
	(0.00)			
$1_{EPM\text{-}TRANSITORY}$		−0.783***		
		(0.00)		
$1_{EPM\text{-}PERMANENT}$		−0.816***		
		(0.00)		
$1_{EPM\text{-}STANDALONE}$			−1.437***	
			(0.00)	
$1_{CO\text{-}EPM}$			−0.305***	
			(0.00)	
$1_{EPM\text{-}Q1}$				−0.487***
				(0.00)
$1_{EPM\text{-}Q2}$				−0.561***
				(0.00)
$1_{EPM\text{-}Q3}$				−0.799***
				(0.00)
$1_{EPM\text{-}Q4}$				−1.397***
				(0.00)
Ret	0.080***	0.080***	0.080***	0.081***
	(0.00)	(0.00)	(0.00)	(0.00)
Vol	0.065***	0.065***	0.066***	0.065***
	(0.00)	(0.00)	(0.00)	(0.00)
Spr	−0.009***	−0.009***	−0.009***	−0.009***
	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.01	0.01	0.01	0.01

of −0.798 standard deviations. Having established the basic result, we next turn to HFT activity during the previously identified EPM types. Column 2 shows that during both transitory and permanent EPMs the normally positive HFT-return relation is significantly reduced. In Column 3, we find the same result for the standalone and co-EPMs, yet the decline is much greater for the standalone EPMs. Similar results emerge in Column 4 that accounts for EPM magnitude; the normally positive relation between HFT behavior and returns is reduced, more so during the largest EPMs. Overall, even in cases when they demand liquidity during the EPM episodes (the co-EPM case), HFTs demand considerably less than they normally would.

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

The 10-second event windows are quite long given the speed of modern trading and may conceal nefarious aspects of HFT behavior. Yang and Zhu (2015) propose and van Kervel and Menkveld (2018) show that HFTs are able to recognize trading patterns after a period of time and switch from supplying liquidity to demanding it. Although van Kervel and Menkveld (2018) focus on time horizons that are much longer than ours, even one second is a long enough time for HFT algorithms to re-evaluate a trading strategy. It is therefore possible that HFTs supply liquidity at the beginning of EPMs yet exacerbate their tail ends.

To examine this possibility, in Fig. 7 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. If HFT algorithms had been designed to quickly switch from liquidity supply to demand after observing large price changes, they would have had sufficient time to do so. The figure contains no evidence of HFT^{NET} switching to positive values. If anything, it remains slightly negative.[5]

Although the time aggregation period in Fig. 7 is finer than that used in the remainder of the study, it is still long relative to HFT reaction speeds. It is possible that HFT^{NET} is positive at the very beginning of some EPMs, perhaps for a few micro- or milliseconds. However, because pinpointing the exact time when an EPM begins is next to impossible, we are unable to examine this issue further. Even if HFT^{NET} is positive during the EPM early stages, its effect is small and does not register in the data.

3.9. Profitability of liquidity provision during EPMs

The data show that HFTs usually provide liquidity to nHFTs during both transitory and permanent EPMs. Since HFTs choose to do so, liquidity provision should be profitable. How are these profits derived? During positive permanent EPMs as described in Fig. 4, if a trader limits liquidity provision to the size of his existing long inventory, he will have bought low and sold high. If however he provides liquidity indiscriminately, in the amount larger than the existing long inventory, he may accumulate a money-losing short position. The same logic, but in reverse, applies to negative permanent EPMs.

During transitory price movements, when the price first moves up and then down (Fig. 4), a skilled trader may profit by initially selling high to the impatient buyers and then buying low when the price reverses. The literature shows that providing liquidity during such reversals is profitable (Hendershott and Seasholes, 2007; Nagel, 2012; So and Wang, 2014). This strategy does not require pre-existing inventory as profits are derived from the inventory accumulated during the EPM. In summary, it is possible that HFTs profit from both permanent and transitory EPMs. Next, we examine the data for evidence of such profits.

Specifically, we estimate HFT trading revenues on EPM days and compare them to the days without EPMs. We follow the approach used by Sofianos (1995), Menkveld (2013), and Brogaard et al., (2014) and assume that for

[5] As in Fig. 3, the non-permanent return components are evident, suggesting lagged adjustment in prices. In addition to generating momentum after $t = 0$, thus adjustment may generate smoothing prior to $t = 0$.

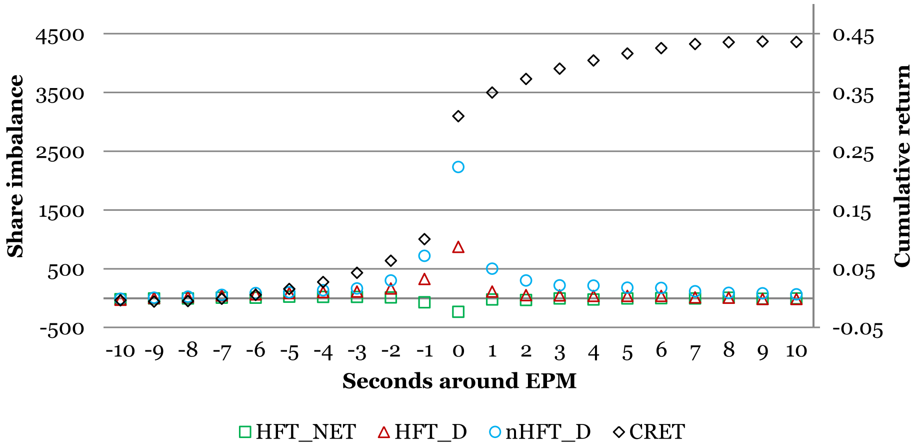

Fig. 7. HFT and nHFT activity during EPMs, a second-by-second view. The figure displays the average second-by-second price path and trading activity during $[-10;+10]$-second windows centered on the largest one-second EPM return. HFT^{D} ($nHFT^{D}$) is liquidity demanded by HFTs (nHFTs) in the direction 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.

each sample stock and each day HFTs start and end the day with zero inventory, and that all inventory accumulated by the end of the day is sold at the closing midpoint. We compute HFT revenue for each stock and each day as:

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

where HFT_n is the number of shares traded by HFTs during the nth transaction, I is the indicator equal to one for buy trades and -1 for sell trades, P_n is the trade price, $invHFT_N$ is the inventory accumulated by HFTs before the end of the day, and P_N is the end-of-day midquote. Following Brogaard et al., (2014), 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. The first term of Eq. (4) represents cash flows to HFTs 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 regression for each stock i on day t:

$$\pi HFT_{it} = \alpha + \beta nEPM_{it} + \varepsilon_{it}, \tag{5}$$

where $nEPM$ captures the number of EPMs. The results are simple, and we report them here rather than in a separate table. The α estimate suggests than HFTs capture \$3,834 in revenue per stock on an average day; whereas the β estimate indicates that the revenue becomes \$219 greater with each EPM. As such, HFT activities during EPMs are potentially profitable. In addition to the general case in Eq. (5), we compute the β estimates for all EPM breakdowns (i.e., permanent, transitory, standalone, co-EPMs, and for four magnitude quartiles). Due to the noisiness of profit calculations, the β estimates for the breakdowns are statistically insignificant. The revenue results should therefore be interpreted with caution. A conservative interpretation would suggest that there is no evidence of HFT losses on average due to EPMs and some evidence of profits.

3.10. HFT activity and future EPMs

Other research has suggested that HFTs trigger EPMs. Golub et al., (2013) report that mini-crashes in individual stocks have increased in recent years and suggest a link between these crashes and HFT. Leal et al. (2016) model a market in which HFTs play a fundamental role in generating flash crashes. To shed light on this issue, we use probit regressions to model the probability of an EPM as a function of lagged values of HFT^{NET}, return, volume, and spread:

$$\begin{aligned} Prob\ (EPM = 1)_{it} &= \alpha + \beta_1 HFT^{NET}_{it-1} + \beta_2 Ret_{it-1} \\ &\quad + \beta_3 Vol_{it-1} + \beta_4 Spr_{it-1} + \varepsilon_{it}, \end{aligned} \tag{6}$$

where all variables are as previously defined and are lagged by one interval.

The results are in Table 8 and show no evidence of HFT being associated with a higher probability of future EPMs. On the contrary, HFT is associated with a lower EPM probability. For instance, in Column 1, the marginal effect of the HFT^{NET} variable implies that the probability of an EPM decreases by 0.6% of the unconditional probability with every standard deviation increase in the pre-EPM HFT^{NET}.

4. Robustness

4.1. Alternative EPM identification techniques

Earlier, we discuss two alternative methods of EPM identification. The first method identifies EPMs as the 99.9th percentile of raw returns, and the second method uses the Lee and Mykland (2012) methodology. In Table 9, we report a brief summary of results arising from these two methodologies. The results are qualitatively similar to those obtained from the main sample. A full version of alternative sample results is reported in the Internet Appendix.

Table 8
EPM determinants.
The table reports the coefficients and the marginal effects from a probit model of EPM occurrence:

$$Prob\ (EPM = 1)_{it} = \alpha + \beta_1 HFT^{NET}_{it-1} + \beta_2 Ret_{it-1} + \beta_3 Vol_{it-1} + \beta_4 Spr_{it-1} + \varepsilon_{it},$$

where 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 interval. HFT^{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 trades, Ret is the absolute return, Vol is total 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.

	All (1)	Standalone (2)	Co-EPMs (3)	Permanent (4)	Transitory (5)
Intercept	−3.237***	−3.446***	−3.382***	−3.430***	−3.469***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HFT^{NET}{}_{t-1}$	−0.002***	−0.002**	−0.004***	−0.001	−0.005***
Marginal effect	−0.006	−0.003	−0.008	−0.002	−0.006
	(0.00)	(0.03)	(0.00)	(0.23)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.15	0.12	0.14	0.13	0.12

Table 9
EPMs defined using alternative methodologies.
Panel A reports HFT^{NET} for the sample of EPMs defined using the 99.9th percentile of raw returns. Panel B reports HFT^{NET} for the sample defined using the Lee and Mykland (2012) methodology. Full results for these and other tests using the two alternative methodologies are available in the Internet Appendix. Asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: 99th Percentile of raw returns

	HFT^{NET}
All	−299.3***
Transitory	−457.6***
Permanent	−323.2***
Q1	−110.8*
Q2	−145.5***
Q3	−293.7***
Q4	−655.5***
Standalone	−1296.9***
Co-EPMs	446.4***

Panel B: Lee and Mykland (2012)

	HFT^{NET}
All	−892.6***
Transitory	−973.2***
Permanent	−1063.9***
Q1	−648.8***
Q2	−748.6***
Q3	−859.2***
Q4	−1312.5***
Standalone	−1811.9***
Co-EPMs	850.7***

Table 10
EPMs defined intraday.
The table examines HFT behavior around EPMs defined for different time-of-the-day distributional cutoffs. First, we split the day into the following seven intervals: 9:35–10:00, 10:00–11:00, 11:00–12:00, 12:00–13:00, 13:00–14:00, 14:00–15:00, and 15:00–15:55. For each interval, we select returns above the 99.9th percentile. This definition allows EPMs to be evenly distributed within an average day. For the newly defined EPMs, we report the average HFT^{NET} statistics as in the previous tables. We also report the statistics for the 9:35-10:00 and 10:00-15:55 intervals. Asterisks *** and ** indicate statistical significance at the 1% and 5% levels.

	$t-20$	$t-10$	t	$t+10$	$t+20$
Seven intervals	9.9	47.3**	−267.3***	−130.6***	−61.2***
9:35–10:00	−20.1	114.4	−607.4***	−236.3**	−98.3
10:00–15:55	12.1	42.6**	−243.4***	−123.0***	−59.0***

4.2. Alternative return distributions

Fig. 1 points to a significant intraday pattern in the number of EPMs, which is consistent with the well-known phenomenon whereby returns are large in the early morning and then level off. It therefore may be useful to check if conditioning the EPM definition on return distributions that are allowed to vary intraday affects our conclusions. Put differently, an early morning return may look extreme with respect to the afternoon returns, but unremarkable with respect to a distribution of price changes in the first half-hour of trading.

To examine this issue, we split the sample into seven intervals: 9:35–10:00, 10:00–11:00, 11:00–12:00, 12:00–13:00, 13:00–14:00, 14:00–15:00, and 15:00–15:55. We then define EPMs as the 99.9th percentile of Eq. (1) residuals in each interval. This approach produces a more even distribution of EPMs throughout the day than that in Fig. 1. We then examine HFT behavior for these newly defined EPMs. The results are in Table 10 and support those obtained for the original sample; HFTs provide liquidity during an average EPM. We obtain similar results when we use two instead of seven intervals (i.e., 9:35–10:00 and 10:00–15:55).

5. Conclusion

We provide novel evidence on the stability of liquidity supply by high frequency traders (HFTs), a dominant subset of liquidity providers in modern markets. HFTs are endogenous liquidity providers (ELPs) and do not have the obligation to supply liquidity during stressful times. We show that HFTs are net suppliers of liquidity to non-HFTs (nHFTs) during extreme price movements (EPMs). HFTs supply liquidity even during the most extreme EPMs and the EPMs that result in permanent price changes.

However, HFT liquidity supply is sensitive to multiple EPMs, as HFTs on average switch to demanding liquidity when multiple stocks simultaneously undergo EPMs and when EPMs persist throughout the day. The switch is due to the liquidity-supplying strategies being more risk averse than the liquidity-demanding strategies. During episodes of multiple simultaneous EPMs, position risk accumulated by HFTs is significantly higher than normal, likely leading to the reduction in their activity, particularly on the supply side. We find some evidence of HFTs' earning positive revenues on days with EPMs. Despite this, the results show that HFTs do not appear to cause EPMs.

While beyond the scope of this paper, more research can help generalize or qualify the findings. For instance, it will be important to know whether the practice of HFT evolved in a way whereby what was true in the late 2000s is no longer the case. Also, it is important to understand how changes in market structure, such as the introduction of limit-up limit-down trading rules or the arrival of a new venue that provides protection to liquidity providers impacted ELPs.

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