The Ambivalent Role of High-Frequency Trading in Turbulent Market Periods *

Nikolaus Hautsch Michael Noé S. Sarah Zhang

August 14, 2018

Abstract

Based on unique and highly detailed data from Eurex Bund Futures trading, we document an ambivalent role of high-frequency traders (HFTs) in periods of fundamental news arrival. As long as market uncertainty is modest, HFTs serve as market makers, post competitive spreads, earn profits predominantly through liquidity supply and contribute less to price variation than non-HFTs. When price uncertainty peaks, however, such as right before news releases or after extraordinary events, as, e.g., after the U.K. Brexit announcement, HFTs rapidly shift their focus from market making to aggressive (not necessarily profitable) directional strategies, contribute to liquidity dry-ups and amplify price variation.

Keywords: High-Frequency Trading, Market Making, News Releases, Futures Market, Brexit

JEL classification: G10, G14

*Nikolaus Hautsch, Department of Statistics and Operations Research, University of Vienna, Research Platform "Data Science @ Uni Vienna", and Center for Financial Studies, Frankfurt, Email: nikolaus.hautsch@univie.ac.at. Michael Noé, Derivatives Market Design, Eurex Frankfurt AG and School of Business and Economics, Humboldt-Universität zu Berlin, Email: michael-noe@web.de. Corresponding author: S. Sarah Zhang, Alliance Manchester Business School, University of Manchester, Email: sarah.zhang@manchester.ac.uk, Booth Street East, Manchester M15 6PB, United Kingdom, Phone: +44 (0) 161 306 3452, Fax +44 (0) 161 275 4023. We thank Eurex for providing the data and insightful discussions. The views expressed here are solely our own. We thank Torben G. Andersen, Joel Hasbrouck (discussant), Rudy de Winne (discussant), Marius Zoican, and participants of the American Finance Association Meetings 2018, 1st Dauphine Microstructure Workshop, the Financial Econometrics and Empirical Asset Pricing Conference Lancaster and the 3rd SAFE Market Microstructure Workshop. All errors are our responsibility.

1. Introduction

The last decade has seen a dramatic increase in the popularity of Algorithmic Trading (AT) and specifically High-Frequency Trading (HFT).[1] One major concern about HFT is its possible destabilizing effect on the market. Specifically, high-frequency traders (HFTs) might withdraw liquidity when it is actually needed, such as during the "Flash Crash" on May 6th, 2010 (cf. Kirilenko *et al.*, 2017) or the more recent U.S. stock market plunge on February 5th, 2018 (cf. Bloomberg, 2018), or provide liquidity which is not accessible by non-high-frequency traders (nHFTs) (cf. Bloomberg, 2015b). They can moreover destabilize the market through excessive aggressive trading during turbulent market situations. Even if HFTs act as high-speed market makers in the sense of Menkveld (2013) during "normal" market periods, it is an open question whether they are still willing to provide this service in periods of high market uncertainty and strong price movements.

In this paper, we analyze trading in the Euro-Bund Futures, one of the most actively traded contracts world-wide and solely traded on Eurex, Frankfurt. Consequently, we focus on HFT in a *non-fragmented* market, i.e., a market setting which substantially differs from, e.g., U.S. equity trading, which is highly fragmented. We thus particularly aim at understanding the role of HFT in an environment where HFT strategies are most likely to be concentrated on one market. Moreover, we perform our analysis for periods where liquidity supply is critical and distinguish between two types of scenarios: On the one hand, we analyze local time windows around *scheduled* macroeconomic announcements with abnormally high price impact. On the other hand, we focus on unforeseen extraordinary events, such as the announcement of the E.U. referendum results in the U.K. on June 24, 2016 ("Brexit"), the announcement of the Greek referendum in June 29, 2015, and the Chinese Black Monday on August 24, 2015.[2]

[1] AT is commonly defined as "the use of computer algorithms to support the trading process" (cf. Hendershott *et al.*, 2011), whereas HFT is considered as a subcategory of AT with specific high-frequency characteristics.

[2] Studying these types of extreme events makes our paper fundamentally different from Brogaard et al. (2017), who analyze HFT behavior on NASDAQ around extreme price movements of particular stocks. The events studied in our paper are extraordinary news events causing a lasting and fundamental effect on the market.

The major question addressed in this paper is to which extent HFTs contribute to liquidity dry-ups and volatility in such market periods. Specifically we ask: (i) How much liquidity do HFTs supply and demand compared to n(on-)HFTs in periods of high price uncertainty? (ii) Do HFTs widen their spreads more than nHFTs in such situations? (iii) Do HFTs supply and demand liquidity in or against the direction of market movements? (iv) How (much) do nHFTs contribute to (local) price variation?

Using a unique data set with trader account identification, we are able to identify market activity originating from HFT firms with very high precision. This institutional identification is complemented by empirical criteria on HFT intraday trading patterns in the spirit of Kirilenko *et al.* (2017), but adjusted to the specific characteristics of the Eurex Bund Futures market. Consequently, we are able to assign each order activity to a HFT or nHFT, respectively. Given the high liquidity in Bund Futures trading, this results into precise statistical inference on (n)HFT activities over short time spans. Moreover, we are able to decompose the quadratic variation of the midquote process over short intervals into components triggered by (n)HFT liquidity supply and demand. This allows us to quantify the relative contribution of specific (n)HFT order submission or cancellation strategies to local price variation.

Analyzing data from 2014 to 2016, we find a dual role of HFTs in turbulent market periods of high price uncertainty: On the one hand, HFTs have stabilizing effects for the market as they continuously provide liquidity around scheduled news announcements and quickly replenish liquidity after the release. Even in extreme periods, such as after the U.K. Brexit announcement, HFTs provide more liquidity than nHFTs. Different from common beliefs (e.g.,NYT (2010)), HFTs typically do *not* intensively engage in aggressive news trading, but rather buy and sell evenly after scheduled news releases. In these situations, they predominantly make their profits by offering (and earning) competitive bid-ask spreads, while nHFTs are mostly responsible for directional trading activities and make profits from positional gains.

On the other hand, we identify different effects of HFT in periods of excessive price uncertainty. In these situations, HFTs significantly contribute to liquidity dry-ups by withdrawing a large amount of liquidity, widening their spreads, and increasing aggressive directional trading.

Their behavior is in line with the activities of an uninformed market maker protecting herself against adverse selection. These situations can occur briefly before the release of fundamental information, but are only short-lived. However, in extraordinary market periods of high uncertainty, HFTs change to aggressive strategies by *increasing* liquidity demand and conducting directional trading activities. For instance, after the Brexit announcement, these directional HFT strategies dominate market activities over longer periods and substantially contribute to price variation. As soon as HFTs become increasingly involved in aggressive directional trading, their market making functionalities are undermined. HFTs are therefore *not* perfect substitutes of designated market makers[3], but follow alternative strategies whenever it becomes profitable. This ambivalent role of HFTs can partly explain why the empirical literature draws different conclusions on the effects of HFT on market quality.

Exploiting the high informativeness of our data enables us to perform a more detailed and differentiated analysis of the effects of HFT on liquidity and volatility than a major body of existing studies. Therefore, our findings complement the empirical literature on the effects of HFT in several ways and thereby offers explanations for the (to some extent conflicting) results in recent HFT literature. First, we find that during periods around *scheduled* news releases, HFTs generally focus more on market making rather than directional trading. In these periods, HFTs generally have stabilizing effects by serving more as liquidity providers than as liquidity demanders and make their profits predominantly from earning liquidity premia. This confirms findings of Menkveld (2013) and existing literature showing positive effects of HFT on market quality[4]

Second, we show that the behavior of HFTs can be substantially different in extreme market conditions triggered by unforeseen news creating substantial price uncertainty, such as, e.g., after the U.K.'s Brexit announcement in June 2016 or the day after the Greek government called for a E.U. referendum in June 2015. During these periods, HFT liquidity provision is limited

[3]Although there are registered liquidity providers for less liquid markets on Eurex, there are no registered liquidity providers or designated market makers for the Bund futures market, making the latter vulnerable to liquidity dry-ups in turbulent market periods.

[4]See, e.g., Chaboud *et al.* (2014), Zhang (2017), Brogaard *et al.* (2014), Brogaard *et al.* (2018), Scholtus *et al.* (2014), and Conrad *et al.* (2015).

and overcompensated by a significantly higher liquidity demand due to aggressive directional trading. This indicates an ambivalent role of HFTs on financial markets and shows that the market making function of HFTs can be substantially impaired in certain market conditions.[5]

Third, by quantifying (n)HFTs' contribution to local (quadratic) price variation, we show that HFTs move prices through both the submission of marketable *and* passive orders. Conversely, nHFTs contribute to realized volatility mainly through the submission of marketable orders. In periods (very) close to a *scheduled* news release, the HFT contribution to (local) realized volatility significantly declines to approximately 40%. Hence, nHFTs are the major drivers for price movements in these market situations. During periods of unforeseen exceptional events, however, the picture changes significantly. On days, as after the Brexit announcement, HFTs are the dominant originators of price movements and contribute more than 70% to quadratic price variation. These results confirm the dual role of HFTs in different market situations and complement studies by Hasbrouck & Saar (2013) and Boehmer *et al.* (2018).

Fourth, by conducting a profit analysis, we provide evidence on the origins of HFT profits. Confirming Menkveld (2013) we find that HFT revenues around macroeconomic news releases predominantly result from net spreads earned by HFTs. Conversely, during periods, such as after the Brexit announcement, positioning profits play a clearly more important role than liquidity premia with HFTs following aggressive momentum strategies. We illustrate that in this context aggressive HFT strategies can also result in significant losses. For instance, on the day after the Greek referendum announcement in June 2015, HFTs obviously cannot exploit their speed advantage and suffer strongly from losses in positional trading.

Finally, our results show that conclusions on the effects of HFT cannot necessarily be transferred from one market to another, but are specific to the asset and market conditions. Analyzing trading in Bund Futures, one of the most liquid futures contracts of the world, yields important complementary insights to studies for other markets, such as Brogaard *et al.* (2018) who use data from the NASDAQ equity market, Kirilenko *et al.* (2017) who use data from the

[5]These results complement the findings of Kirilenko *et al.* (2017) for an extraordinary event as the Flash Crash on May 6, 2010 or of Brogaard *et al.* (2017) for the financial crisis in 2008.

U.S. E-mini futures market, and Baron *et al.* (2017) who use data from the Scandinavian equity market. An important result is to show that the effects of HFT depend on the market situation.[6]

Our findings have important policy implications, as they demonstrate the ambivalent role of HFT on a market without market fragmentation. On the one hand, our results suggest that HFT market making stabilizes markets, improves market quality and should be fostered rather than be subjected to stricter regulation. On the other hand, regulation should ensure that in extreme periods, the rapid shift of HFT from market making activities to aggressive order placement strategies does not threaten market stability by a sudden dry-up of liquidity. Particularly in light of recent Markets in Financial Instruments Directive II (MiFID II) regulation which came into effect on January 3, 2018, regulation seems to focus on market making strategies rather than aggressive trading. While some of these regulatory rules might have beneficial effects on market quality, they might have detrimental effects on market stability in turbulent market conditions. Therefore, regulation rules should attempt to mitigate the risks of HFTs by reducing their incentives to perform aggressive trading strategies, while still keeping the benefits of HFT market making.

The remainder of the paper is structured as follows: In Section 2, we describe the institutional details of the Eurex market structure and present the data and corresponding descriptive statistics. We moreover discuss our methodology to identify HFT and show descriptive statistics of HFT activity. In Section 3, we analyze the contribution of (n)HFTs to liquidity dry-ups. Section 4 analyzes the contribution of (n)HFTs to price variation in turbulent market periods. In Section 5, we analyze trading profits and their determinants. Finally, Section 6 concludes.

[6] In this sense, our study complements findings by Schlepper (2016) who also uses data from Eurex Futures trading, however, without individual trader account identification and based on a significantly smaller sample.

2. Data and HFT Identification

2.1. Institutional Details of Bund Futures Trading

We focus on one of the most actively exchange traded products, the Euro-Bund Futures contract (FGBL).[7] The Bund Futures is a futures contract on German sovereign debt, with a time to maturity of 10 years and a coupon of 6%. It is the most important fixed income futures in Europe and one of the most important fixed income futures world-wide. An important property of the Bund Futures contract is that it is exclusively traded on Eurex, and thus there is no market fragmentation.[8] Eurex is the largest exchange for European equity index and fixed income futures world-wide. The Eurex trading system is fully electronic and operates as an order-driven market platform without designated market-makers, trading obligations and maker-taker fees. Trading times for the most liquid futures are from 8 a.m. CET to 10 p.m. CET. Trading starts with an opening auction, which is followed by a continuous trading period, and closes with a closing auction.

The Bund Futures is quoted in percentage points (of par) with a tick size of 0.01 points or 10 Euros, corresponding to a contract value of 100,000 Euros. The Bund Futures expiration months are March, June, September, and December. The contract is settled via delivery of the underlying German sovereign, with the delivery taking place on the 10th of the contract expiration month (or the following exchange day, if the 10th is not an exchange day). The last trading day of the expiring futures contract is two trading days before delivery. Price discovery typically occurs in the front-month contract, i.e., the contract with the closest expiration date. During the roll-over period, traders roll their position from the front-month contract to the back-month contract (with the second shortest maturity). Therefore, liquidity as well as price discovery switches during this period from the front-month contract to the back-month contract.

[7] Based on the average daily trading volume and compared to benchmark products across the exchange landscape.

[8] This makes cross-exchange arbitrage opportunities as discussed by van Kervel (2015) impossible, as there is no trading on other markets. However, other forms of (statistical) arbitrage (cf. Budish *et al.*, 2015) cannot be ruled out. In our study, we focus primarily on HFTs operating on the FGBL market and might not capture certain HFT strategies that operate across markets.

Since we focus on "normal" trading periods rather than roll-over periods, we exclude the last two trading days of the expiring futures contract.

To interpret news-implied price reactions in the following sections, it is required to understand the functionality of the Bund Futures contract in an investor's portfolio. After negative news causing high market uncertainty, market participants tend to exhibit a flight to higher-quality bonds by selling their equity positions and investing the cash flow into less risky assets, such as German sovereigns. This causes a decline in the implied bond yield and a corresponding rise in the bond price. Short-term portfolio adjustments are typically done via futures contracts as they are cheaper to trade than the actual bond itself due to higher liquidity and lower transaction costs. Thus, we generally expect the price of the Bund Futures to increase if equity markets decline and vice versa.

2.2. Data and Summary Statistics

We use proprietary order message data provided by Eurex. The time period ranges from January 1, 2014 (after the latest major release of the Eurex Trading System T7 in November 2013 (see Eurex (2013)), to October 31, 2015, corresponding to 448 trading days after excluding the last two trading days of the roll-over period. The order message data is time stamped to the nanosecond and consists of all order submissions, modifications, cancellations, executions as well as member and trader account identification for each message.

The order message data contains the timestamp, underlying product, order ID, message type (submission, cancellation or modification), order type, buy-sell indication, imposed price limit, corresponding quantity, and most importantly, the member ID and trader ID, indicating who submitted, modified or cancelled the order. The member ID indicates a registered company at Eurex. The trader can be an individual at a trading desk of the company as well as a group of traders routing their orders during the corresponding single trader ID. We conduct our HFT identification on trader level, but cross-check our identification using member information and in-house expertise from Eurex. Using order message data, we are further able to reconstruct each level of the order book on a tick-by-tick basis.

The trade data contains the timestamp, the underlying product, the order type of the marketable order, the buy-sell indicator, the trade price, and the traded quantity. Additionally, we distinguish between the liquidity demand and supply side of a trade. A liquidity demander is a trader who submits a marketable order, whereas a liquidity supplier is a market participant who has submitted a non-marketable order against which a marketable order is executed.

Table A1 in Appendix A provides summary statistics on activities of the Bund Futures market over the period under consideration. We report aggregated statistics and distinguish between "news days" and "no-news days". Panel A shows that the Bund Futures market is highly liquid with around 160,000 trades per day on average, a daily volume of more than 1.1 million contracts and more than 810,000 order submissions per day. The quoted spread, computed as the difference between the best bid and ask price, $QS := (P_1^A - P_1^B)$, is often at its minimum of one tick (i.e., 0.01 percentage points). The market depth, computed as $Depth\,x := \frac{1}{2}\sum_{k=1}^{x} Q_k^A + Q_k^B$, with Q_k^A (Q_k^B) being the ask (bid) quantity on price level k in number of contracts, is around 160 contracts per market side on the best price level. We observe higher activity (in terms of trades, traded volume and orders) and lower liquidity (measured by QS, $Depth1$ and $Depth5$) on news-days than on no-news days. According to Panel B, there is clear evidence for intraday periodicity which is (partly) explained by the opening and closure of related markets. Particularly, at 9:00 a.m. CET, the most liquid German equity market, Xetra, opens, at 3:30 p.m. the U.S. markets opens and at 5:30 p.m., Xetra closes. Thus, the time period between 9:00 a.m. and 5:30 p.m. is the most active and liquid period of the trading day.

2.3. Identification of High-Frequency Trading in the Bund Futures Market

According to the U.S. Securities and Exchange Commission (SEC), HFT is mainly characterized by a high speed, submissions of numerous orders cancelled shortly after submission, and flat end-of-day positions (see SEC, 2010, p.45 for details). Since HFT strategies are manifold and vary for different markets and assets, these criteria provide a valid basis for HFT identification. However, not all criteria can be easily applied due to typical data limitations. Previous literature therefore proposes different proxies and methodologies to measure HFT activity based on empirical criteria and institutional information. Hendershott *et al.* (2011) employ an empirical identification scheme by utilizing message traffic as a proxy for AT activity.[9] This methodology has the advantage of being applicable to public data. However, it usually focusses on one specific criterion, either latency or message intensity, which might have the disadvantage of not necessarily capturing all HFT activity. Other papers use HFT identifiers provided by the exchange based on its in-house expertise. For example, Brogaard *et al.* (2014) and Hagströmer & Nordén (2013) use NASDAQ data. A similar internal HFT flag is used by Schlepper (2016) for Eurex Bund Futures data. This identification may suffer from lack of transparency and reproducibility (as long as the exchange does not provide full information on how the identifier is exactly reconstructed). A third type of identification uses empirical criteria based on the identification of trader accounts. Malinova *et al.* (2013) use data from the Canadian stock market and Biais *et al.* (2016) utilize French stock market data. However, even if it is possible to identify underlying trader accounts, it is often impossible to uniquely identify whether the particular trader account is associated with a HFT trading desk. To minimize the risk of misclassification, empirical identification criteria are still required on top of institutional information on trader accounts.

We apply an identification scheme which exploits (i) information on trader accounts, (ii) empirical criteria on latency, order activity and end-of-day positions, and (iii) Eurex in-house expertise to validate identifications based on (i) and (ii). Our empirical criteria for HFT identification are in line with the criteria used by Kirilenko *et al.* (2017) for the E-mini futures market, but are adapted according to the specific characteristics of HFT companies trading at Eurex. Specifically, Kirilenko *et al.* (2017) identify traders as HFTs if they trade a given volume, do not have significant overnight positions, and do not have large variations in their intraday po-

[9]Similar empirical identification proxies for AT and HFT activity are used by Jiang *et al.* (2015) and Scholtus *et al.* (2014).

sition. We further augment these criteria by requirements on the latency of order activity.[10] Accordingly, we classify a trader ID as an HFT if its aggregated trading behavior across all active trading days fulfills the following criteria:

1. A minimum median of 800 order submissions per trading day.
2. A median end-of-day position relative to traded volume <5%.
3. At least one of the following latency measures should apply:
   (a) 5%-quantile of order lifetimes (time between order submission and deletion) <2.5 ms.
   (b) 5%-quantile of the time between two consecutive order submissions <1.0 ms.
   (c) 5%-quantile of reaction times (time between submission and execution of a passive order by a marketable order of the trader) <0.5 ms.

Applying these identification rules, we classify 236 out of 4,233 trader IDs as HFTs acting in the Bund Futures market which corresponds to 5.58% of all trader IDs. The HFT IDs are based on 75 Eurex member firms, compared to 336 active members during our sample period. Therefore HFT members have on average less trader IDs compared to the other Eurex members. We cross-check our identified HFT IDs using member information and in-house expertise from Eurex and find that our identification scheme captures a significant portion of HFT accounts. While we do not claim that our identification captures all HFT activity, we argue that we capture the majority of HFT accounts which focus their activities on this market.

In order to differentiate between HFTs with different levels of order aggressiveness, we group the identified trader IDs into three categories based on their demand ratio, computed as the liquidity demanding volume relative to total trading volume. If HFTs trade more than 90% of their volume using liquidity demanding orders, we classify them as being "aggressive". If they trade less than 10% using liquidity demanding orders (i.e., more than 90% of their volume

[10]These criteria account for the fact that HFTs are fast at deleting own orders and in submitting consecutive orders. This especially applies to HFTs that act as market makers as they need to be able to cancel orders quickly to avoid losses in case of a substantial price movement. Alternatively, we require HFT activity to reveal short reaction times, as HFTs acting as liquidity demanders (especially statistical arbitrageurs and news traders) need to be fast to be profitable (Foucault *et al.*, 2016).

is executed via liquidity supplying limit orders), we classify them as "passive" HFTs. Typical aggressive HFT strategies are directional strategies such as (statistical) arbitrage and news trading while passive HFTs are usually market makers. The remaining trader IDs (between 10% and 90% of their volume traded via liquidity demanding orders) are classified as "mixed" HFTs which run a mix of market making and directional strategies. Based on these criteria, we classify 16 trader IDs as aggressive HFTs (6.78% of all HFT trader IDs), 92 are classified as mixed HFTs (38.98%), and 128 as passive HFTs (54.24%). Thus, we conclude that the majority of identified HFTs in the Bund Futures market follow market making strategies.

Table 1 presents summary statistics of (n)HFT trading and order activity as well as HFT "participation rates". The participation rates give the proportional amount of trades or trading volumes where HFTs and nHFTs, respectively, contribute either on the liquidity demand or liquidity supply side. Accordingly, we count (n)HFT activities on *both* the liquidity demand and supply side, leading to a double-counting. We observe on average around $70,500$ trades per day (50% of $141,010$), where HFTs participate approximately 83,400 times as liquidity demanders (i.e., trade initiators) and/or liquidity suppliers (trade counterparts). Hence, in many trades, HFTs obviously participate on both sides of the trade, resulting into an overall HFT participation rate of 59.14%.[11]

Overall, HFTs which represent only 5.58% of all trader IDs, play an important role in the market: They participate in more than half of all trades and contribute to more than one third of the overall trading volume. On average, around 70% of their own total trading volume stems from liquidity supply (248,000 contracts compared to 143,000 contracts). Overall, HFTs submit 71% of all orders, which is considerable but not excessive in comparison to their total trading activity. The corresponding statistics on trading volumes, however, show that HFTs participate in only 38.81% of all supplied and demanded contracts, where they make nearly 50% of the liquidity supply and only 28% of the liquidity demand. Hence, HFTs generally trade smaller volumes and rather act as liquidity suppliers than liquidity demanders.

[11]Note that if HFTs would be on both sides of *all* trades (i.e., HFTs would trade with HFTs only), the respective number would be $141,010$, corresponding to a participation rate of 100%.

Table 1: Trading Statistics for the Groups of HFTs and nHFTs The table shows daily averages of key variables in our sample. *Trades* measures the average number of trades for both the liquidity demand and supply side. This double-counting is necessary to differentiate between liquidity supplying and liquidity demanding activity. The category *HFT* (*nHFT*) gives the sum of all trades where HFTs (nHFTs) participate as liquidity demanders and suppliers. Due to double-counting, the number under *Overall* gives *twice* the daily average of executed transactions. *Volume* is the number of traded contracts overall (double-counted) and decomposed into the number of contracts where HFTs and nHFTs participate as liquidity demanders (*Liquidity Demand*) and suppliers (*Liquidity Supply*), respectively. The column *HFT participation rate* provides HFT-specific averages relative to the overall market averages. *Order Submissions* gives the total number of submitted orders (including market/ marketable orders). Panel B decomposes the HFT-specific daily averages reported in Panel A into the corresponding statistics for the three HFT subgroups "aggressive", "passive", and "mixed" according to Section 2.3.

Panel A: HFT and nHFT Trading Statistics

	Units	Overall	HFT	nHFT	HFT participation rate (in %)
Trades	# 1,000 Trades	141.01	83.40	57.62	59.14
Trading Volume	1,000 Contracts	1,008.27	391.32	616.95	38.81
Liquidity Demand	1,000 Contracts	504.14	143.15	360.99	28.40
Liquidity Supply	1,000 Contracts	504.14	248.17	255.97	49.23
Order Submissions	# 1,000 Orders	700.84	499.95	200.89	71.34

Panel B: Trading Statistics for the HFT subgroups (participation rates in % in brackets)

	Units	Aggressive HFTs		Mixed HFTs		Passive HFTs	
Trades	# 1,000 Trades	3.96	(2.81)	37.64	(26.69)	41.79	(29.64)
Trading Volume	1,000 Contracts	86.43	(8.57)	163.66	(16.23)	141.23	(14.01)
Liquidity Demand	1,000 Contracts	86.34	(17.13)	49.92	(9.90)	6.89	(1.37)
Liquidity Supply	1,000 Contracts	0.09	(0.02)	113.75	(22.56)	134.34	(26.65)
Order Submissions	# 1,000 Orders	41.19	(5.88)	228.53	(32.61)	230.23	(32.85)

Panel B of Table 1 shows the corresponding statistics for the sub-groups of "aggressive", "mixed" and "passive" HFTs. The reported statistics naturally reflect the construction of the sub-groups based on the underlying liquidity demand ratio. Consequently, by definition, a large portion of HFT liquidity demanding activity is traced back to "aggressive" HFTs. Conversely, "passive" and "mixed" HFTs rather act as liquidity suppliers and account for a majority of order submissions.

To illustrate trade and order characteristics based on individual trade accounts, we compute corresponding daily statistics, which are averaged on a trader account level for both HFT and nHFT accounts. Table A2 in Appendix A reports daily trade and order characteristics for an average HFT and nHFT account. We find that an average HFT account participates on the liquidity demand or supply side of more than $1,000$ trades, compared to just around 30 trades of an average nHFT account. Likewise, average HFT order submission rates are 63 times higher than nHFT order submission rates. Though the average HFT account trades significantly smaller sizes than a nHFT account (5.4 contracts vs. 21.9 contracts), the account-specific HFT trading volume is still 15 times as high as trading volume executed by a nHFT account. Finally, we observe a strong variation across the HFT subgroups. The aggressive HFT group is the most distinctive group with considerably higher trading volume, larger trade sizes, and more order submissions compared to the others. We observe a striking difference between order-to-trade ratios of 346 for aggressive HFTs and 26 for passive HFTs (compared to around 5 for nHFTs). It is worth noting, however, that the group of aggressive HFTs consists of only 6.78% of all HFT trader IDs and just 0.4% of all trader IDs. We thus conclude that on the Eurex Bund Futures market, extreme message traffic, which is commonly associated with HFT (cf. IIROC (2012)), primarily stems of a very small group of aggressive HFTs.

2.4. Identification of Periods of High Price Uncertainty

Our analysis focusses on periods of high price uncertainty coming along with abnormal price movements and volatility. We distinguish between two types of scenarios. First, we analyze HFT behavior around *scheduled* macroeconomic news releases. Second, we focus on the analysis of turbulent periods after (widely) unforeseeable exceptional events.

In order to study HFT behavior around macroeconomic releases, we focus on local time windows around the corresponding news arrivals. Since the Bund Futures is known to react to macroeconomic news from the U.S. (see, e.g., Hautsch *et al.*, 2011), we utilize all major U.S. releases as also analyzed by Jiang *et al.* (2015) and Scholtus *et al.* (2014). Moreover, we include E.U. announcements as used by Jiang *et al.* (2012). Table B1 in the Appendix gives an overview of the macroeconomic announcements during the sample period. We focus on scheduled announcements during the most active period between 9.00 a.m. and 5.30 p.m.[12] We group all announcements by their market impact, measured by the price range (the difference between the highest and lowest mid-quote observed) during a 5-min period after the time of the news release. We focus on the top 25% announcements with the highest market impact.[13] The resulting sample consists of 179 distinct announcements with an average absolute log return of 0.04% through the 5-min period after the news release.[14]

We further categorize each announcement according to the sign of the local price trend around the announcement. To obtain a classification, which is widely robust to the choice of the underlying period, we consider mid-quote changes ΔP_{ba}, measured from different time points b before the announcement through time points a thereafter. We consider the intervals $\{b, a\} = \{0, 1min\}, \{0, 5min\}, \{-1min, 1min\}, \{-5min, 5min\}$, and assign a direction to the announcement if at least three of the corresponding price changes have the same sign. Otherwise we do not assign a direction. This classification results into 86 announcements with upward price movements, 92 announcements with downward price movements and one interval with no distinct classification.

For our analysis, we focus on market activity during a period of 30 minutes before and after a news release. Within this one-hour "event-window", we compute different measures of liquidity and trading activity based on a one-second grid. A high second-to-second variability of liquidity and trading characteristics around news releases, however, makes local smoothing inevitable. We therefore consider local averages over rolling windows of $m = 60$ seconds. Accordingly, the local average of a given variable s around second i is given by

$$s_i^* = \frac{1}{1 + 2 \cdot m} \sum_{j=i-m}^{i+m} s_j. \tag{1}$$

[12]Panel B in Table A1, Appendix A shows that trading activity is considerably lower after 5.30 p.m. As some news announcements occur simultaneously, we observe 914 announcements at 687 distinct points in time.

[13]The results for the remaining announcements are qualitatively similar and available upon request.

[14]A 5-min log return of 0.04% corresponds to more than 1000% on an annual basis.

Averaging across a local 1-minute window is necessary to exclude outliers in our results while still illustrating high-frequency dynamics at a 1-second level.

To analyze turbulent periods after unexpected influential events, we focus on the E.U. referendum in the U.K. in June 2016, the climax of the Greek debt crisis in June 2015, and the Chinese Black Monday in August 2015, which caused extreme volatility on financial markets. The nature of these events is different from that of scheduled macroeconomic announcements, as the specific timing of news arrivals is much less obvious and in the given cases happened overnight. Moreover, such periods create a higher and long-lasting level of market uncertainty than scheduled news announcements. We analyze all three events by applying the same HFT identification as in Section 2.3. In contrast to the case of scheduled news announcements, however, we apply these criteria only locally based on order activities on the event day and the day before.

As the first extraordinary event, we analyze the effects of the announcement of the U.K.'s E.U. referendum on Thursday, June 23, 2016. The result of the U.K.'s leave vote (so-called "Brexit") was announced early Friday morning, June 24, 2016. European markets were among the most severely affected, with the Euro Stoxx losing 7.7% and the German DAX losing 6.8% (see Wall Street Journal (2016)). As shown in Figure 1, we observe an extreme overnight price jump which materializes at the market opening. At the market opening, the price increased by almost 5 percentage points compared to the previous day closing price, from 163.69 to 168.50. During the day, prices declined and the FGBL closed with a 2 percentage points decrease compared to the opening. Trading volume steeply increased to around 400,000 traded contracts (around 50% of the total daily volume) until 11:30 a.m.

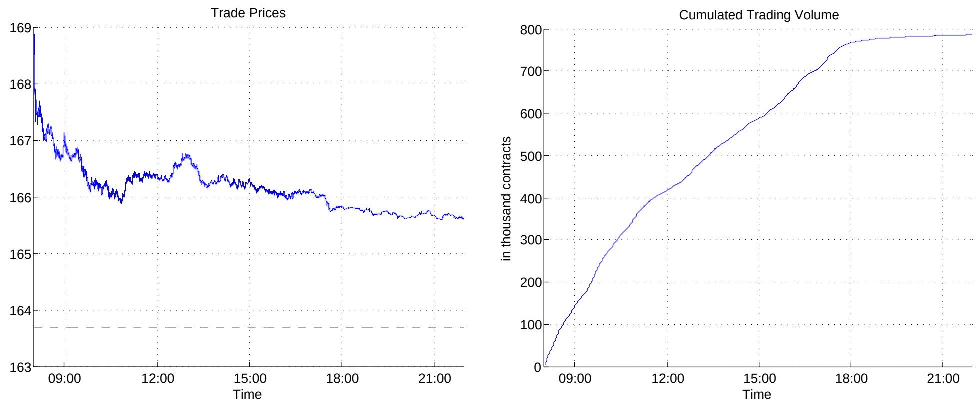


Figure 1: Prices and Trading Volumes on June 24, 2016. The dashed line represents the previous day's closing price of 163.69. The opening price is 168.50.

As a further extraordinary event, we utilize the climax of the Greek debt crisis on June 29, 2015. Due to the failure of the Greek government to make an IMF loan repayment on June 30, 2015, and the Eurozone members' rejections of the proposals made by the Greek government, the Greek government broke off negotiations on Friday evening, June 26, 2015, and called in a referendum to approve or reject the Troika's proposal. This announcement of the Greek referendum immensely increased the probability of a Greek exit from the Eurozone, which was also reflected in the market reaction when financial markets opened on Monday, June 29, 2015. While the Greek banks and stock market remained closed that day, European and U.S. markets experienced a significant drop at the market opening and throughout the day. Figure D.1 in the Appendix documents the developments of FGBL prices and cumulative trading volume on June 29, 2015. Compared to the previous day's closing price, we observe an increase of 2.5 percentage points at market opening, reflecting the negative nature of the announcement for European and German markets. Similarly to the Brexit day, however, the market tends to overshoot. Thus, prices are corrected downwards until approximately 3:30 p.m. (when U.S. markets opened), before they rose back to a level approximately 2 percentage points higher than the opening price.

The third event is the Chinese Black Monday on August 24, 2015, which was preceded by a decline of Chinese stock markets from the end of May 2015 and major price drops on May 28 and June 26. The slide in stocks culminated in a plunge of the Shanghai Composite

Index by 8.5% on August 24, 2015, corresponding to the largest one-day percentage loss since 2007 (see Bloomberg (2015a)). Global markets were affected by the crash, with the Dow Jones Industrial Average losing an unprecedented 1,000 points at market opening. As shown in Figure D.7 in the Appendix, the opening price increases by 0.2 percentage points compared to the previous day's closing price and then subsequently declines. The decline is interrupted by the U.S. market opening at 3.30 p.m., as U.S. markets were severely affected by the crash in China. Correspondingly, almost one third of the day's total trading volume is traded between 3.30 p.m. and 5.30 p.m.

3. HFT and nHFT Contribution to Liquidity Dry-Ups

3.1. Liquidity Supply and Demand around Scheduled News

In this section, we analyze the liquidity demand and supply by HFTs and nHFTs around macroeconomic announcements using limit order book and transaction data. Figure 2 shows the across-event averages and the corresponding 2.5% and 97.5% quantiles of the market depth on top of the order book (computed as the average depth on the best ask and bid level), and the corresponding HFT participation rate, i.e., the proportion of the first-level depth that is supplied by HFTs. On average, the market depth during announcement periods is slightly lower than during all other periods and declines by more than 70% prior to a release. As shown by the HFT participation rate, this drop is mainly due to a reduction of HFT-induced liquidity supply, which is reduced from around 50% of the first-level market depth up until 10 min before the news arrival to 33% directly before the release.[15]

Hence, HFTs withdraw more than 70% of their liquidity supply prior to the announcement and thus induce a considerable dry-up of liquidity supply. This behavior is clearly more pronounced for HFTs than for nHFTs. We therefore conclude that HFTs refrain from strategically positioning themselves in the market but rather withdraw liquidity until market uncertainty is

[15] Results are qualitatively similar for higher order book levels.

resolved. Such behavior is in line with the strategy of an non-informed market maker who protects himself against the risk of getting adversely selected as soon as the market is moving against him.

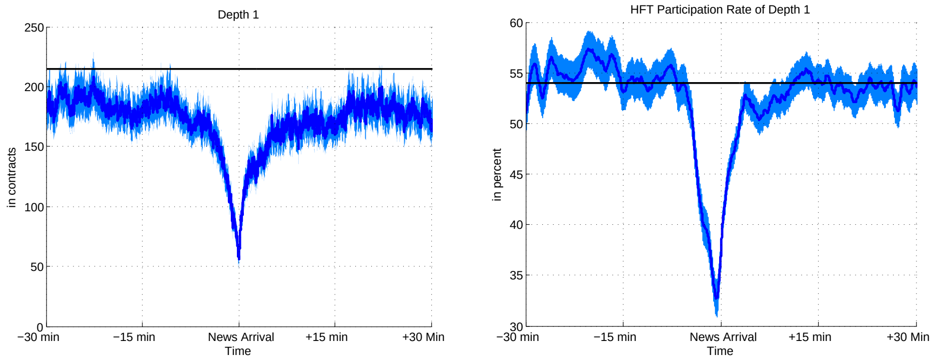


Figure 2: Market Depth and HFT Participation Rate at Order Book Level 1. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the news releases.

Figure 3 displays HFT participation rates in liquidity supply based on the number of transactions. In order to analyze which type of HFTs is responsible for the liquidity withdrawal, we distinguish between “aggressive”, “mixed” and “passive” HFTs as described in Section 2.3. Similarly to the corresponding plot in Figure 2, the left graph in Figure 3 indicates that on average more than 55% of the *traded* volume consumes liquidity supplied by HFTs. This ratio drops to less than 35% prior to the announcement. The right figure shows that this decline is due to both passive HFTs and mixed HFTs, who obviously change their liquidity supply strategies around news arrivals. Interestingly, the quick replenishment of liquidity supply after the release is mainly due to mixed HFTs. Pure passive HFTs seem to be more reluctant to quickly re-position themselves after the news event and await the general reaction of the market. In contrast, aggressive HFTs generally supply less than 1% of the liquidity in the limit order book and do not change their behavior during announcement periods.

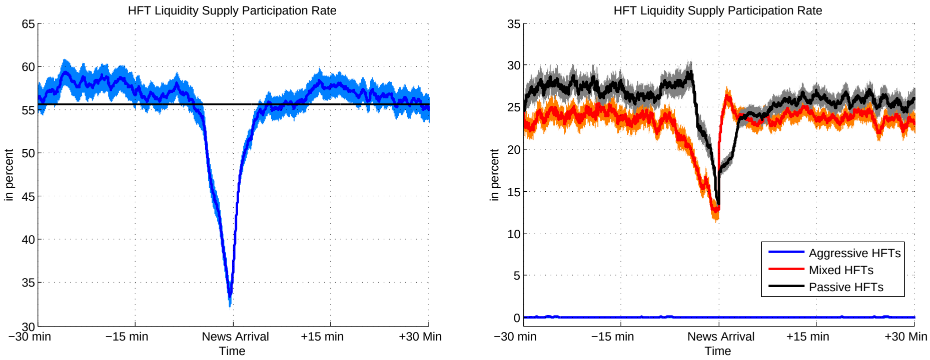


Figure 3: HFT Liquidity Supply and HFT Participation Rate in Traded Contracts. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid line is the overall mean across all trading days *excluding* a one-hour window around the news releases.

Likewise, Figure 4 gives the corresponding quantities for the liquidity *demand* in traded contracts. We observe that during non-event periods less than 20% of the traded contracts are initiated by HFTs. This proportion, however, increases during the event window and peaks at nearly 30% shortly *after* the news arrival. Such an increase in liquidity demand indicates directional trading strategies requiring prompt order executions instantaneously after the announcement. Alternatively, such patterns might stem from active position management of passive HFTs who close their positions in order to avoid losses due to extreme news-implied price changes.

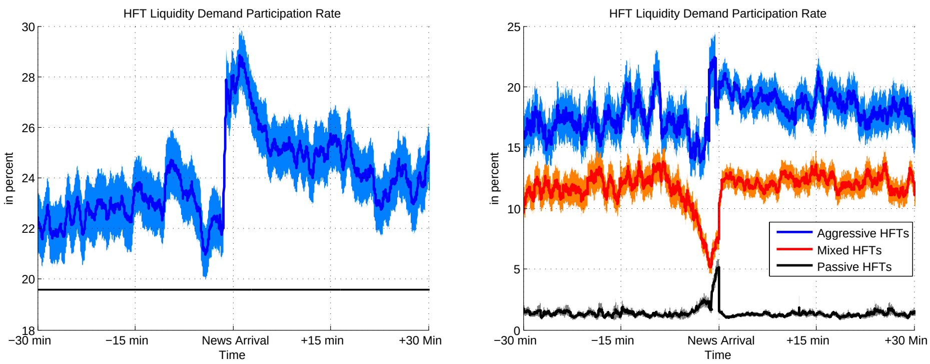


Figure 4: HFT Liquidity Demand and Participation Rate in Traded Contracts. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid line is the overall mean across all trading days *excluding* a one-hour window around the news releases.

Despite their reduction in liquidity supply around news releases, HFTs still provide more liquidity than they consume it. This is indicated by the HFT "demand ratio", computed as the volume of *HFT-initiated* transactions relative to their total traded volume, as shown in Figure 5. Overall, the ratio is around 22%, indicating that HFTs take more than three times more often the passive side than the active side in a trade. For comparison, Kirilenko *et al.* (2017) find a corresponding ratio of around 45% in E-mini futures trading before the Flash Crash on May 6th 2010. In this period and for this asset, HFTs obviously operate significantly more aggressively than during normal market conditions. The distinct differences between the three sub-group-specific levels displayed in Figure 5 are due to the construction of these groups in terms of (average) demand ratios. Nevertheless, it is striking that the passive HFTs subgroup's demand ratio exhibits a five-fold increase prior to news arrivals. Such pattern indicates active inventory management activities and a reduction of market making services by (otherwise) passive HFT liquidity suppliers in periods where the uncertainty in the market peaks.

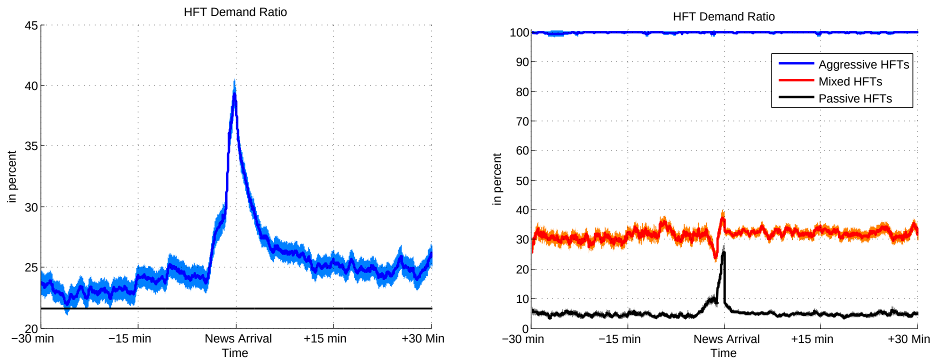


Figure 5: HFT Demand Ratio. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the news releases.

After the release of macroeconomic information, HFTs replenish liquidity much faster than nHFTs. This is illustrated in Table 2, reporting the average time that HFTs and nHFTs need to re-fill a certain proportion of the pre-news depth level (corresponding to the average depth through the interval starting 30 minutes prior to the event and ending 15 minutes prior to it). We observe that after 5 seconds, 25% of market depth is replenished, while it takes on average

51 seconds to replenish 95%. The HFT participation rate, however, grows at a much faster rate, indicating that HFTs replenish their liquidity supply much faster than the rest of the market. In fact, the HFT participation rate reaches 50% of its pre-news share in first-level depth within less than 3 seconds (on average). Hence, HFTs quickly react to changing market situations and thus are able to replenish liquidity as soon as uncertainty is resolved.

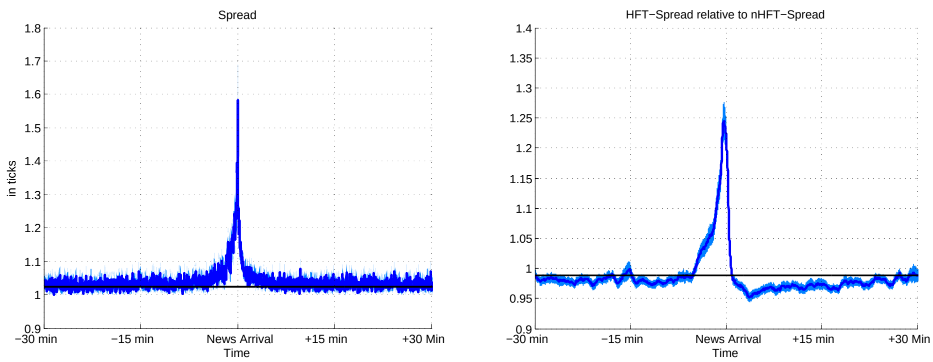
Table 2: Resiliency statistics for order book depth The table reports the average time (in seconds) which is needed to re-fill a given percentage of the *pre-announcement* level of the total depth and the HFT-implied proportion on top of the book, respectively. The pre-announcement level is the average depth recorded from 30 minutes prior the release to 15 minutes prior to the release. This analysis is performed based on the raw (i.e., non-smoothed) data.

Threshold	Depth 1	HFT participation rate of Depth 1
25%	5.02	1.74
50%	14.64	2.60
75%	32.32	5.13
95%	51.06	11.47

We summarize that HFTs are generally important liquidity suppliers in the market. They contribute more than 50% of the overall liquidity supply and serve as liquidity demanders in less than 25% of their traded volume. Prior to news arrivals and thus in periods of high uncertainty however, HFTs significantly reduce liquidity supply. In this way, they behave similarly to a "traditional" (designated) market maker reducing his adverse selection risk. An important difference to a designated market maker, however, is that HFTs can adapt their liquidity supply quickly and to large extent. Such rapid dry-ups of liquidity supply prior to an announcement are likely to be stronger than in a comparable market with traditional market makers and can undermine market making functionalities. These effects are amplified by a simultaneous increase in HFT liquidity demand due to increasing speculative trading activities and inventory management. These phases, however, are obviously only very short-lived. Since the news-implied increase of liquidity demand is still moderate, we can refute concerns of HFTs systematically drawing liquidity from the market in these periods. In fact, shortly after the news arrival, HFT liquidity demand quickly drops to its (low) pre-announcement level. At the same time, HFTs rapidly replenish liquidity supply and contribute to re-stabilize the market.

3.2. Costs and Accessibility of Liquidity around Scheduled News

An important question is whether the HFT liquidity is more expensive than nHFT liquidity and whether corresponding transaction costs change around news releases. We quantify the transaction costs by the quoted spread, $QS = Ask - Bid$. We define the so-called "HFT spread" ("nHFT spread") as the quoted spread QS of the best bid and ask prices provided by HFTs (nHFTs). The ratio of the HFT spread to the nHFT spread allows us to directly compare differences in trading costs implied by HFT and nHFT liquidity supply.



(a) Quoted Spread (b) HFT to nHFT Spread Ratio

Figure 6: Quoted Spread and Ratio of Quoted HFT Spread to nHFT Spread. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the news releases.

Figure 6 shows the across-event averages of the quoted spread and the corresponding HFT/nHFT spread ratio around news releases. Quoted spreads are on average around one tick in non-event periods, but increase by approximately 60% during the last 5 minutes prior to a news arrival. Panel (b) shows that the average HFT/nHFT spread ratio is slightly below one, indicating that HFT-provided liquidity on the best price level is slightly cheaper than liquidity provided by nHFTs. Shortly before and after the news arrival, however, HFTs reduce not only their provided depth (as shown in Section 3.1), but also post less competitive quotes and thus widen the spread. Around the time of the news release, HFT spreads are around 25% larger than nHFT spreads, making HFT provided liquidity significantly more expensive than liquidity provided by nHFTs.

To compare the trading costs *paid* by nHFTs and HFTs, Figure 7 shows the average effective spreads of HFTs and nHFTs around news arrivals. We compute the *effective spread* as twice the absolute difference between the trade price and the mid-quote, $ES = 2 \cdot |TPrice - Mid|$. In contrast to the quoted spread, the effective spread measures the actual transaction costs paid by liquidity *demanders*. While effective spreads faced by HFTs are generally only slightly lower (approx. 2-3%) than those faced by nHFTs, this picture significantly changes during periods of news arrivals. We find that HFTs pay effective spreads which are more than 20% (approximately 0.2 ticks) lower than effective spreads paid by nHFTs.

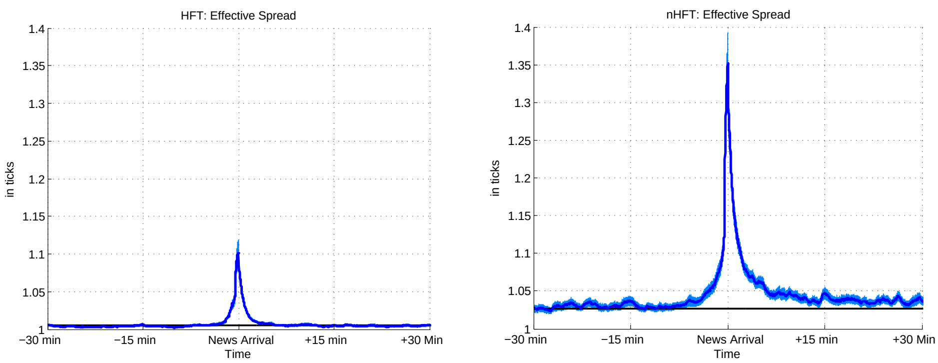


Figure 7: Effective Spreads. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the news releases.

To analyze the determinants of the higher costs paid by nHFTs, we re-compute the effective spreads based on quotes which are ultimately matched. Figure C.2 in Appendix C shows the effective spreads evaluated whenever an nHFT order is executed against an HFT or nHFT order, respectively. We observe that both effective spreads are of similar magnitude and show similar patterns around the time of the news release.[16] We can therefore conclude that HFT liquidity supply is accessible and – if actually executed – *not* more expensive than liquidity offered by nHFTs. Hence, nHFTs are generally not overreached if they trade against HFTs.

Possible reasons for the lower effective spreads paid by HFTs might be their better market monitoring capabilities (see Menkveld (2013) or Hendershott & Riordan (2012)) or the fact that HFTs use smaller trade sizes and thus avoid price impact beyond the first price level. In order to distinguish between these effects, we compute the so-called *adverse price movement (APM)*, defined as the difference between the effective spread and the quoted spread, $APM = (TPrice - Ask)$ for buy trades and $APM = (TPrice - Bid)$ for sell trades. It equals zero if the marketable order is executed on the first price level and is positive if the order "walks up" the order book. It is therefore a measure for the additional costs which are paid on top of the quoted spread when a large order is executed. As shown in Figure 8, HFTs manage to widely avoid APMs and actually face almost no costs induced by orders walking up the book during normal trading periods. In contrast, nHFTs face significantly higher costs induced by order matching beyond the first level, which is about 10 times higher than for HFTs.

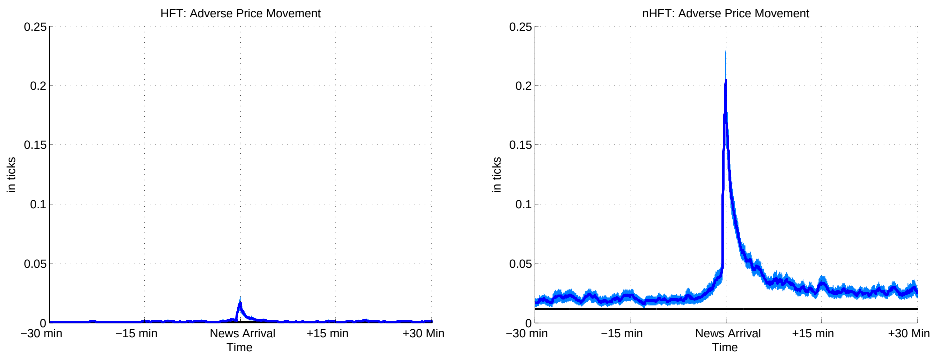


Figure 8: Adverse Price Movement (APM). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the news releases.

[16]The corresponding ratio of effective spreads against HFT orders to effective spreads against nHFT orders (available upon request) is very close to one and generally confirms the conclusions drawn based on *quoted* spreads.

To evaluate whether this effect is due to the choice of smaller trade sizes, we calculate the effective spread for different trade size groups. Specifically, we define "small trades" for trade sizes of less than or equal to 3 contracts, "medium trades" for trade sizes between 4 and 10 contracts, "large trades" for trade sizes between 11 and 100 contracts, and "very large trades" for trade sizes above 100 contracts. The effective spreads for the different trade size groups are presented in Appendix C, Figure C.1 and show significant differences between the effective spreads paid by HFTs and nHFTs within the *same* trade size group. We therefore conclude that the lower transaction costs paid by HFTs originate from superior market monitoring capabilities rather than from a choice of smaller trade sizes.

In summary, we show that the costs of HFT-induced liquidity supply are widely similar to the costs of liquidity supplied by nHFTs. Prior to the announcement, HFTs react in the same way as traditional market makers would do: they widen the spreads in order to compensate for higher uncertainty. They do this, however, to a larger extent than nHFTs. This makes HFT liquidity more expensive in periods when it is most needed. HFTs thus require an extra premium for liquidity supply in periods of high uncertainty. In these situations, they gain on the supply side by offering higher spreads *and* on the demand side by paying lower transaction costs due to better market monitoring abilities.

3.3. Liquidity Supply and Demand After Extraordinary Events

Figure 9 shows the market depth and the corresponding HFT participation rate on top of the book (i.e., on the first order book level) on June 24, 2016, one day after the announcement of the U.K. Brexit (blue lines). To benchmark the computed statistics on these days with corresponding measures on "normal" trading days, we additionally compute the corresponding statistics for *all* trading days in the sample *excluding* one-hour windows around all announcements listed in Table B1 (shaded areas).

Compared to the average level on "normal" days, on the (post-)Brexit day, the market is generally less liquid, with the first-level depth being approximately 25-30% lower and the spread being approximately 10% higher. According to Figure 9, the relative contribution of HFTs to liquidity supply on top of the book is 10 to 20 percentage points higher than on "normal" days. With an overall level of approximately 70%, it is also higher than on days of news releases.

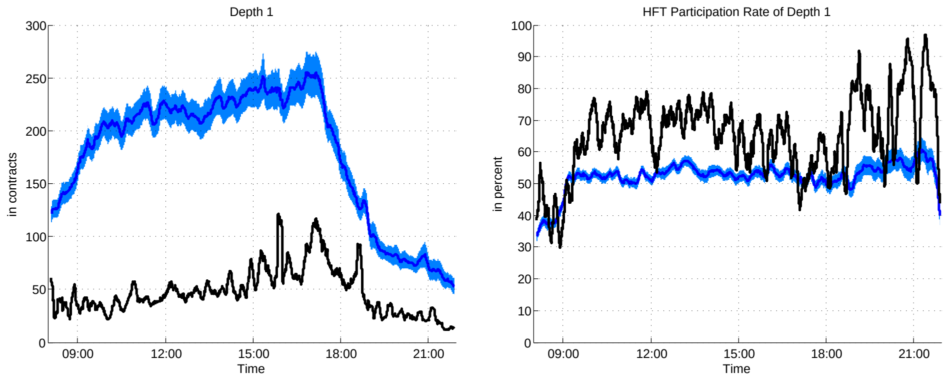


Figure 9: Market Depth and HFT Participation Rate at Level 1 on June 24, 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minutes as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

The increasing importance of HFT liquidity is confirmed by the HFT participation in *traded* liquidity supply, as documented in Figure 10 showing that the HFT participation rate in liquidity demand is considerably higher throughout the day after the Brexit announcement than on normal days. Likewise, the HFT to nHFT spread ratio in Figure 11 shows that HFT liquidity is significantly cheaper than nHFT liquidity on "normal" days. Specifically, HFT spreads are on average around 20% *below* nHFT spreads. We thus have evidence that on a day after an unexpected extraordinary event such as the Brexit announcement, HFT liquidity supply plays an even more important role than during periods of scheduled news releases.

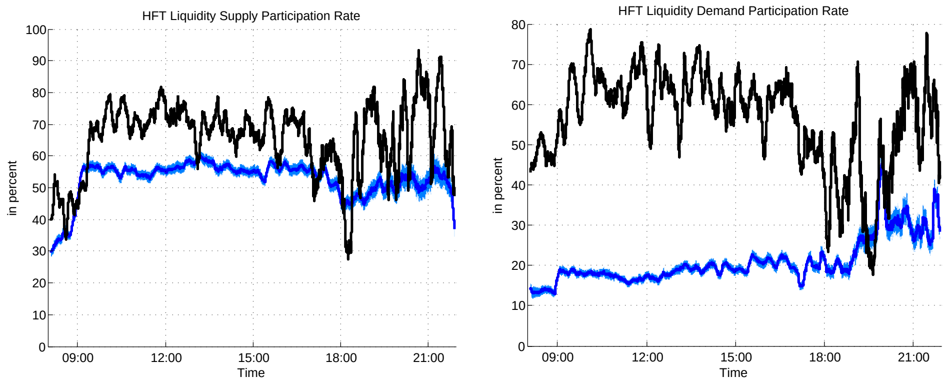
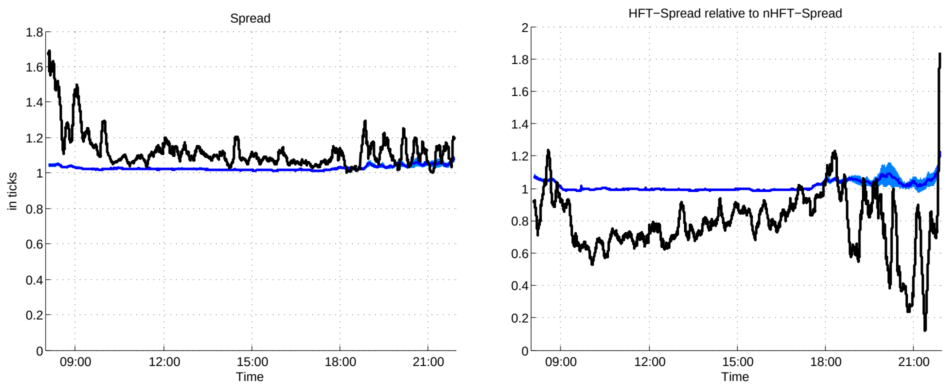


Figure 10: HFT Participation Rate in Liquidity Supply and Demand on June 24, 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minutes as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.



(a) Absolute Quoted Spread

(b) HFT to nHFT Spread Ratio

Figure 11: Spread Measures on June 24, 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minutes as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

The results for the Greek referendum announcement and Chinese Black Monday are qualitatively similar. We therefore report the corresponding figures for depth, spreads, and liquidity demand and supply participation rates in Figures D.4 and D.10 in Appendix D.1 and D.2. Similar to the Brexit announcement day, for both events, liquidity is generally lower than on "normal" days. Figures D.2 and D.8 in the Appendix report that for both days, depth on the best price level amounts to on average around 50 to 100 contracts, which represents around 50%-60% of the liquidity on "normal" days. Likewise, the quoted spread is approximately 10-20% higher than the average on "normal" days. Furthermore, spreads are generally higher than on “normal” days, with HFT-implied spreads being lower than nHFT-implied spreads (cf. Figure D.3 and D.9). However, while HFT liquidity supply during the Chinese Black Monday becomes important, the effect is not observed for the Greek referendum announcement, where HFTs provide a similar amount of liquidity compared to normal market conditions.

We can conclude that on distinct days of high market uncertainty, HFTs still serve as important liquidity providers in the market. Compared to the findings around scheduled news, HFTs provide a relatively larger proportion of liquidity to the market and their quoted spreads are on average lower than those quoted by nHFTs. However, in comparison to periods around news releases, the liquidity *demanded* by HFTs is significantly higher. Hence, during turbulent market periods, HFTs tend to be more aggressive than in periods around news releases. This points towards a mixture of trading strategies followed by HFTs: depending on the market conditions, HFTs seem to switch to more aggressive strategies rather than to withdraw from the market. This is in contrast to traditional market makers who focus on market making activities rather than aggressive trading activities and withdraw from markets when volatility is high. This finding of increased aggressive trading is generally in line with the results by Kirilenko *et al.* (2017) who find that HFTs do not behave like traditional market makers, but follow latency arbitrage strategies even throughout the Flash Crash on May 6, 2010.

4. Directional Trading and Volatility

In this section, we focus on the contribution of (n)HFTs to price variation in turbulent market periods. In fact, situations, where liquidity supply becomes very unbalanced and one side of the market dries out, can significantly threaten market stability. We therefore study the *net trading* activities of HFTs and nHFTs, defined as the contracts bought minus contracts sold per second, and their actual contribution to (quadratic) variation in mid-quotes.

4.1. Directional Trading around Scheduled News Releases

Figure 12 shows the cumulative net trading of liquidity demanders (i.e., trade initiators) during periods starting 30 minutes before the announcement. Consistent with other papers (e.g. Brogaard *et al.*, 2014), we observe that both nHFTs and HFTs actively trade in the direction of the news, therefore perform negative net trading for falling markets and positive net trading for rising markets. We find, however, that liquidity demanding nHFTs are clearly more involved in news trading as they cumulate a significantly larger net trading position in the direction of the market than liquidity demanding HFTs. In contrast, HFTs build up only a small net position and tend to evenly buy and sell around announcements rather than actively trading on information. In this sense, HFTs play a stabilizing role in such periods as they tend to balance both sides of the market.

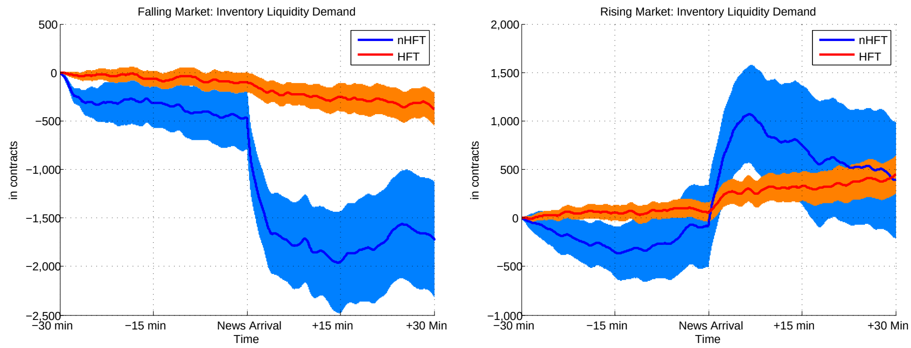


Figure 12: Cumulative Net Trading Through Liquidity Demand. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

Figure 13 shows the cumulative net trading for liquidity suppliers. Again we find that nHFTs build up significantly larger net positions than HFTs. These liquidity supply positions are positive in case of falling markets and negative in case of rising markets. Hence, nHFTs build up significant net positions *against* the direction of market movements and thus face considerable adverse selection costs. In contrast, HFTs manage to keep their net positions relatively flat. This is consistent with other studies (Brogaard *et al.*, 2014; Zhang, 2017) and indicates that HFTs are able to avoid high adverse selection costs by withdrawing liquidity in the direction of the market. Therefore, HFTs do not lean against market movements while nHFTs get adversely selected and "catch falling knives".

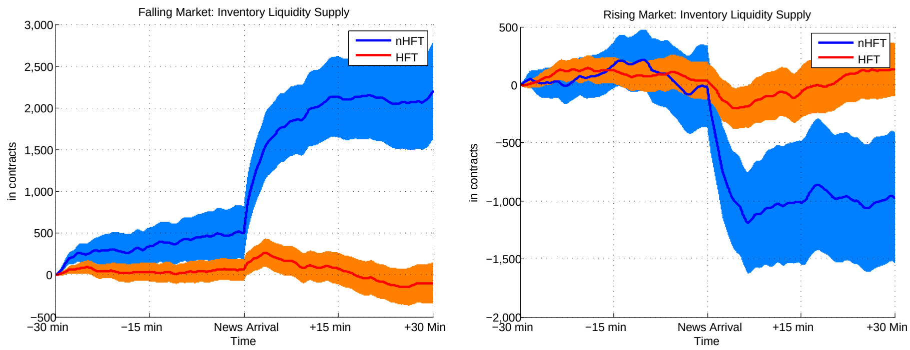


Figure 13: Cumulative Net Trading Through Liquidity Supply. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

The analyses above therefore show that liquidity supply close to news releases is predominantly provided by nHFTs, which forces them to build up considerable net positions against the direction of the market and thus confronts them with inventory risks. In contrast, HFTs tend to avoid risks of adverse selection and inventory imbalances. At the same time, they require a considerable premium to compensate for their costs and risks. In these situations, market making services by nHFTs gain a greater importance than those by HFTs.

In order to analyze if some directional trading of a specific group of HFTs is offset by market making activities of another HFT group, we classify the cumulative net trading of HFTs by their respective type (see Section 2.3). As shown in Figure 14, inventory in the direction of market movements is primarily due to *passive* rather than aggressive HFTs. Hence, HFT market makers efficiently adapt the direction of their liquidity supply after uncertainty is resolved on the market and the market direction induced by the news has been incorporated into market prices. Similar results are obtained by van Kervel & Menkveld (2017) who find that HFTs initially trade against large institutional orders, but eventually change their direction and trade in the same direction of informed orders. Our results show that this is true not only in case of institutional orders. Obviously, HFTs initially learn from different types of information and use this information to revert their trading strategy.[17]

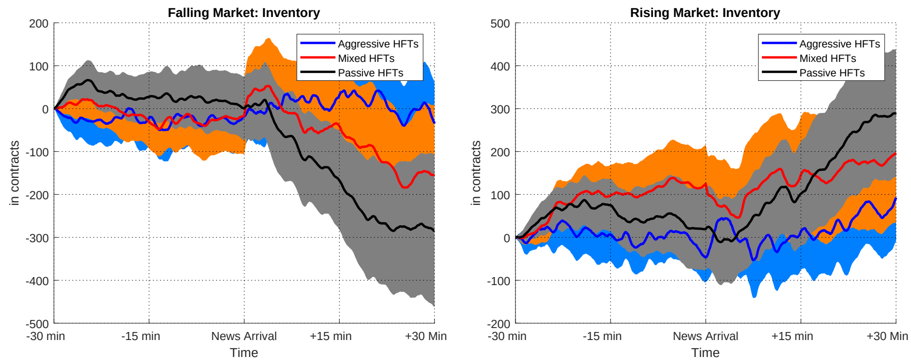


Figure 14: Cumulative Net Trading by HFT Groups. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

In summary, our results show that aggressive HFTs widely avoid directional strategies around news arrivals while passive HFTs are able to trade in the direction of market prices. Since the window of opportunity for benefitting from trading on macroeconomic news is very short and the risk of being on the wrong side of the market is too high, these strategies might be unprofitable. In fact, in Section 5 we confirm that in these situations excessive news trading is unprofitable on average and that HFTs strongly benefit from liquidity provision rather than from news trading. However, in the next section we will illustrate that there are situations where HFTs give up their well-balanced positions but follow directional strategies and build up considerable inventory positions over longer period.

4.2. Directional Trading After Extraordinary Events

Figure 15 shows the cumulative net trading for HFTs and nHFTS on June 24, 2016. Both types of traders build up significant net positions over the course of the trading day. Particularly HFTs exhibit extensive selling behavior in line with the downward price correction throughout the

[17] An additional effect might be that risk management strategies prevent HFTs from excessive trading against the market but forces them to actively reduce their exposures whenever certain risk limits are exceeded.

day. Separating between inventories resulting from liquidity demand and supply (Figure 16), we find that both liquidity demanding HFTs and nHFTs cumulate a large negative inventory throughout the day. This behavior is particularly untypical for HFTs and differs from behavior observed in periods around news releases. On the liquidity *supply* side, however, nHFTs face significant long positions against the direction of the market, while HFTs manage to build up inventory in line with the movement of the market. Therefore, we find further evidence that HFTs do *not* lean against market movements, while liquidity-supplying nHFTs get adversely selected by better informed traders.

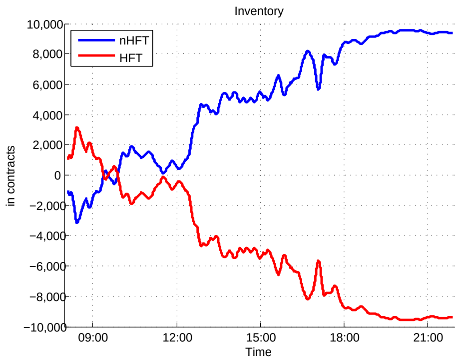


Figure 15: Cumulative Net Trading on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

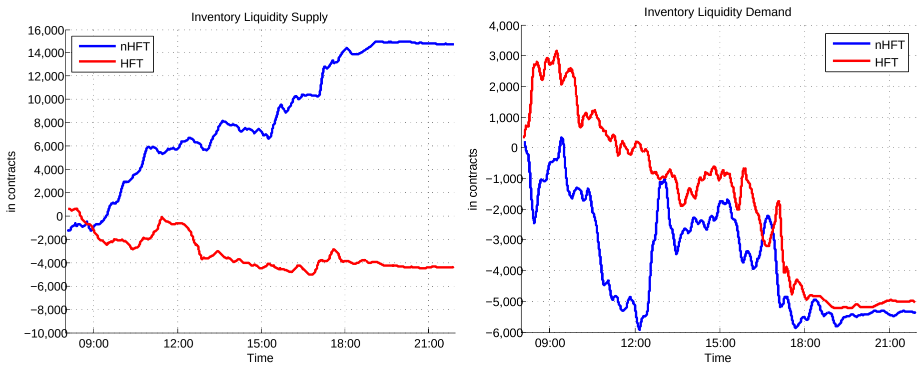


Figure 16: Cumulative Net Trading Liquidity Supply and Demand on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

Interestingly, after the Greek referendum announcement, HFTs do *not* strongly trade in the direction of the market, but try to keep a relatively balanced inventory position resulting from liquidity demand unlike nHFTs (cf. Figure 17). This is different from the behavior on the Brexit announcement day and might be due to the fact that price movements after the Greek referendum are less distinct. A similar picture emerges on the liquidity supply side, where HFTs manage to finish the trading day with a more balanced inventory as nHFTs. Nevertheless, we observe that liquidity supplying HFTs build up significantly higher positions opposite to market movements than on the Brexit announcement day. Hence, on this day, it seems to be more difficult for HFTs to avoid adverse selection risks.

Similarly on Chinese Black Monday, HFTs manage to keep their inventories resulting from liquidity demand and supply more balanced than nHFTs, but nevertheless build up significant positions throughout the day (see Figure 18).

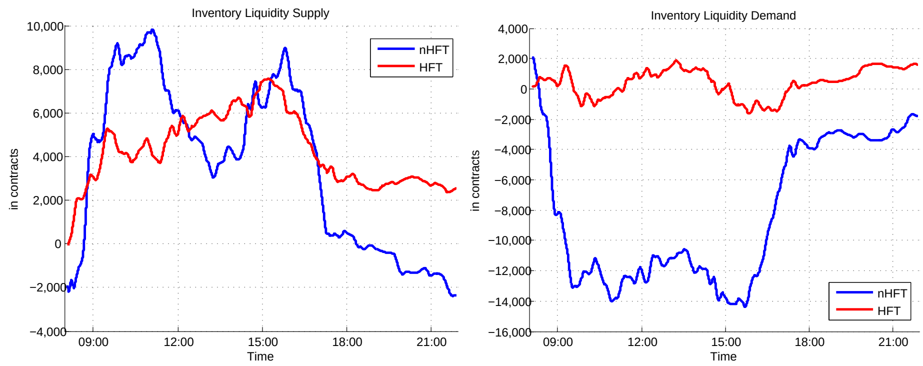


Figure 17: Cumulative Net Trading Liquidity Supply and Demand on June 29, 2015. Smoothed with 10-minute averages as described in Section 3.

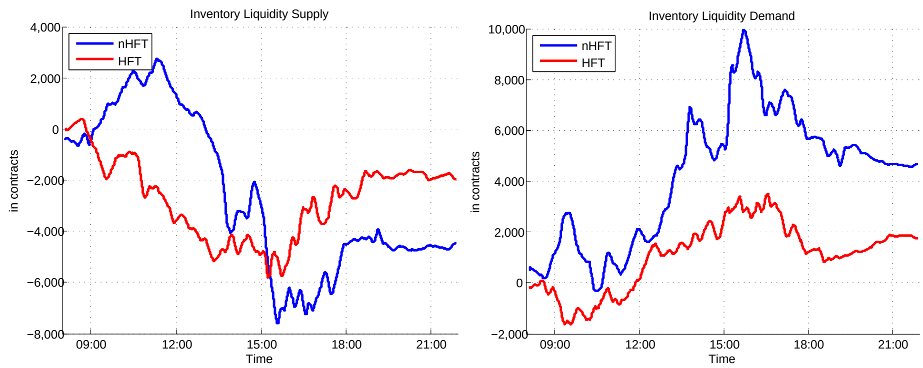


Figure 18: Cumulative Net Trading Liquidity Supply and Demand on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

In summary, we identify an important difference between HFT behavior on days of scheduled news announcements and extraordinary days with local price adjustments as analyzed above. While HFTs widely refrain from directional strategies around news releases, they position themselves more strategically on extraordinary event days. We observe that during these periods, HFTs build up significant positions in the direction of price changes. Particularly on the day after the Brexit announcement, HFTs make considerable positional profits and reveal behavior which is significantly different from that of a traditional market maker.

The reason why this behavior is observed only to a small extent during periods around news releases is likely due to the fact that such information is published under strict lock-up conditions. Accordingly, prices adjust very quickly and even for HFTs the window of opportunity for directional trading is very short. In fact, as illustrated in Section 3, the aggressiveness of HFTs strongly increases for only a few seconds around the release. Once prices have adjusted, directional trading becomes unprofitable or too risky and thus HFTs rely on market making activities. In contrast, on a day such as after the Brexit decision, the prospects of directional trading (and possible cross-market trading against similar assets) are obviously higher.

An important result from this study is that HFTs indeed operate very much similarly to traditional market makers – but only when directional trading does not appear to be promising. In market conditions, however, where trading profits from directional strategies can be expected, HFTs shift their activities from market making to more aggressive speculative trading. In Section 5, we quantify the realized trading revenues of HFTs and nHFTs in order to analyze whether this switch of trading strategies results in higher trading profits.

4.3. Contribution to Quadratic Price Variation

In the following section, we shed some light on the contribution of (n)HFT activties on the quadratic mid-quote price variation during short intervals on days of news releases or extraordinary events. Denote t as the time index for second-to-second intervals and k is the index for the mid-quote changes during the t-th second-to-second interval. Then, we estimate the quadratic variation through the interval $[t-n+1;t]$ by the realized mid-quote variance given by

$$RV_t = \sum_{i=1}^{n} \sum_{k=1}^{o_{t-i+1}} r_{t-i+1,\,k}^2 = \sum_{j=1}^{m} \sum_{i=1}^{n} \sum_{k=1}^{o_{t-i+1}} r_{t-i+1,\,k}^2 \cdot 1_{A_{t-i+1,\,k}=j}, \tag{2}$$

where $r_{i,\,k}$ denotes the k-th tick-to-tick mid-quote return during the i second-to-second interval, o_i is the number of mid-quote changes during the i-th second-to-second interval and $A_{i,\,k}$ is an indicator variable which equals one if the return $r_{i,\,k}$ is triggered by a specific (n)HFT activity j. We define $m = 6$ "types" of mid-quote changes originating from specific activities: $A_{i,\,k} = 1$ if a nHFT submits a limit order; $A_{i,\,k} = 2$ if a HFT submits a limit order; $A_{i,\,k} = 3$ if a HFT cancels a limit order; $A_{i,\,k} = 4$ if a HFT cancels a limit order; $A_{i,\,k} = 5$ if a nHFT submits a market(able) order; and $A_{i,\,k} = 6$ if a HFT submits a market(able) order. Under mild conditions, RV_t is a consistent estimator for the quadratic (mid-quote) price variation through the interval $[t-n+1;t]$ with asymptotic theory provided, e.g., by Barndorff-Nielsen & Shephard (2002). Accordingly, the proportion of the realized variance due to a specific activity j

$$RV\%_{t,j} = \frac{\sum_{i=1}^{n} \sum_{k=1}^{o_{t-i+1}} r_{t-i+1,\,k}^2 \cdot 1_{A_{t-i+1,\,k}=j}}{RV_t} \tag{3}$$

is a consistent estimator of the relative contribution of returns of type j to the quadratic price variation.

Both statistics RV_t and $RV\%_{t,\,j}$ are computed based on rolling intervals that are rolled-over on a second-to-second basis and utilizing tick-to-tick returns $r_{i,\,l}$. We choose n as $n = 300$, corresponding to (rolling) intervals covering 5 minutes. Accordingly, for each second we obtain an estimate of the quadratic mid-quote variation through the last 5 minutes.

Figure 19 shows the across-event averages of second-to-second estimates of RV_t, averaged across a local 1-minute window according to (1), for the period around a scheduled news release. We observe a strong jump in RV_t after the release. Due to the computation of RV_t as an *ex-post* measure utilizing data through the *last* 5 minutes, the spike occurs slightly after the announcement. In the sequel, the level of quadratic variation returns back to its initial level approximately 30 minutes after the news release.

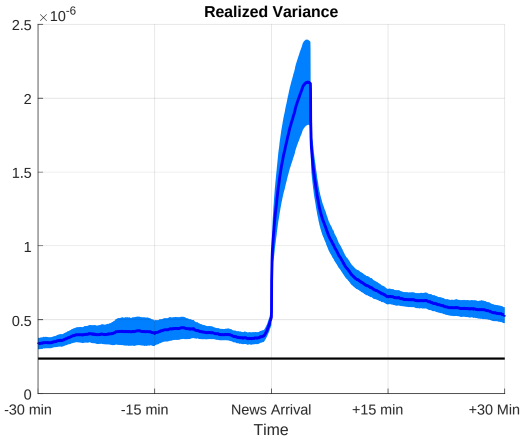


Figure 19: Realized Midquote Variance. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days excluding a one-hour window around the release.

Figure 20 reports the (smoothed) average proportions $RV\%_{t,j}$ due to (n)HFTs order submissions or cancellations. During normal market periods, HFTs contribute around 55% to the quadratic price variation. However, in periods (very) close to the news release, we observe a significant decline of HFTs' contribution to realized variances, reaching approximately 40% shortly after the news release. Hence, during this period, nHFTs are the major contributors to price variation. This contribution mainly originates from the submission of marketable orders.

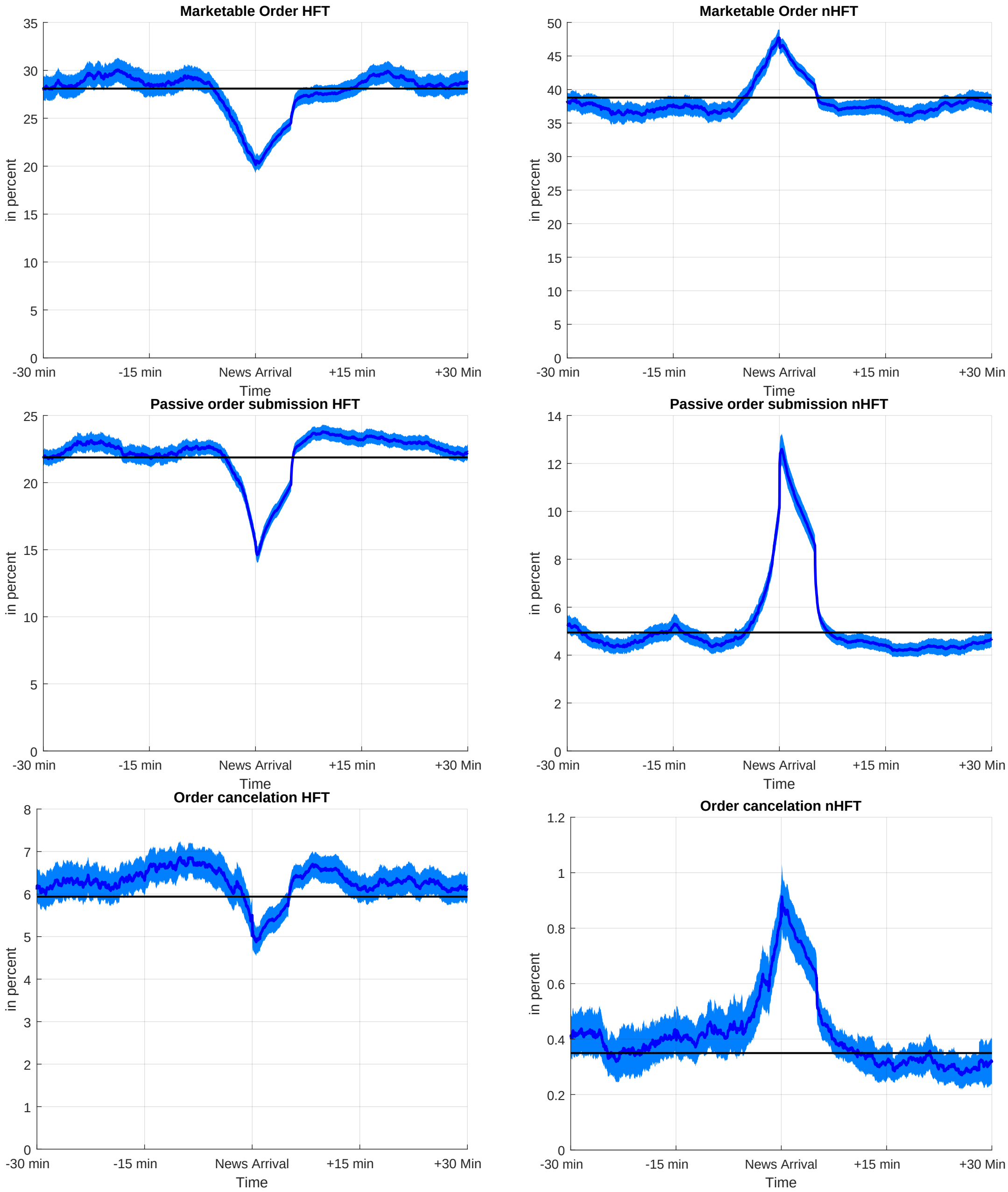


Figure 20: Relative HFT and nHFT Contribution to Realized Variance. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days excluding a one-hour window around the release.

Moreover, we can summarize the folllowing findings: First, HFTs contribute to the price variation using both marketable and passive orders. In contrast, nHFTs mainly contribute via submitting marketable orders, which are more likely to ”walk up” the book and thereby move the mid-quote. A possible reason is that nHFTs have lower market monitoring capabilities to position their orders more strategically in order to avoid price impact. As shown in Section 3.2, this behavior results in higher transaction costs paid by nHFTs than by HFTs. Second, HFTs are more willing to post aggressive limit orders that establish new (i.e., more competitive) price levels. In contrast, nHFTs tend to add to the liquidity on one price level, but avoid posting more competitive quotes. This difference in behavior can be explained by specialized HFT market makers who are able and willing to provide riskier quotes. They use their speed advantage to continuously update their orders depending on new information and changes in their own position, and to cancel their orders if the market moves unfavorably. The latter is confirmed by HFTs contribution to the quadratic price variation through order cancellations. For HFTs, this contribution is well above 6%, while nHFTs contribution is below 1%. This implies that HFTs cancel limit orders with competitive prices more actively than nHFTs and thereby move the mid-quote.

Comparing these results with corresponding findings for the three extraordinary events yields interesting insights in to what extent HFTs change their behavior in extreme market conditions. Figure 21 shows (smoothed) 5-min realized variances through June 24, 2016, the day after the Brexit announcement. We observe that realized variances spike after opening and decrease throughout the trading day. This pattern is similar to the first trading day after the Greek referendum announcement on June 29, 2015 (see Figure D.5 in Appendix D) and partly also resembles the intraday trajectory on Chinese Black Monday August 24, 2015 (while the latter is also subject to a pronounced spike at the time of the U.S. market opening, see Figure D.11 in Appendix D).

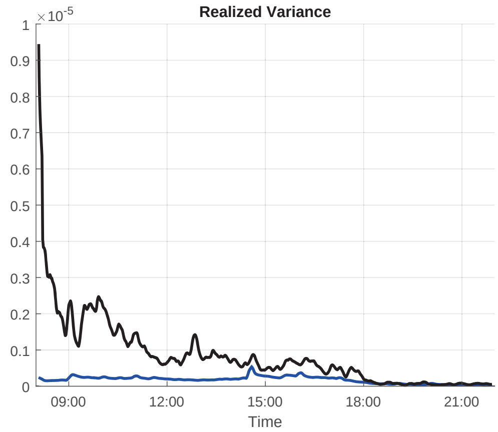


Figure 21: Realized Variance on 24 June 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

Figure 22 shows that after opening on June 24, 2016, nHFTs' contribution to quadratic price variation is higher than the contribution of HFTs. This is mainly through the submission of marketable orders causing price impact and limit orders which are obviously picked up. This pattern resembles the behavior of nHFTs in periods (close) to macroeconomic news releases and indicates that they aim at repositioning at the begining of the trading day.

In contrast, HFTs behave quite differently than on news announcement days. Apart from the very beginning of the trading, HFTs are the major drivers of the price variation. This is reflected by an overall contribution of around 70%, mainly resulting from market order and limit order placements, each ranging between 30% and 40%. Hence, confirming the results above, on such an extraordinary day of a turbulent market, HFTs do not only perform passive market making but perform aggressive directional trading and therefore significantly contribute to price variation. This is confirmed by the fact that HFTs' contribution to realized variances through cancellations is non-trivial and partly strongly exceeds 10%.

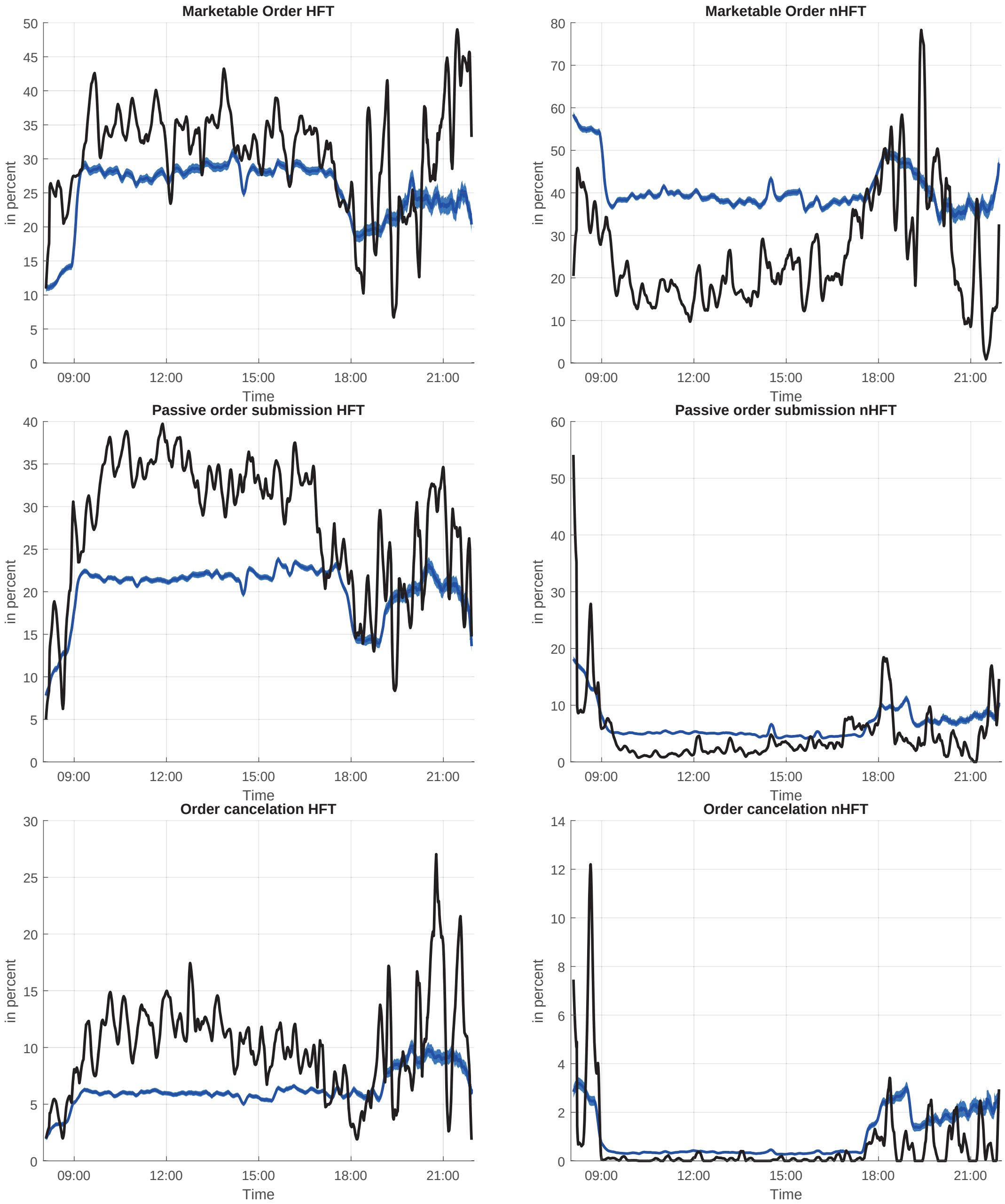


Figure 22: Relative HFT and nHFT Contribution to Realized Variance on 24 June 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

We observe comparable patterns on the day preceding the announcement of the Greek referendum and the Chinese Black Monday, as illustrated in Figure D.6 and Figure D.12 in the Appendix. On both days, HFTs contribute significantly more to local quadratic price variation than nHFTs and relatively more than on "normal" trading days, both in terms of marketable and passive order submissions and order cancellations.

In summary, we show that in extreme market conditions, HFTs' contribution to (quadratic) price variation significantly exceeds that of nHFTs. This behavior is in clear contrast to the behavior around scheduled news announcements (and on non-announcement days). These results confirm that the role of HFTs strongly depends on market conditions. In fact, compared to their role as (widely) passive market makers in situations around scheduled news releases, their role reverses on such days of (or after) extraordinary events.

5. HFT Trading Profits in Turbulent Market Periods

HFT profits within very short time periods can vary considerably and are highest during highly volatile market periods (cf. WSJ, 2015). While exact profit numbers are not published, an estimate for daily HFT profits on the U.S. stock market is around EUR 20 million according to Baron *et al.* (2017). In order to gain insights into trading profits and their origins during extraordinary events on the Bund Futures market, we decompose profits into a *positioning profit* and a *net spread component* (cf. Hasbrouck & Sofianos (1993) and Menkveld (2013)). The positioning component is computed as the change in value of the inventory, while the net spread component corresponds to the transaction costs paid for liquidity demand and earned through liquidity supply. This helps us to distinguish between a speculative component of profits, a cost component paid by liquidity demand and a profit component gained by liquidity supply.

Following Menkveld (2013), we compute the gross profits π_i in second i as

$$\pi_i = \underbrace{\sum_{j=1}^{n_i} Inv_{i,j-1} \cdot \Delta p_{i,j}}_{PositioningProfit} + \underbrace{\sum_{j=1}^{n_i^S} V_{i,j}^P \cdot \left(\frac{ES_{i,j}}{2} - \tau\right) - \sum_{j=1}^{n_i^D} V_{i,j}^A \cdot \left(\frac{ES_{i,j}}{2} + \tau\right)}_{NetSpread=SpreadEarned-SpreadPaid}, \qquad (4)$$

where $Inv_{i,j}$ is the inventory before trade j in second i, n_i denotes the number of trades in i, and $\Delta p_{i,j}$ is the corresponding mid-quote change since the most recent trade in second i. Accordingly, the *"positioning profit"* captures the change in value of the net position built up. The last two terms sum up to the so-called *"net spread"*, the spread earned through passive liquidity supplying orders minus the spread paid through aggressive liquidity demanding orders. Here, n_i^S and n_i^D denote the number of liquidity supplying and demanding trades, respectively, with $V_{i,j}^S$ and $V_{i,j}^D$ being the corresponding trade sizes and $ES_{i,j}$ denoting the effective spread associated with trade j. Finally, τ is a trading fee, which is currently EUR 0.20 per Euro-Bund Futures contract traded. The profit defined above is a *gross* profit, accounting for trading fees per contract but not for transaction fee rebates[18] or for fixed costs, such as costs for the connection to Eurex or for data feeds. As we are not able to account for either costs or rebates due to lack of data, profit estimates might be skewed.

According to Menkveld (2013), the decomposition into the *"positioning profit"* and the *"net spread"* helps distinguishing between two different sources of profits: aggressive speculation and passive market making. An aggressive speculator incurs costs from spreads, but gains through his positioning profit if his prediction of future market price movements is correct and his position is consistent with the direction of future price movements. A passive market maker earns the spread, but might incur a negative positioning profit if he trades against an informed trader and the price moves against him.

The trading profits can be separately computed for liquidity demanders as

$$\pi_{i,dem} = \underbrace{\sum_{j=1}^{n_i} Inv_{i,j-1} \cdot \Delta p_{i,j}}_{PositioningProfit} \underbrace{- \sum_{j=1}^{n_i^D} V_{i,j}^D \cdot \left(\frac{ES_{i,j}}{2} + \tau\right)}_{NetSpread=SpreadPaid}, \tag{5}$$

[18]Eurex has no maker-taker fees, but applies a trade size rebate for large trades as well as a volume rebate for Eurex members whose monthly trading volume exceed certain thresholds. For more information regarding the Eurex fee schedule, we refer to Eurex (2016).

and for liquidity suppliers as

$$\pi_{i,supp} = \underbrace{\sum_{j=1}^{n_i} Inv_{i,j-1} \cdot \Delta p_{i,j}}_{PositioningProfit} + \underbrace{\sum_{j=1}^{n_i^S} V_{i,j}^S \cdot \left(\frac{ES_{i,j}}{2} - \tau \right)}_{NetSpread=SpreadEarned}. \tag{6}$$

As discussed above, the profit measures should be seen as an approximation of the actual realized profits as we do not account for fixed fees and rebates. Furthermore, they rely on assumptions about inventory and aggregate PnL for across different trader IDs. In the analysis below, however, we focus on the dynamics and *relative* comparisons of trading profits and their components for different trader groups rather than on the *total* amount of trading profits.

5.1. Trading Profits around Scheduled News Releases

Figure 23 shows the total trading gross profit of HFTs and nHFTs. We observe that during the hour around the news release, HFT profits continuously increase while nHFT profits continuously decline. The decomposition into positioning profits and net spread profits (under the assumption of a zero inventory at the beginning of the trading day) in Figure 24 shows that the *net spread* component represents a major part of the profits. By exceeding the positioning profits by an order of magnitude, the net spread is *the* major driver for the profits of HFTs and nHFTs.

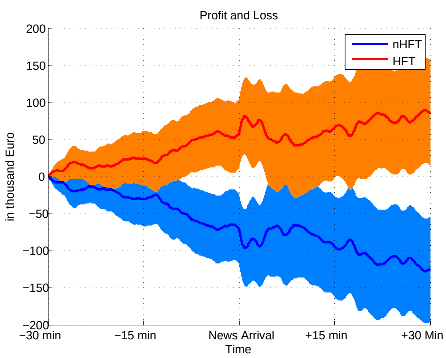


Figure 23: Total Profits (Real Inventory Through the Day). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

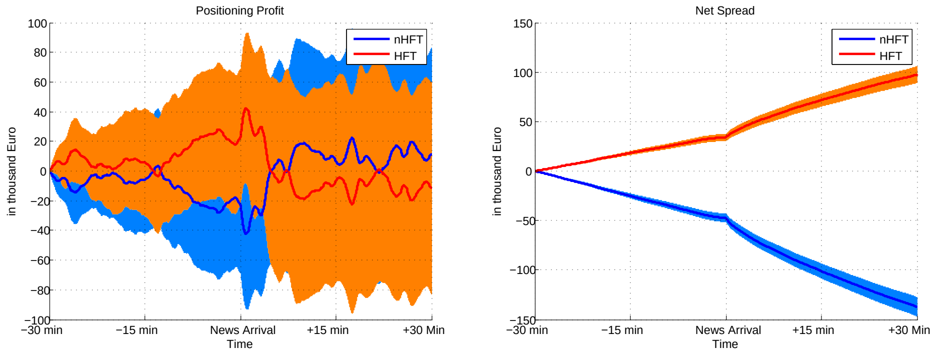


Figure 24: Positioning Profits and Net Spread (Real Inventory Through the Day). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

Figure 25 gives the corresponding total profits and positioning profits resulting from liquidity *demand* under the assumption that liquidity demanders start with a zero inventory 30 minutes before the announcement.[19] We find that the positioning profit from liquidity demand is positive for both HFTs and nHFTs and monotonously increases particularly after the announcement. Interestingly, the increase is significantly larger for nHFTs than for HFTs which is obviously driven by higher news trading activity of nHFTs. Thus, nHFTs use liquidity demanding orders after the announcement in order to quickly trade on the information and thereby make a positive positioning profit. The analysis of the total profits, however, indicates that these positioning profits are nearly completely consumed by the net spread, i.e., the costs of liquidity demand. Hence, the costs induced by active news trading eat up positional gains and lead, on average, to significantly losses during the hour around the news release. In contrast, liquidity demanding HFTs avoid such losses and incur, on average, a small profit of EUR 20,000. The significantly better performance of HFTs obviously originates from less involvement in positional trading and better market monitoring capabilities confronting them with lower effective spreads. Consequently, HFTs face significantly lower transaction costs, which allows them to keep their profits marginally positive.

[19]This assumption is necessary as inventory solely based on either liquidity demand or supply can be quite large when it is built up over the course of the day. This is different to inventory resulting from the sum of *both* demand and supply which is typically relatively close to zero. Therefore, to avoid to large fluctuations, we restrict the time period, over which the inventory is computed, to 30 minutes.

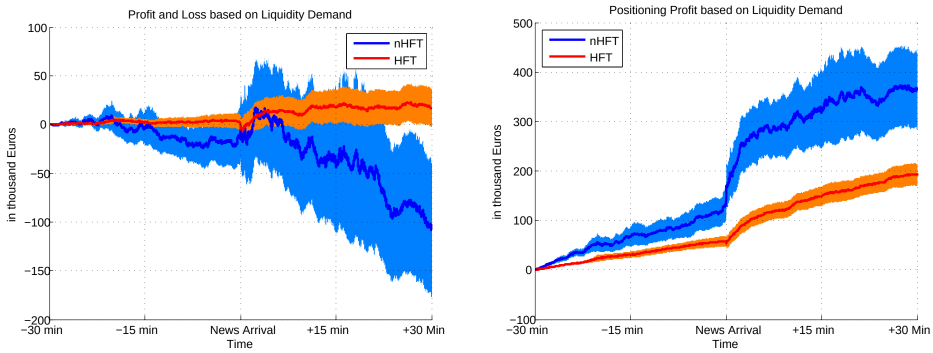


Figure 25: Total Profits and Positioning Profits from Liquidity Demand (Real Inventory Through 30 Minutes). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

Figure 26 shows the corresponding quantities for liquidity *suppliers*. We find that the positioning profit for both HFT and nHFT liquidity suppliers is negative. This indicates that liquidity suppliers face adverse selection costs as the market moves in the opposite direction of their position. These positioning losses, however, are significantly lower for HFTs. This is in line with findings of Brogaard *et al.* (2014) that HFTs are able to avoid adverse selection more effectively than nHFTs by withdrawing their liquidity quickly from the market. The trajectory of the total costs shows that liquidity supplying HFTs in fact can overcompensate adverse selection costs through earnings from the net spread. By more effectively managing liquidity supply, they experience even a slight increase in average profits after the announcement. Conversely, nHFTs incur losses since their benefits from the net spread are significantly smaller than for HFTs.

We can therefore summarize, that in the Bund Futures market, HFT firms make most of their profits from liquidity supply. We show that in aggregate, the net spread component of trading profits significantly outweighs inventory components made from actively building up trading positions. As such, we confirm statements that HFT profits, which solely stem from fast aggressive trading, have declined, but show that substantial profits can still be gained from high-frequency market making activities. One key determinant of the increase in HFT profits is the increase of spreads around announcements, which allows them to overcompensate inventory risks and adverse selection costs. A further driving force is their ability to quickly replenish liquidity after the news release which enables them to provide considerable liquidity when it is needed. This in turn allows them to make significant profits through the spread component. At the same time, HFTs manage to avoid significant costs through liquidity demand as they have better market monitoring abilities and place marketable orders more strategically (and thus cost-efficiently) than nHFTs.

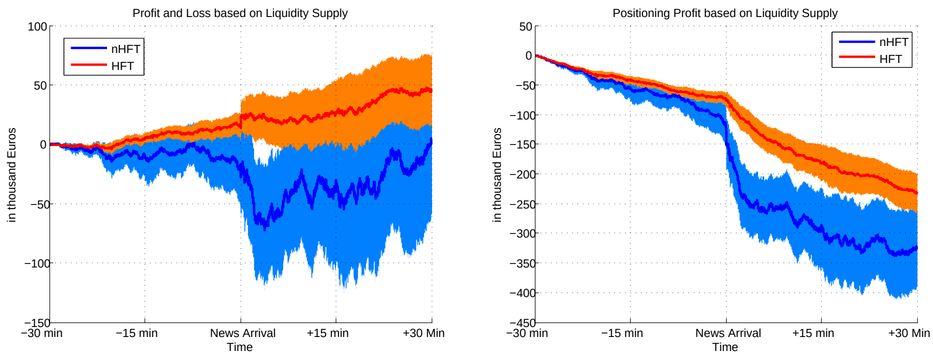


Figure 26: Total Profits and Positioning Profits from Liquidity Supply (Real Inventory Through 30 Minutes). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

5.2. Trading Profits After Extraordinary Events

Figure 27 shows that the overall HFT profits on June 24, 2016, the day after the Brexit announcement, are approximately EUR 4 Mio (after trading fees as defined in (4)), whereas nHFTs lose nearly EUR 4 Mio. Figure 28, however, reveals that the driving forces of these profits are different when compared to news release days: We find that HFTs make only moderate gains from the net spread component, but considerable gains from positioning profits. Through the day, HFTs gain only around EUR 50,000 based on the net spread component compared to EUR 100,000 during the hour around macroeconomic announcements. In contrast, more than EUR 4 million are earned through positioning profits. According to Figure 29, the positioning profits predominantly originate from HFTs serving as liquidity suppliers (which realized a profit of EUR 4m) rather than demanders (which realized a loss of EUR 500,000). In contrast, liquidity demanding nHFTs tend to be more often on the “wrong” side of the market, therefore making temporary losses and earning only approximately EUR 500,000 throughout the day.

We thus conclude that during this day, HFTs refrain from market making strategies, but focus on directional strategies in order to profit from high volatility. HFTs generally manage to serve as sellers in times of falling prices and serve as buyers in times of rising prices. These directional strategies are particularly successful on the liquidity supply side, where HFTs make significant gains to the disadvantage of nHFTs.

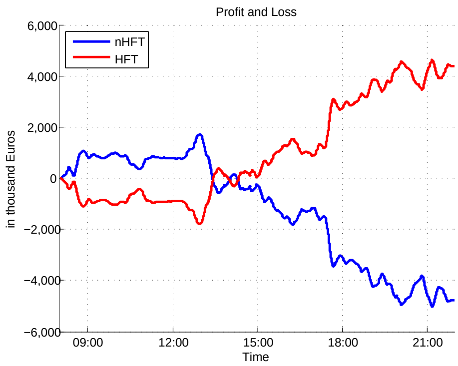


Figure 27: Total Profits on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

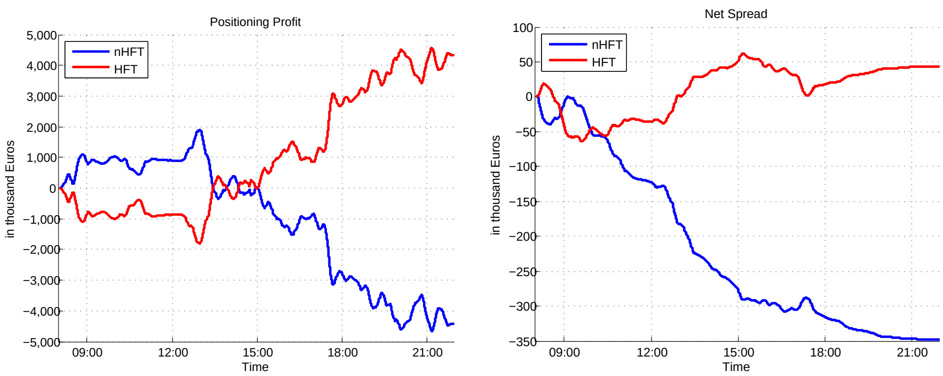


Figure 28: Positioning Profit and Net Spread on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

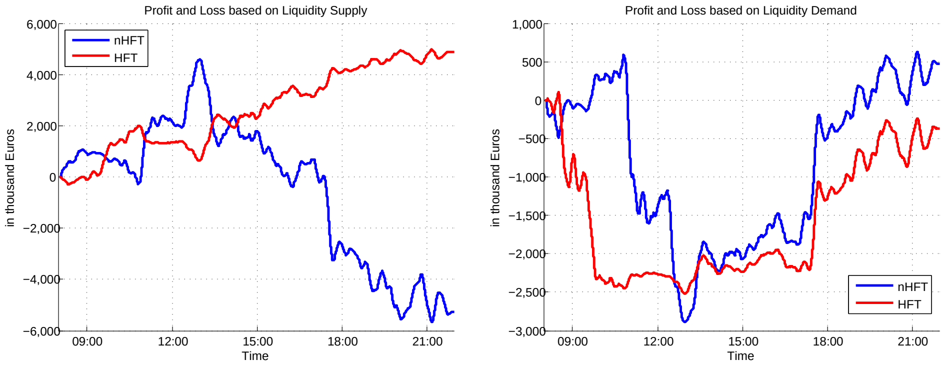


Figure 29: Total Profits from Liquidity Supply and Demand on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

In contrast, the day after the Greek referendum is an example, where HFTs do not generate any profits despite their strong contribution to daily trading and quoting activities. Figure 30 shows that HFTs lose more than EUR 2 million on this day. These losses are predominantly due to positioning profits, particularly on the liquidity demand side (see Figure 31). As on the Brexit day and unlike during a macroeconomic news release period, the net spread component is much less important and contributes less than 20% to the total profit (see Figure 32).

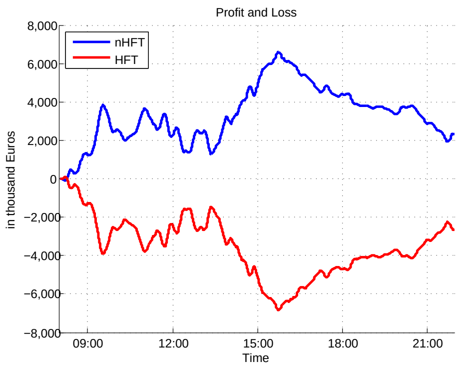


Figure 30: Total Profits on June 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

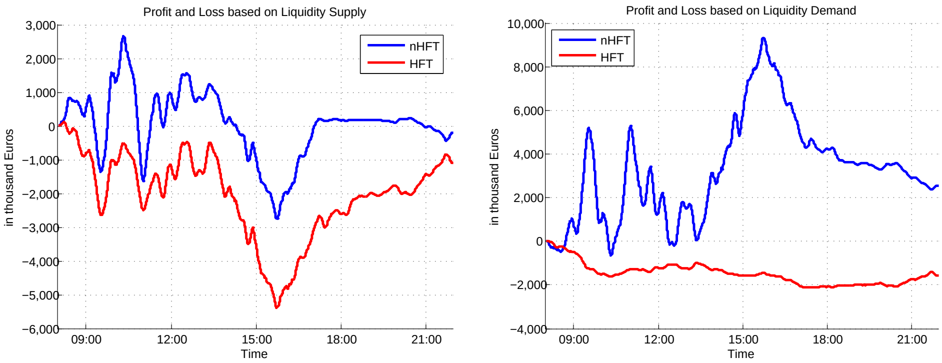


Figure 31: Total Profit from Liquidity Supply and Demand on 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

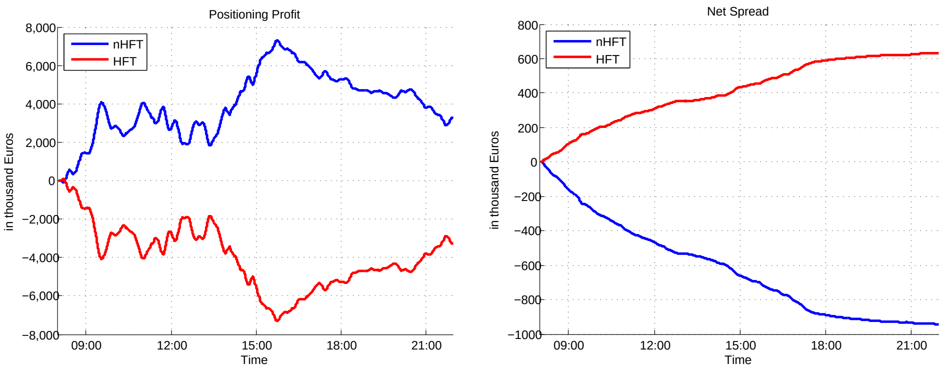


Figure 32: Positioning Profit and Net Spread on 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

Though China's Black Monday is the event with the weakest market effects out of the three extraordinary events considered, we still find comparable results. Figure 34 shows that HFTs are more profitable on the liquidity supply side than on the liquidity demand side. As in the two other events discussed above, profits and losses are dominated by the positioning components (cf. Figure 35). Therefore, HFTs seem to focus more on market making activities and realize most of their profits from liquidity supplying activities.

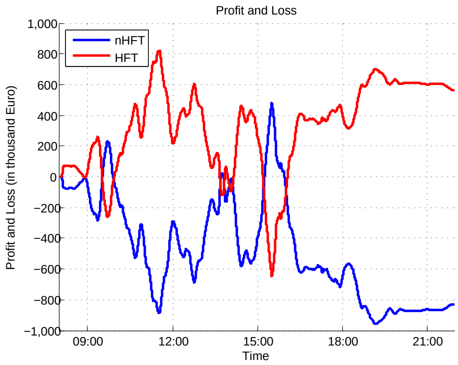


Figure 33: Total Profit (Real Inventory) on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

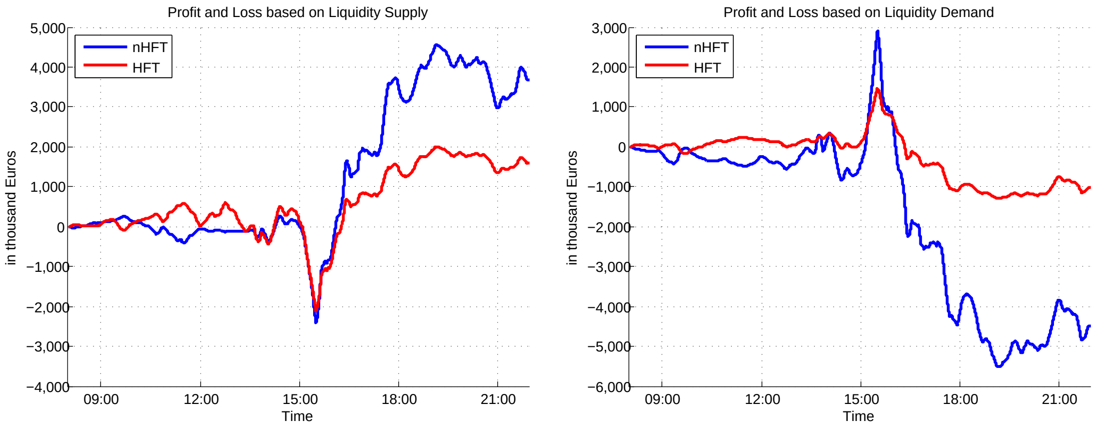


Figure 34: Total Profit from Liquidity Supply and Demand on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

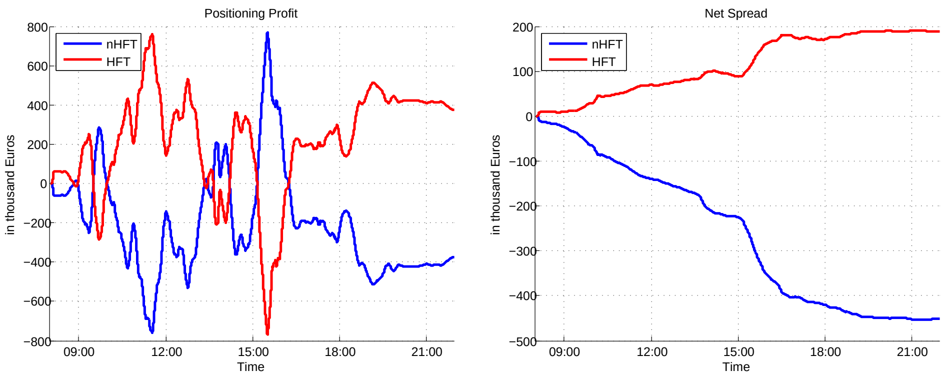


Figure 35: Positioning Profit and Net Spread on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

We can thus conclude that for extraordinary events, profits and losses predominantly originate from positioning profits rather than from the spread. This effect is particularly strong for the Brexit and Greek announcement day and causes a major difference to days of scheduled news announcements. It indicates that speculative directional trading becomes more important when volatility is high and that HFTs switch to these type of strategies whenever they appear to be profitable. The success of these strategies, however, strongly varies. While HFTs make significant profits after the Brexit announcement, they face significant losses after the Greek referendum announcement. According to our evidence, these losses predominantly result from liquidity demanding strategies. Therefore, in most scenarios studied in this paper, HFT strategies on the liquidity supply side are more profitable than on the liquidity demand side. Potential reasons are that liquidity *demanding* strategies obviously suffer from costs originating from the bid-ask spread. Moreover, these strategies might be part of cross-asset (e.g., arbitrage) strategies whose ultimate outcome cannot be observed given the data at hand.

6. Conclusions

In this paper, we draw a mixed picture of HFT's influence on liquidity provision and volatility in turbulent market periods. On the one hand, we can identify that HFTs play an important stabilizing and intermediary role in situations where directional trading does not seem to be beneficial. For instance, around scheduled news releases, HFTs widely act as passive market makers, continuously provide liquidity to the market and quickly replenish liquidity after the information is released. In these situations, HFTs refrain from trading aggressively in the direction of news, but tend to evenly buy and sell and contribute less to local price variation than nHFTs.

On the other hand, we show that the picture strongly reverts in situations of extreme price uncertainty. In periods (very) close to the arrival of macroeconomic news, HFTs contribute to liquidity dry-ups by withdrawing a significant amount of their liquidity, widening their spreads and increasing their liquidity demand. In periods of high uncertainty and extreme market distress, such as after the Brexit announcement in June 2016, HFTs moreover switch to more aggressive (directional) trading strategies, significantly contribute to price variation, and aim at benefitting from positioning profits.

There are some limitations of our paper that we would like to point out before drawing inferences on the results. First, we focus on the most active HFT accounts on Eurex rather than ensuring completeness of including every single HFT account. Even though we might not include all HFT accounts and might neglect those with low trading activity, we believe it has a minor effect on our results. Secondly, we emphasize the institutional differences between the Euro Bund futures market and other markets, such as U.S. stock markets. Therefore, some results might be influenced by institutional differences and different market structures. Finally, we want to point out that we are analyzing the overall group of HFTs and three large subgroups based on liquidity demand ratios. Minor groups of manipulative strategies are outside the scope of our paper and might or might not be identified in our sample depending on their trading volume and their compliance with our HFT criteria. Thus, we rather provide an overall picture of the impact of HFT rather than a detailed picture on the influence of specific strategies.

Our findings have important policy implications for regulators in order to maintain fair, orderly, and efficient markets. One aspect is to ensure a certain level of market stability. In the context of a new European financial market regulation (i.e. Market in Financial Instruments Directive (MiFID) II), regulatory authorities such as the European Securities and Markets Authorities (ESMA) suggest to introduce stricter requirements on market makers and specifically on HFTs, as, e.g., the requirement of a minimum amount of liquidity supply throughout the trading day (cf. ESMA, 2014). Our findings show that HFTs already comply with the latter as they continuously provide liquidity even in times of market distress. Our results also imply a complementary role of HFTs and nHFTs: while nHFTs process information and actively trade on it, the majority of HFTs are intermediaries that provide market liquidity and stand ready as trading counterparts. Accordingly, they make a large portion of their profits from market making rather than from directional trading.

Some regulators further suggest more restrictions for HFTs, such as minimum order lifetimes. A minimum order lifetime, however, might have serious implications for HFT market makers: They would not be able to quickly withdraw from the market in times of market uncertainty, which would increase adverse selection risks and would force them to limit their overall liquidity supply. Likewise, stricter regulation of market making obligations of HFTs in terms of volume and spreads could remove any benefits from market making and could be a disincentive for HFTs to perform such strategies. Stricter regulation of this kind might have detrimental effects on overall liquidity and market stability. MiFID II increases the requirements on HFTs acting as market makers (i.e., liquidity supply on bid and ask prices throughout more than 50% of the trading period) by forcing them into a formal market making agreement with the respective trading venue. (cf. ESMA, 2014).

Our results show that, different from more traditional market makers, HFTs switch to more aggressive directional strategies in times of high market volatility and make a significant amount of their profits from directional trading activities. MiFID II, however, does not impose any obligations on those *aggressive* HFT strategies but only focusses on market making. Therefore, regulation rules should attempt to mitigate the risks of HFTs by reducing their incentives to perform aggressive (e.g., directional or cross-market) trading strategies, while still keeping the benefits of HFT market making. Introducing "speed bumps" by removing speed advantages beyond a given threshold for specific order flow (e.g., 350 microseconds as on the U.S. exchange IEX, see Financial Times (2016)) appears to be a viable option to target specific types of aggressive latency arbitrage strategies and mitigating ongoing technological arms races for speed advantages. Moreover, in light of recent Flash Crashes such as on February 5, 2018, safeguards such as circuit breakers and trading pauses (see, e.g., Hautsch & Horvath (2017)) and smart market monitoring tools are inevitable for investor protection and ensuring a certain level of market stability in turbulent market periods.

References

Barndorff-Nielsen, Ole E., & Shephard, Neil. 2002. Estimating quadratic variation using realized variance. *Journal of Applied Econometrics*, **17**(5), 457–477.

Baron, Matthew, Brogaard, Jonathan, Hagströmer, Björn, & Kirilenko, Andrei. 2017. Risk and Return in High Frequency Trading. *Journal of Financial and Quantitative Analysis*, forthcoming.

Biais, Bruno, Declerck, Fany, & Moinas, Sophie. 2016. *Who supplies liquidity, how and when?* Working Paper.

Bloomberg. 2015a (Aug 24th). *China's Stocks Sink Most Since 2007 as State Intervention Fails*. http://www.bloomberg.com/news/articles/2015-08-24/chinese-stock-index-futures-tumble-after-last-week-s-retreat. Accessed 2016-07-22.

Bloomberg. 2015b (Jan 21st). *Fake Liquidity Prompts European Probe Into High-Speed Trading*. http://www.bloomberg.com/news/articles/2015-01-21/fake-liquidity-prompts-european-probe-into-high-speed-trading. Accessed 2016-01-07.

Bloomberg. 2018 (Feb 5th). *Fake Liquidity Prompts European Probe Into High-Speed Trading*. https://www.bloomberg.com/news/articles/2018-02-05/dow-s-15-minute-plunge-had-elements-of-a-flash-crash-isi-says. Accessed 2018-02-06.

Boehmer, Ekkehart, Li, Dan, & Saar, Gideon. 2018. The Competitive Landscape of High-Frequency Trading Firms. *Review of Financial Studies*, forthcoming.

Brogaard, Jonathan, Hendershott, Terrence, & Riordan, Ryan. 2014. High Frequency Trading and Price Discovery. *Review of Financial Studies*, **27**(8), 2267–2306.

Brogaard, Jonathan, Hendershott, Terrence, & Riordan, Ryan. 2017. High Frequency Trading and the 2008 Short Sale Ban. *Journal of Financial Economics*, Forthcoming.

Brogaard, Jonathan, Carrion, Al, Moyaert, Thibaut, Riordan, Ryan, Shkilko, Andriy, & Sokolov, Konstantin. 2018. High-Frequency Trading and Extreme Price Movements. *Journal of Financial Economics*, forthcoming.

Budish, Eric, Cramton, Peter, & Shim, John. 2015. The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response. *The Quarterly Journal of Economics*, **130**(4), 1547–1621.

Chaboud, Alain P., Chiquoine, Benjamin, Hjalmarsson, Erik, & Vega, Clara. 2014. Rise of the machines: Algorithmic trading in the foreign exchange market. *Journal of Finance*, **69**(5), 2045–2084.

Conrad, Jennifer, Wahal, Sunil, & Xiang, Jin. 2015. High-frequency quoting, trading, and the efficiency of prices. *Journal of Financial Economics*, **116**(2), 271–291.

ESMA. 2014 (Dec 19th). *Consultation Paper - Annex B, Regulatory technical standards on MiFID II/MiFIR, ESMA/2014/1570*. `https://www.esma.europa.eu/sites/default/files/library/2015/11/2014-1570_cp_mifid_ii_part_2.pdf`.

Eurex. 2013. Eurex Exchange's T7 Release 2.0: Important information for production start. *Eurex circular*, **240/13**.

Eurex. 2016. *Price List for Eurex Clearing AG*. `https://www.eurexchange.com/blob/252898/e3e71eb0c309a62eb22f09a7e7196df2/data/price_list_clearing_en_ab_2016_08_02.pdf`. Accessed 2016-08-16.

Financial Times. 2016 (September 2nd). *IEX finishes transition to stock exchange*. https://www.ft.com/content/f8eb8b33-4249-3e30-906d-e49bc48eb6cd. Accessed 2016-10-28.

Foucault, Thierry, Hombert, Johan, & Rosu, Ioanid. 2016. News Trading and Speed. *Journal of Finance*, **71**(1), 335–382.

Hagströmer, Björn, & Nordén, Lars. 2013. The diversity of high-frequency traders. *Journal of Financial Markets*, **16**(4), 741–770.

Hasbrouck, Joel, & Saar, Gideon. 2013. Low-latency trading. *Journal of Financial Markets*, **16**(4), 646–679.

Hasbrouck, Joel, & Sofianos, George. 1993. The Trades of Market Makers: An Empirical Analysis of NYSE Specialists. *Journal of Finance*, **48**(5), 1565.

Hautsch, Nikolaus, & Horvath, Akos. 2017. *How Effective are Trading Pauses?* Working Paper.

Hautsch, Nikolaus, Hess, Dieter, & Veredas, David. 2011. The impact of macroeconomic news on quote adjustments noise, and informational volatility. *Journal of Banking and Finance*, **35**(10), 2733–2746.

Hendershott, Terrence, & Riordan, Ryan. 2012. Algorithmic Trading and the Market for Liquidity. *Journal of Financial and Quantitative Analysis*, **48**(4), 1001–1024.

Hendershott, Terrence, Jones, Charles M., & Menkveld, Albert J. 2011. Does Algorithmic Trading Improve Liquidity? *Journal of Finance*, **66**(1), 1–33.

IIROC. 2012. *The HOT Study: Phases I and II of IIROC's Study of High Frequency Trading Activity on Canadian Equity Marketplaces*. Release No. 34-67090, May 31st, 2012.

Jiang, George J., Konstantinidi, Eirini, & Skiadopoulos, George. 2012. Volatility spillovers and the effect of news announcements. *Journal of Banking & Finance*, **36**(8), 2260–2273.

Jiang, George J., Lo, Ingrid, & Valente, Giorgio. 2015. *High-Frequency Trading in the US Treasury Market: Liquidity and Price Efficiency around Macroeconomic News Announcements*. Working Paper.

Kirilenko, Andrei, Kyle, Albert S., Samadi, Mehrdad, & Tuzun, Tugkan. 2017. The Flash Crash: High Frequency Trading in an Electronic Market. *Journal of Finance*, **72**, 967–998.

Malinova, Katya, Park, Andreas, & Riordan, Ryan. 2013. *Do Retail Traders Suffer from High Frequency Traders?* Working Paper.

Menkveld, Albert J. 2013. High Frequency Trading and The New-Market Makers. *Journal of Financial Markets*, **16**, 712–740.

NYT. 2010 (Dec 22nd). *Computers That Trade on the News*. http://www.nytimes.com/2010/12/23/business/23trading.html. Accessed 2018-02-01.

Schlepper, K. 2016. *High-frequency trading in the Bund futures market*. Working Paper.

Scholtus, Martin, Dijk, Dick van, & Frijns, Bart. 2014. Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking & Finance*, **38**, 89 –105.

SEC. 2010. *Concept Release on Equity Market Structure*. Release No. 34-61358, January 14th, 2010.

van Kervel, V. 2015. Competition for Order Flow with Fast and Slow Traders. *Review of Financial Studies*, **28**(7), 2094–2127.

van Kervel, Vincent, & Menkveld, Albert J. 2017. High-Frequency Trading around Large Institutional Orders. *Journal of Finance*, forthcoming.

Wall Street Journal. 2016 (June 24th). *The Markets' New Target After 'Brexit' Vote: Europe* . http://www.wsj.com/articles/brexit-shockwaves-ripple-through-eurozone-markets-1466751539 . Accessed 2016-07-22.

WSJ. 2015 (Aug 24th). *Historic Profits for High-Frequency Trading Firm*. http://www.wsj.com/articles/historic-profits-for-high-frequency-trading-firm-today-1440446251. Accessed 2016-01-07.

Zhang, S. Sarah. 2017. Need for Speed: Hard Information Processing in a High-Frequency World. *Journal of Futures Markets*.

Appendix A. Descriptive Statistics

Table A1: This table reports descriptive statistics on different liquidity measures. *Trades* is the number of trades from a traders perspective accounting for both liquidity supply and demand. While liquidity demand is the initiating side of the trade, and liquidity supply is the other side of the trade were the order rested in the book. *Trading Volume* denotes the cumulative volume based on all trades, and *Orders* is the number of order submissions. *QSpread* is the difference between best ask and best bid price. $Depth\, x$ is the average number of contracts on the buy and sell side up to price level x. Panel A shows daily descriptive statistics of liquidity measures. The column "NoNews" shows daily averages on days without news announcements, while the column "News" reports averages on days with announcements. Panel B gives averages of 1 second intervals for four intraday trading periods.

Panel A: Daily Statistics

	Units	Mean	Std. Dev.	Min	Median	Max	NoNews	News
Trades	# 1,000 trades	163.90	55.34	33.20	158.23	431.61	147.87	168.76
Volume	# 1,000 contracts	1,138.71	378.45	201.36	1,095.48	3,091.01	1,036.18	1,169.79
Orders	# 1,000 orders	811.48	302.53	119.53	750.85	2,377.65	724.72	837.78
Trade Size	#contracts	5.55	0.75	3.12	5.66	7.47	5.52	5.56
Order Size	#contracts	6.18	0.78	4.00	6.15	8.53	6.15	6.18
QSpread	#ticks	1.03	0.06	1.00	1.02	2.00	1.03	1.04
Depth1	#contracts	175.01	62.90	35.38	180.95	313.05	180.11	173.47
Depth5	#contracts	1,620.95	600.85	318.95	1,693.41	2,914.45	1,664.07	1,607.92

Panel B: Intraday Statistics

	Units	8:00-9:00 a.m.	9:00 a.m.-3:30 p.m.	3:30-5:30 p.m.	5:30-10:00 p.m.
Trades	#trades	2.73	4.39	5.33	0.81
Volume	#contracts	16.41	31.35	38.17	4.41
Orders	#orders	6.62	12.43	16.56	2.84
Trade Size	#contracts	4.76	5.82	5.81	4.10
Order Size	#contracts	6.09	5.77	5.76	4.82
QSpread	#ticks	1.03	1.01	1.01	1.03
Depth1	#contracts	159.86	245.34	266.92	121.60
Depth5	#contracts	1,501.24	2,286.70	2,456.30	1,094.67

Table A2: Trading Statistics for Individual HFT and nHFT Trader Accounts The table shows HFT-specific and nHFT-specific averages of daily trader-ID-specific averages of trade and order statistics. *Trades* gives the number of trades, (double-)counted from both the liquidity suppliers' and liquidity demanders' perspective. *Trading Volume* reports all (double-counted) traded contracts per trader account from both the liquidity suppliers' and liquidity demanders' perspective. *Demand Ratio* is the ratio (in %) of liquidity demanding volume (i.e., volume of initiated trades) to total volume. *Trade Size* is the number of contracts traded per transaction (irrespective whether supplied or demanded), *L. Demand/Supply* is the number of contracts per liquidity demanding or liquidity supplying trade, respectively. *Order Submissions* is the number of orders (including market and marketable orders) per account, and the *Order-to-Trade ratio* is the ratio of the number of order submissions to the number of trades. The column *HFT* shows the averages across all trader IDs identified as HFT, while the column *nHFT* shows averages across all other trader IDs. The columns *HFT Aggressive*, *HFT Mixed* and *HFT Passive* shows the averages across all HFT trader IDs for the corresponding subgroups.

	Units	HFT	nHFT	HFT Aggressive	HFT Mixed	HFT Passive
Trades	#Trades	1,020.40	30.45	707.42	819.12	1,204.19
Trading Volume	Contracts	4,928.61	316.93	19,441.10	3,759.20	3,955.06
Demand Ratio	in percent	22.44	65.39	97.43	31.71	6.41
Trade Size	Contracts	5.43	21.86	21.65	4.65	3.97
Tradesize (L. Demand)	Contracts	6.54	29.74	21.62	7.06	4.29
Tradesize (L. Supply)	Contracts	3.79	12.73	2.42	3.89	3.88
Order Submissions	#Orders	7,082.44	111.83	13,278.71	5,845.76	7,196.77
O/T ratio		79.86	5.46	346.14	108.09	26.29

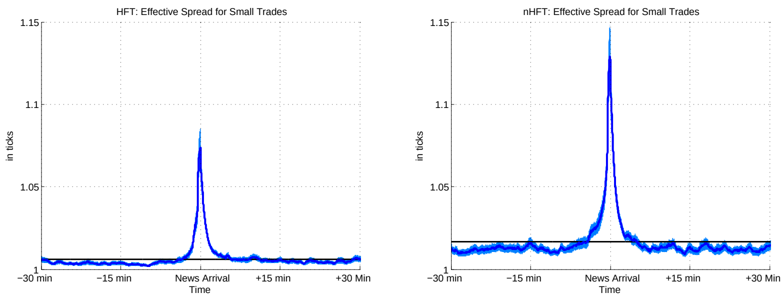
Appendix B. Macroeconomics Announcements

Table B1: This table gives an overview of the macroeconomic announcements used in this study. *Country* is the country where the announcement is reported, *Time* is the time of the announcement (European announcements in CET, U.S. announcements in EST). The columns strong, medium and weak indicate the number of announcements in the respective category. The news are classified into these groups by their market impact after the announcement.

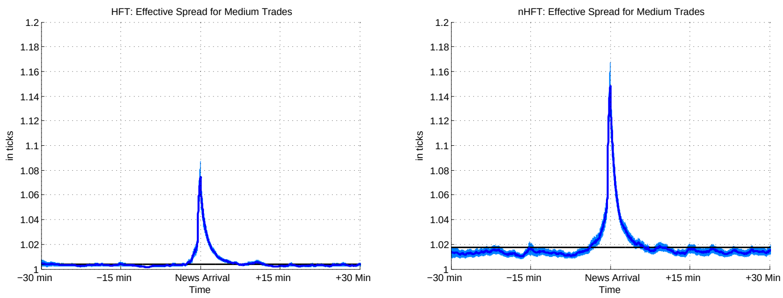
Panel A: European and German News							
Name	Country	Time (CET)	Frequency	Count	Strong	Medium	Weak
Consumer Confidence & Flash	EU	11:00 / 16:00	Monthly	45	7	14	24
Consumer Price Index & Flash	EU	11:00	Monthly	45	12	16	17
ECB Interest Rate Decision	EU	13:45	Monthly	19	4	6	9
Gross Domestic Product s.a.	EU	11:00	Monthly	17	3	6	8
IFO - Business Climate	GE	10:00	Monthly	22	4	15	3
Producer Price Index	EU	11:00	Monthly	22	4	8	10
Retail Sales	EU	11:00	Monthly	22	3	8	11
ZEW Survey - Economic Sentiment	GE	11:00	Monthly	22	3	12	7

Panel B: U. S. News							
Name	Country	Time (EST)	Frequency	Count	Strong	Medium	Weak
ADP Employment Change	US	08:15 AM	Monthly	22	9	9	4
Building Permits	US	08:30 AM	Monthly	22	9	9	4
Business Inventories	US	10:00 AM	Monthly	22	3	3	16
Capacity Utilization	US	09:15 AM	Monthly	22	1	7	14
CB Leading Indicator	US	10:00 AM	Monthly	22	4	11	7
Chicago Purchasing Managers' Index	US	09:45 AM	Monthly	22	4	10	8
Construction Spending	US	10:00 AM	Monthly	22	8	12	2
Consumer Confidence	US	10:00 AM	Monthly	22	4	13	5
Consumer Price Index	US	08:30 AM	Monthly	22	13	9	0
Durable Goods Orders	US	08:30 AM	Monthly	22	10	9	3
Existing Home Sales Change	US	10:00 AM	Monthly	22	4	9	9
Factory Orders	US	10:00 AM	Monthly	22	1	8	13
Gross Domestic Product Annualized	US	08:30 AM	Monthly	22	15	6	1
Housing Starts	US	08:30 AM	Monthly	22	9	9	4
Industrial Production	US	09:15 AM	Monthly	22	1	7	14
Initial Jobless Claims	US	08:30 AM	Weekly	95	43	37	15
ISM Manufacturing PMI	US	10:00 AM	Monthly	22	9	11	2
ISM Non-Manufacturing PMI	US	10:00 AM	Monthly	22	5	8	9
Michigan Consumer Sentiment Index	US	09:55 AM / 10:00 AM	Monthly	44	5	20	19
New Home Sales Change	US	10:00 AM	Monthly	22	2	13	7
Nonfarm Payrolls	US	08:30 AM	Monthly	22	17	2	3
NY Empire State Manufacturing Index	US	08:30 AM	Monthly	22	6	11	5
Pending Home Sales	US	10:00 AM	Monthly	22	2	8	12
Personal Income	US	08:30 AM	Monthly	22	6	8	8
Personal Spending	US	10:00 AM	Monthly	22	6	8	8
Philadelphia Fed Manufacturing Survey	US	10:00 AM	Monthly	22	4	11	7
Producer Price Index	US	08:30 AM	Monthly	22	7	12	3
Retail Sales	US	08:30 AM	Monthly	22	17	5	0
Trade Balance	US	08:30 AM	Monthly	22	10	8	4
Unemployment Rate	US	08:30 AM	Monthly	22	17	2	3

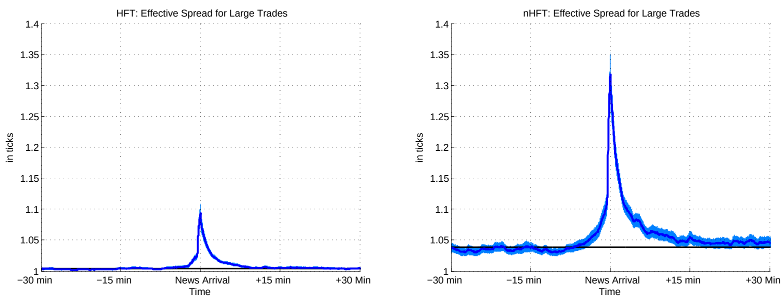
Appendix C. Effective Spreads



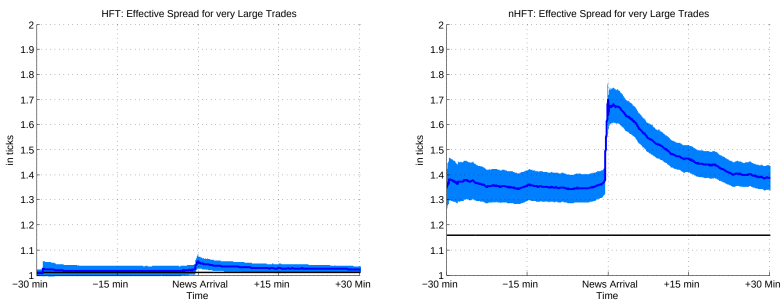
(a) Small trade (trade size <= 3 contracts)



(b) Medium trade (trade size > 3 contracts and <= 10 contracts)



(c) Large trade (trade size > 10 contracts and <= 100 contracts)



(d) Very large trade (trade size > 100 contracts)

Figure C.1: Effective Spreads for Different Trade Sizes. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the release.

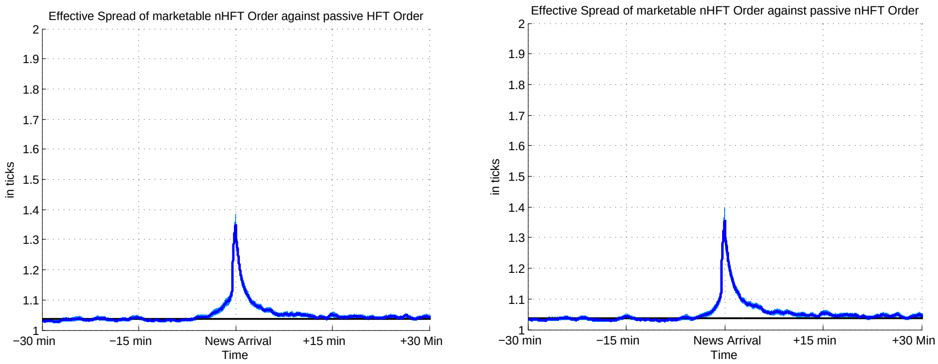


Figure C.2: Effective Spreads of Marketable nHFT Orders executed against HFT and nHFT Orders. The effective spreads are computed whenever an nHFT order is executed against an HFT order (left) or nHFT order (right), respectively. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the release.

Appendix D. Extreme Event Results

D.1. Greek referendum announcement

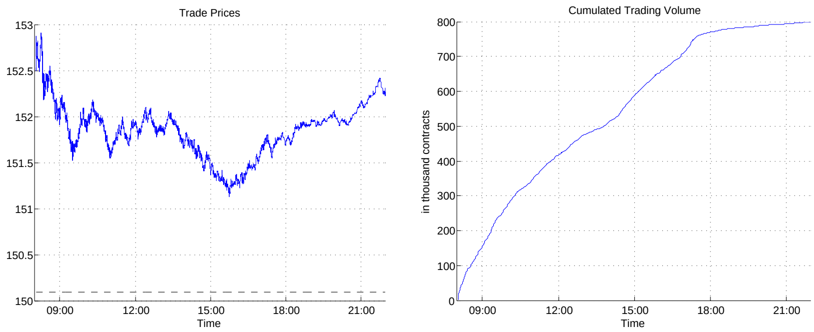


Figure D.1: Price and Cumulative Volume on 29 June 2015. The dashed line represents the previous days closing price of 150.09. The opening price is 152.53.

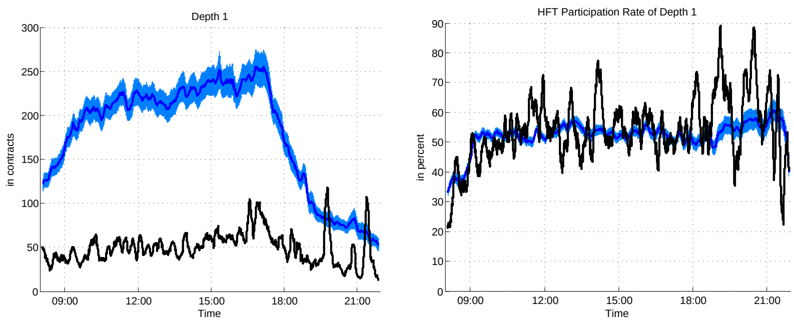
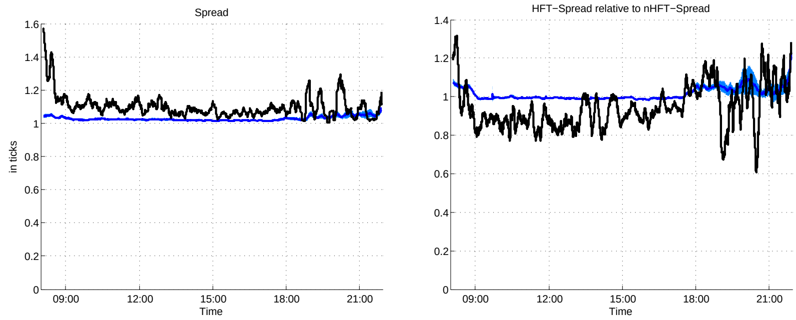


Figure D.2: Market Depth and HFT Participation Rate at Level 1 on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.



(a) Absolute Quoted Spread (b) HFT to nHFT Spread Ratio

Figure D.3: Spread Measures on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

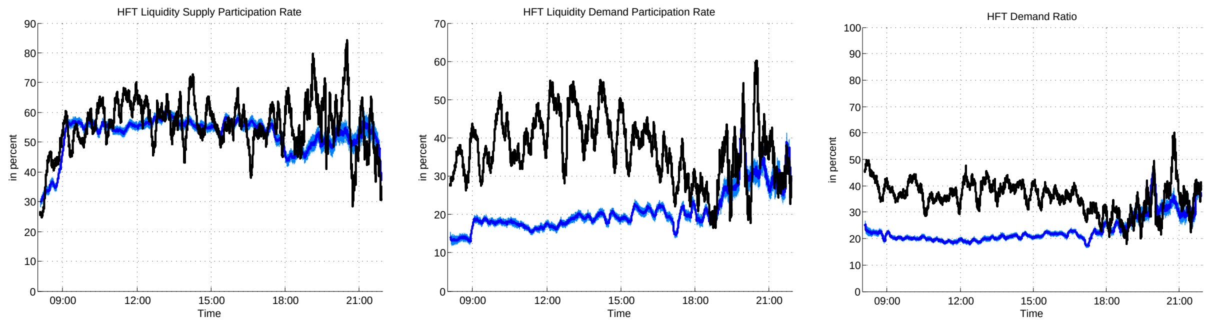


Figure D.4: HFT Participation Rate in Liquidity Supply and Demand and Demand Ratio on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

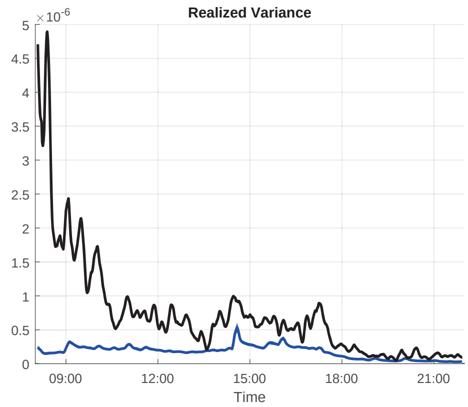


Figure D.5: Realized Variance on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

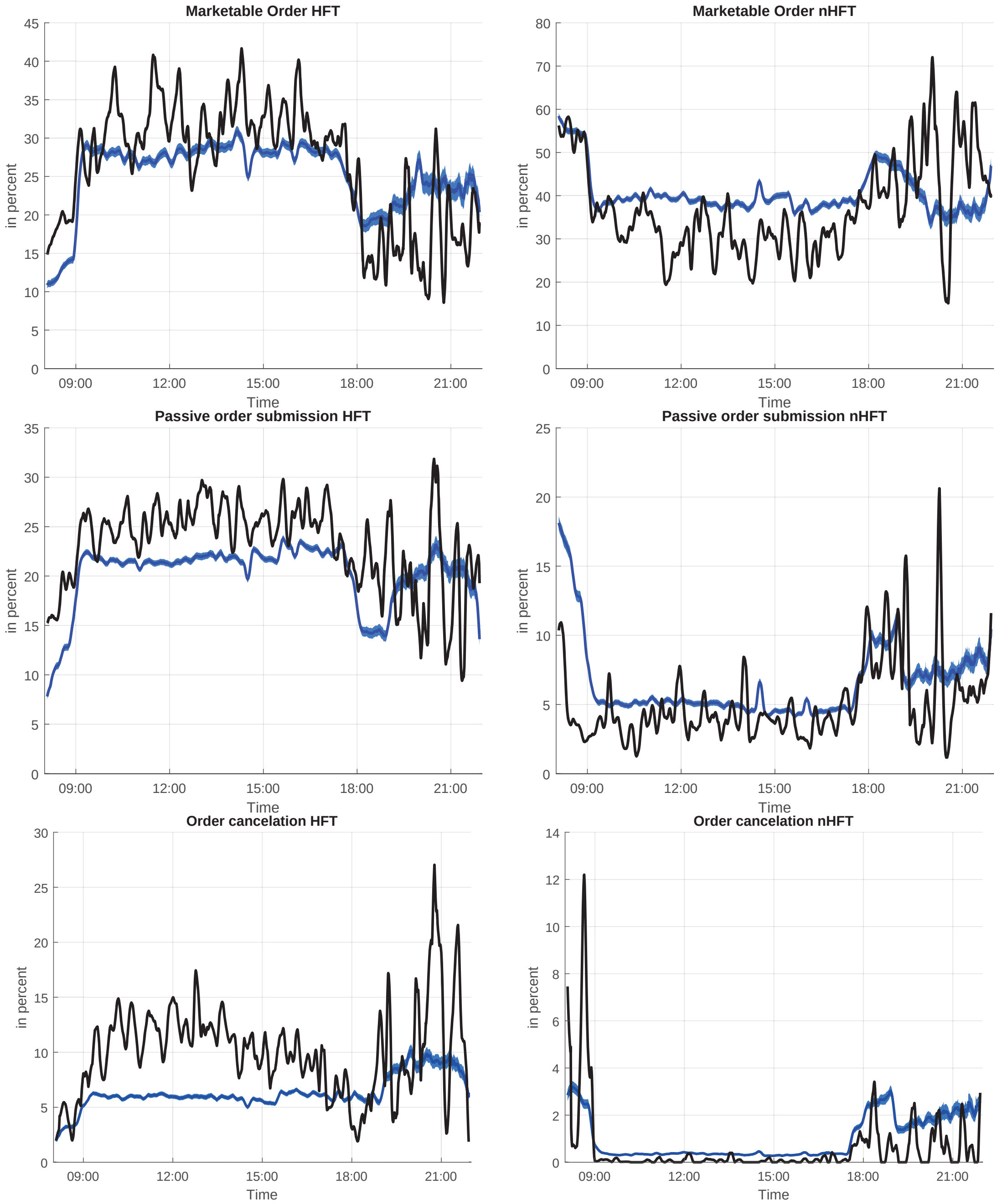


Figure D.6: Relative Contribution of HFT and nHFT Activity to the Realized Variance on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

D.2. China's Black Monday

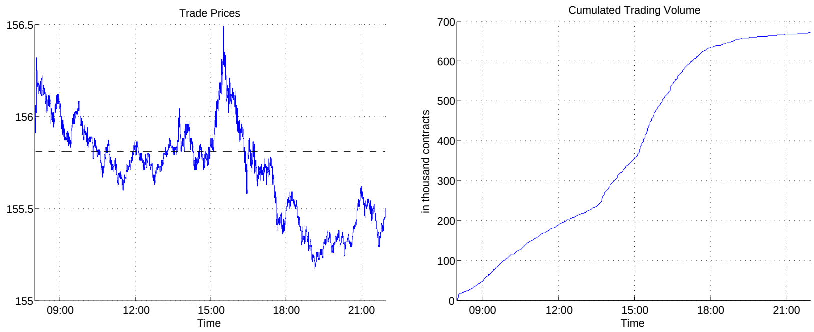


Figure D.7: Price and Cumulative Volume on August 24, 2015. The dashed line represents the previous day's closing price of 155.81. The opening price is 155.99.

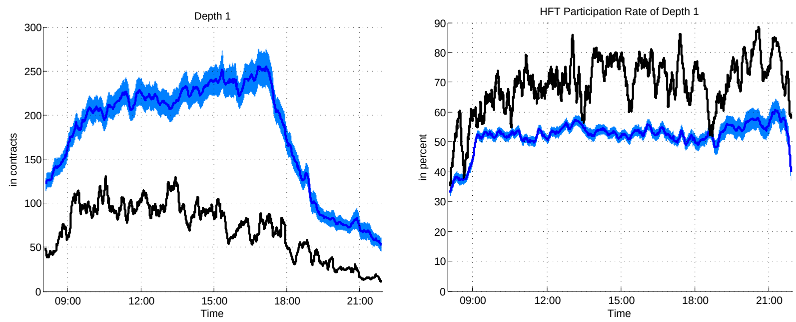
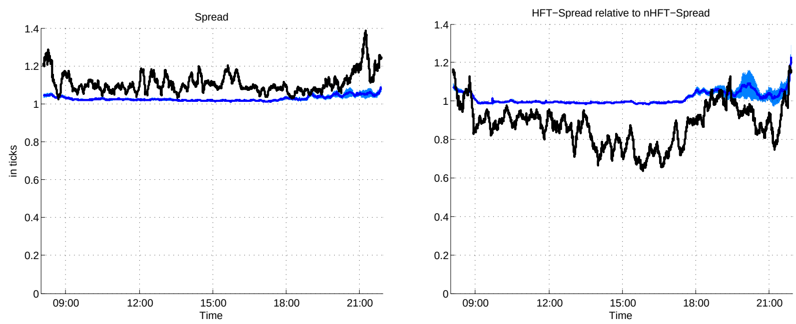


Figure D.8: Market Depth and HFT Participation Rate at Level 1 on August 24, 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.



(a) Absolute Quoted Spread (b) HFT to nHFT Spread Ratio

Figure D.9: Spread Measures on August 24, 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

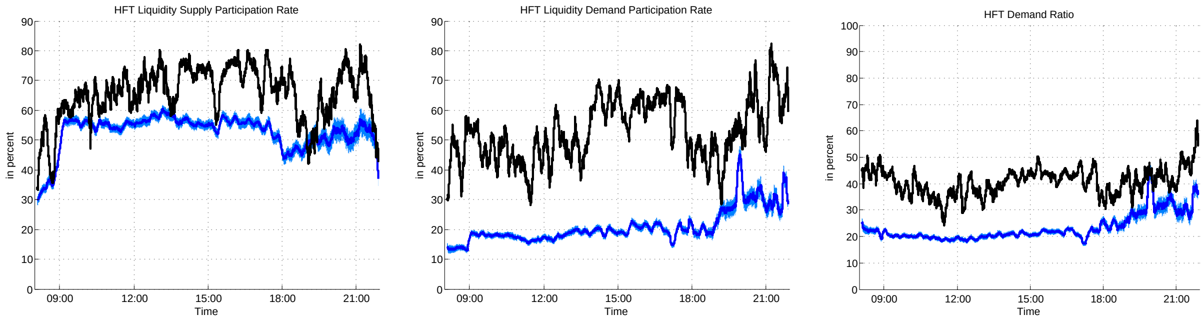


Figure D.10: HFT Participation Rate in Liquidity Supply and Demand and Demand Ratio on August 24, 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

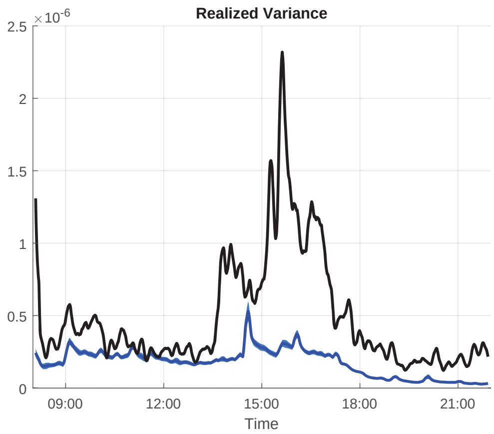


Figure D.11: Realized Variance on 24 August 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

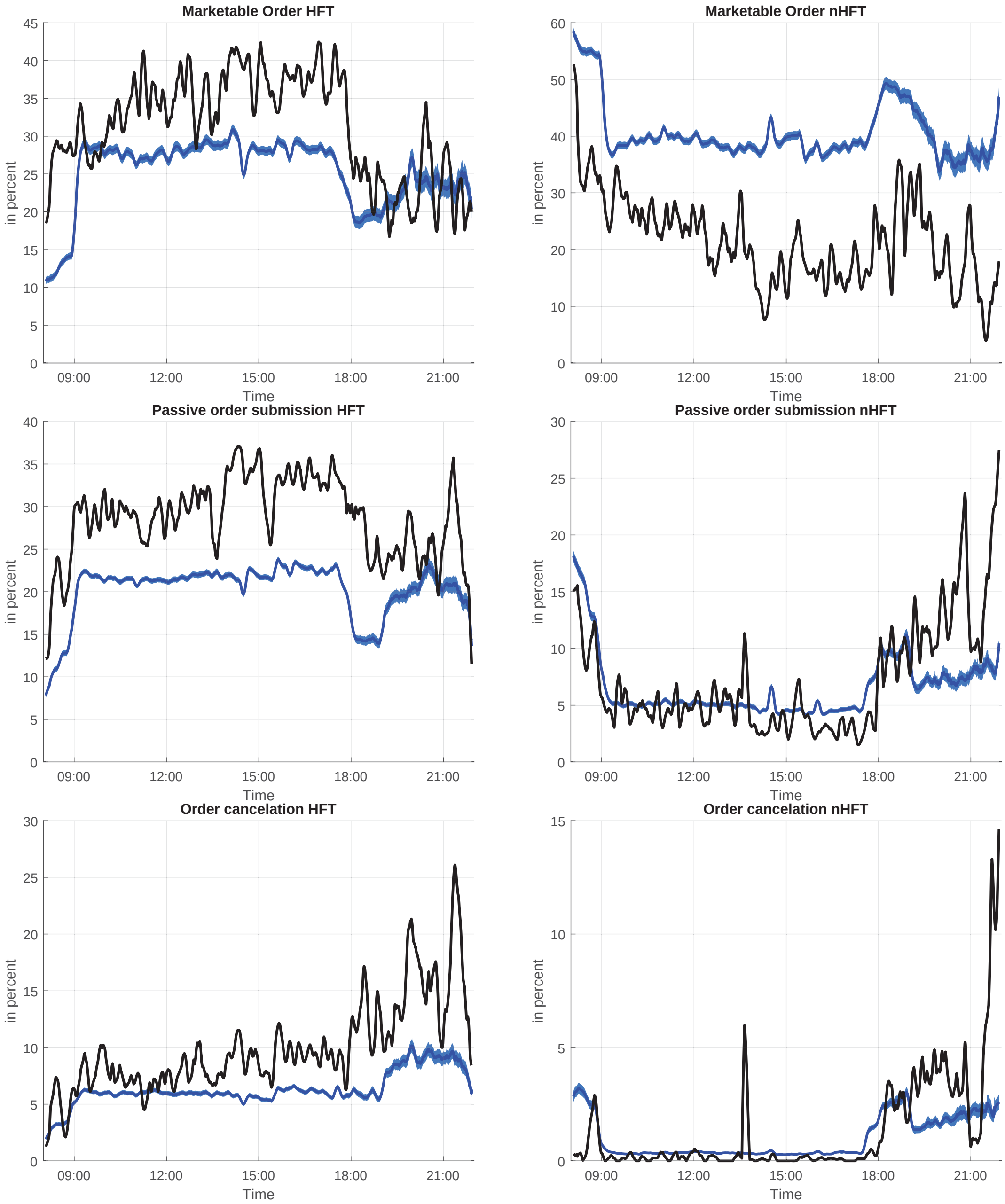


Figure D.12: Relative Contribution of HFT and nHFT Activity to the Realized Variance on 24 August 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.