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

Nikolaus Hautsch Michael Noé S. Sarah Zhang

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Abstract

We show an ambivalent role of high-frequency traders (HFTs) in the Eurex Bund Futures market around high-impact macroeconomic announcements and extreme events. Around macroeconomic announcements, HFTs serve as market makers, post competitive spreads, and earn most of their profits through liquidity supply. Right before an announcement, however, HFTs significantly widen spreads and cause a rapid but short-lived dry-up of liquidity. In turbulent periods, such as after the U.K. Brexit announcement, HFTs shift their focus from market making activities to aggressive (but not necessarily profitable) directional strategies. Then, HFT activity becomes dominant and market quality can degrade.

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, 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. 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, Rudy de Winne, Marius Zoican, participants of the 1st Dauphine Microstructure Workshop, the Financial Econometrics and Empirical Asset Pricing Conference Lancaster and the 3rd SAFE Market Microstructure Workshop. All errors are ours.

1. Introduction

The last decade has seen a dramatic increase in the popularity of Algorithmic Trading (AT) and specifically High-Frequency Trading (HFT).[1] Large investments, e.g., into microwave technology, are still being made to scrap nanoseconds of latency between servers on marketplaces (cf. Budish *et al.*, 2015). 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 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.[2]

The major question adressed in this paper is to which extent HFTs fulfill the function of market makers and serve as a substitute for designated market makers in the sense of classical specialists, see, e.g., Venkataraman & Waisburd (2007). 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 such a service in periods of high market uncertainty and strong price movements. In particular, do they provide liquidity in periods where liquidity is most needed or do they change their strategy and trade aggressively in the direction of the market? More specifically, we focus on the following research questions: (i) How much liquidity do HFTs supply and demand relative to non-HFTs (nHFTs) and how does this potentially change in periods of high market uncertainty? (ii) Is liquidity provided by HFTs in such periods accessible and more expensive than liquidity provided by nHFTs? (iii) Do HFTs profit more from market making or directional strategies in periods of high uncertainty?

We analyze trading in the Euro-Bund Futures, one of the most actively traded contracts world-wide and solely traded on Eurex, Frankfurt. By focusing on a non-fragmented market, we particularly aim at understanding the role of HFT in an environment where cross-market

[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] See, e.g., Baron *et al.* (2015), who show that HFTs make excessive profits from aggressive trading.

arbitrage strategies are widely ruled out and HFT strategies are most likely to be concentrated on one market. We conduct such analysis specifically for periods where liquidity supply is important and analyze local time windows around macroeconomic announcements with the highest price impact in our sample from 2014-2015. We moreover include three extreme events, the announcement of the E.U. referendum results in the U.K. in June 2016 (so-called Brexit), the announcement of the Greek referendum in June 2015, and the Chinese Black Monday in August 2015.

Using a unique data set with identifiers of individual trader accounts, we are able to identify market activity originating from HFT firms. This institutional identification is complemented by empirical criteria on HFT intraday trading patterns as commonly applied in the empirical literature (see e.g. Kirilenko *et al.* (2017)), such as high speed, excessive order submissions per day and restrictions on end-of-day positions. These criteria allow us to identify typical HFT strategies. We moreover provide evidence on the origins of HFT profits by decomposing the latter into a positioning and a net spread component. This allows us to distinguish between the speculative component of profits as well as spread costs for liquidity demand and spread gains for liquidity supply.

We find that around periods of fundamental news releases, HFT activity is dominated by high-frequency market making. In these periods, HFTs mostly serve as passive liquidity suppliers, stabilize the market after news announcements, and supply a substantial amount of market liquidity. Different from common beliefs, HFTs typically do *not* intensively engage in aggressive news trading, but rather buy and sell evenly after macroeconomic news releases. They predominantly make their profits by offering competitive bid-ask spreads.

We nevertheless identify important limitations: When market uncertainty peaks, market making is temporarily undermined by a dry-up of liquidity, rising costs of HFT-provided liquidity, and aggressive directional order placement. These situations can occur very rapidly briefly before the release of fundamental information but are only short-lived. In turbulent periods, such as after the U.K. Brexit in June 2016, however, aggressive directional HFT strategies can dominate market activities over longer periods. Then, market making functionalities are undermined as soon as HFTs become involved in aggressive (positional) order placement and momentum strategies. We therefore conclude that HFTs do *not* operate as substitutes of designated market makers in the classical sense but follow alternative strategies whenever it becomes profitable. This dual side of high-frequency market making partly explains why the empirical literature draws different conclusions on the effects of HFT on market quality.

In this sense, our findings therefore complement the empirical literature on the effects of HFT in several ways: First, our results show that during periods around scheduled news announcements, HFTs primarily focus more on market making rather than directional trading. They try to maintain a balanced position throughout event periods in order to avoid adverse selection costs and make profits predominantly from earning liquidity premia. In these periods, HFTs generally serve as liquidity providers rather than active contributors to price discovery and have stabilizing effects. These results are in line with existing literature showing positive effects of HFT on market quality.[3]

Second, by identifying severe limitations of HFT liquidity provision, we confirm Kirilenko *et al.* (2017) who criticize HFT's withdrawal of liquidity during the May 2010 Flash Crash and Brogaard *et al.* (2017) who report negative effects of HFT on liquidity during the financial crisis in 2008. We show that briefly before the release of fundamental information, the decline in HFT liquidity supply can be substantial and can occur very rapidly. In these situations, HFTs require a high premium for adverse selection risk and make liquidity more expensive. During these extreme and rather short-lived periods, HFTs trade aggressively in the direction of new information.

Third, we provide novel evidence on the effects of HFT in turbulent periods after distinct extreme events such as, e.g., the Brexit announcement in June 2016 or the day after the Greek government broke off negotiations with the Eurozone members and called for a referendum (June 2015). We show that on these days, the behavior of HFTs is clearly different from their behavior on "normal" days or during periods around scheduled news releases. Studying such

[3]See, e.g., Chaboud *et al.* (2014), Zhang (2017), Hasbrouck & Saar (2013), Brogaard *et al.* (2014), Brogaard *et al.* (2015), Scholtus *et al.* (2014), and Conrad *et al.* (2015).

days of high market uncertainty thus complements existing research by providing insights into the variability and diversity of HFT strategies. By conducting a profit analysis similarly to Menkveld (2013), we show that during extreme events, such as after the Brexit announcement in the U.K., positioning revenues play a clearly more important role than liquidity premia as HFTs conduct aggressive momentum strategies. We moreover illustrate that aggressive HFT strategies can also result in significant losses. For instance, on a day of high market uncertainty, as the day after the announcement of the Greek referendum in June 2015, HFTs obviously cannot exploit their speed advantage and suffer from losses in positional trading.

Fourth, by analyzing Bund Futures trading, we complement research on HFT and fast trading in other assets, such as Kirilenko *et al.* (2017) who use data from the U.S. E-mini futures market, Baron *et al.* (2015) who use data from the Scandinavian equity market, and Biais *et al.* (2016) who use data from the French equity market. Our results show that conclusions on the effects of HFT cannot necessarily be transferred from one market to another, but tends to be specific to the asset and the underlying market structures. The fact that Bund Futures trading is concentrated on *one* market platform, might be an obvious reason why HFTs are generally less aggressive than on equity markets and primarily make their profits from market making strategies.[4]

Finally, we contribute to the literature on the effects of news arrivals, such as, e.g., Fleming & Remolona (1999), Green (2004), Andersen *et al.* (2003) and Hautsch *et al.* (2011). Our results thus provide novel insights into liquidity dynamics of HFTs and nHFTs around scheduled announcements as well as after distinct events such as the Brexit referendum. In particular, we support Green (2004) who shows higher adverse selection costs in such periods. We illustrate that this argument strongly applies for market making HFTs who withdraw their liquidity supply and widen spreads before the announcement.

Our findings have important policy implications as they demonstrate the ambivalent role of HFT on a market which does not suffer from fragmentation and where cross-market arbitrage

[4]In this sense, our study complements findings by Schlepper (2016) who also uses data from Eurex Futures trading, but without individual trader account identification. Her focus, however, is different from ours.

strategies are widely ruled out. On the one hand, our results suggest that HFT market making functionality stabilizes markets, improves market quality and should be fostered (and *not* impeded) by regulation. On the other hand, regulation should ensure that in extreme periods, the rapid shift of HFT from market making activities to aggressive and one-sided order placement strategies does not threaten market stability by a sudden dry-up of liquidity. For instance, introducing speed bump functionalities can be a viable instrument to (partly) preserve market making services while reducing the incentives for aggressive and directional HFT strategies.

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. Section 3 presents trading behavior of HFTs and nHFTs and their influence on market liquidity. In Section 4, we analyze trading profits and its components for HFTs and nHFTs. Section 5 analyzes HFT behavior during three extreme events, the E.U. referendum in the U.K., the Greek debt crisis, and the Chinese Black Monday. Finally, Section 6 concludes.

2. Data and HFT Identification

2.1. Institutional Details

We focus on one of the most actively exchange traded products, the Euro-Bund Futures contract (FGBL).[5] The Bund Futures is a futures contract on German sovereigns, 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.[6]

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

[6]This makes cross-exchange arbitrage opportunities as discussed by van Kervel (2015) impossible as there is no activity on other markets. Other forms of (statistical) arbitrage (cf. Budish *et al.*, 2015), however, cannot be ruled out.

Eurex is the largest exchange for European equity index and fixed income futures worldwide. 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 these period from the front-month contract to the back-month contract. 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 rise 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. We focus on normal trading hours between 9:00 a.m. and 5:30 p.m., as commonly used in the literature. The order message data are time stamped to the nanosecond and include all order submissions, modifications, cancellations, executions as well as member and trader account identification for each message. Based on the raw message data, we use three different types of data for our analyzes: order message data, trade data and order book data.

The order message data contains the time stamp, the underlying product, the order ID, the message type (submission, cancellation or modification), the order type, the trader ID (indicating who submitted, modified or cancelled the order), the buy-sell indication, the imposed price limit, and the corresponding quantity. Most importantly, the message information contains the member ID and trader ID of the submitting party. 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 that 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.

The trade data contains the time stamp, 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.

Using order message data, we are able to reconstruct each level of the order book on a tick-by-tick basis. The order book data includes the time stamp, the underlying product, the buy or sell side, the number of orders and the volume pending on each price level, including trader information of individual orders.

Table A1 in the Appendix 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

According to the U.S. Securities and Exchange Commission (SEC), HFT is associated with typical characteristics, such as high speed, submission 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 guidance 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. Similar empirical identification proxies for AT and HFT activity are used by Jiang *et al.* (2015), Scholtus *et al.* (2014), and Boehmer *et al.* (2015). These methodologies have the advantage that they can be applied to public data. However, they usually focus 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. For example, Brogaard *et al.* (2014) and Hagströmer & Nordén (2013) use NASDAQ data for which the exchange provides identification based on its in-house expertise. A similar internal HFT flag is used by Schlepper (2016) based on 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 criterion is the identification of trader accounts. In this line, data from the Canadian stock market is used by Malinova *et al.* (2013), French data is used by Biais *et al.* (2016), and U.S. futures market data is used by Kirilenko *et al.* (2017). 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 therefore 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 specifics 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 position. We further augment these criteria by requirements on the latency of order activity. 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 which act as liquidity demanders (especially statistical arbitrageurs and news traders) need to be fast to be profitable (Foucault *et al.*, 2016). 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.

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 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 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: 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)

Table 1 presents summary statistics of HFT and nHFT trading and order activity as well as so-called "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 HFT and nHFT activities on *both* the liquidity demand and supply side, leading to a double-counting. Accordingly, we observe on average approximately $70,500$ 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%.[7]

Hence, 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.

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.

[7] 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 2: 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

To analyze 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 2 reports daily trade and order characteristics for an average HFT and nHFT account. We find that an average HFT account participates on either liquidity demand/-supply side of more than $1,000$ trades (we sum over both the liquidity supplying and liquidity demanding side), compared to just approximately 30 trades of an average nHFT account. A majority of these trades, however, stem from passive HFTs. A passive HFT account participates in even more than $1,200$ trades on average. This confirms the findings of Table 1 that HFTs tend to serve as liquidity suppliers rather than liquidity demanders. 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). Likewise, we observe a demand ratio of 97% for aggressive HFTs vs. 6% for passive HFTs (and 65% 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.

3. HFT Liquidity around Extreme News-Implied Price Movements

In order to study HFT behavior during periods of high price uncertainty, we focus on local time windows around the arrival of scheduled macroeconomic news announcements. 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 A2 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.[8] 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

[8] As some news announcements occur simultaneously, we observe 914 announcements at 687 distinct points in time.

period after the time of the news release. We focus on the top 25% announcements with the highest market impact[9]. The resulting sample consists of 179 distinct announcements implying an average absolute log return of 0.04% through the 5-min period after the news release.[10]

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 30 minutes before and 30 min after a macroeconomic announcement. 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 on a given day is given by

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

In this way, we can identify the timing of market activity up to a precision of a minute. Utilizing this sample of local windows around news arrivals with large price impact, we analyze (i) HFTs' contribution to liquidity supply and demand, (ii) transaction costs implied by HFT market making, and (iii) directional trading by HFTs related to the direction of news.

[9]The results for the remaining category are similar and are available upon request.
[10]A 5-min log return of 0.04% corresponds to more than 1000% on annual basis.

3.1. HFT Liquidity Supply and Demand

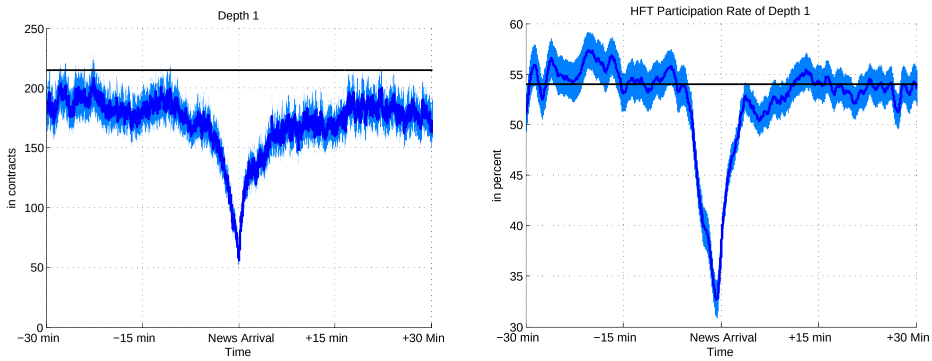


Figure 1: Market Depth and HFT Participation Rate at Order Book Level 1. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding*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

Figure 1 shows the across-event averages and the corresponding 2.5% and 97.5% empirical quantiles of the market depth on top of the order book, $Depth_1 = 1/2(Biddepth_1 + Askdepth_1)$, 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 obviously mainly due to a reduction of HFT-induced liquidity supply. While HFTs contribute on average around 50% of the first-level depth until 10 min before the announcement, this proportion reduces to approximately 33% directly before the release.[11] 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 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.

[11] Approximately the same holds true for deeper order book levels.

Table 3: 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

After the release, however, HFTs replenish liquidity much faster than nHFTs. This is illustrated in Table 3, 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 the event). 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 higher 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.

Figure 2 displays HFT participation rates in liquidity supply that is ultimately matched and results in transactions. The proportions are therefore computed based on the number of *traded* contracts. We distinguish between "aggressive", "mixed" and "passive" HFTs as described in Section 2.3. Similarly to the corresponding plot in Figure 1, the left graph in Figure 2 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 HFTs running mixed strategies, who obviously change their liquidity supply strategies around news arrivals. Interestingly, the quick replenishment of liquidity supply after the release is mainly due to the HFTs performing mixed strategies. 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.

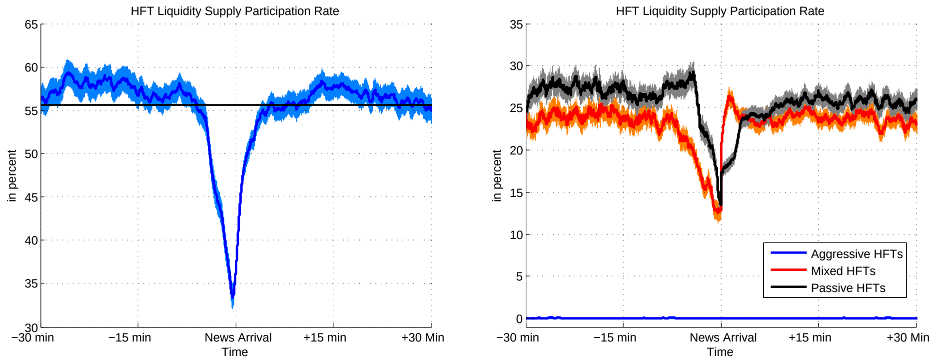


Figure 2: HFT Liquidity Supply and HFT Participation Rate in Traded Contracts. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid line is the overall mean across all trading days *excluding* a one-hour window around the release.

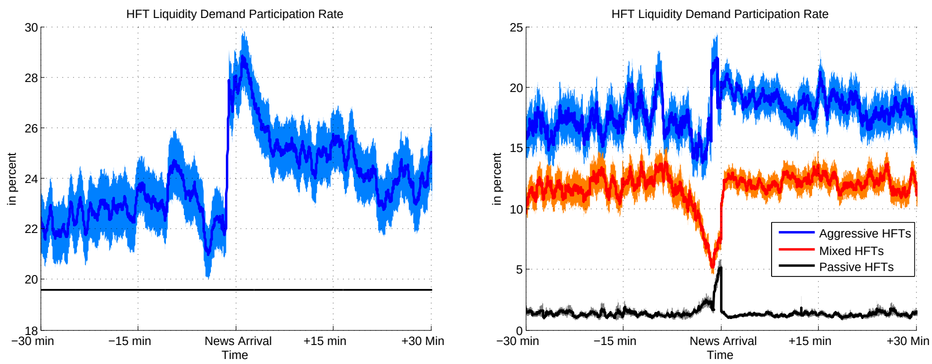


Figure 3: HFT Liquidity Demand and Participation Rate in Traded Contracts. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid line is the overall mean across all trading days *excluding*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

Likewise, Figure 3 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 a 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.

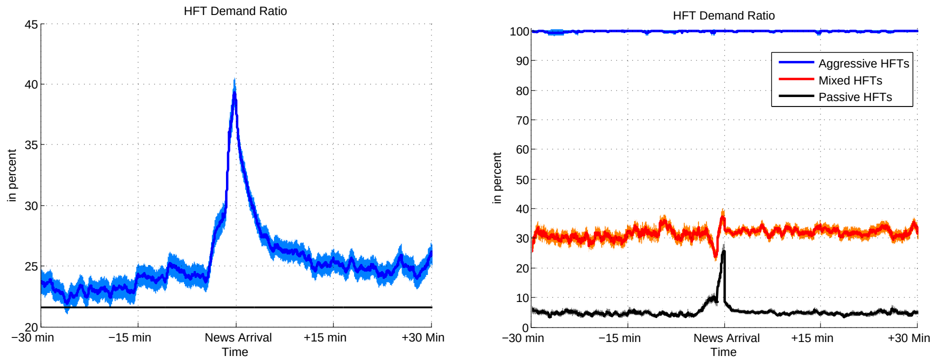


Figure 4: HFT Demand Ratio. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour window around the release.

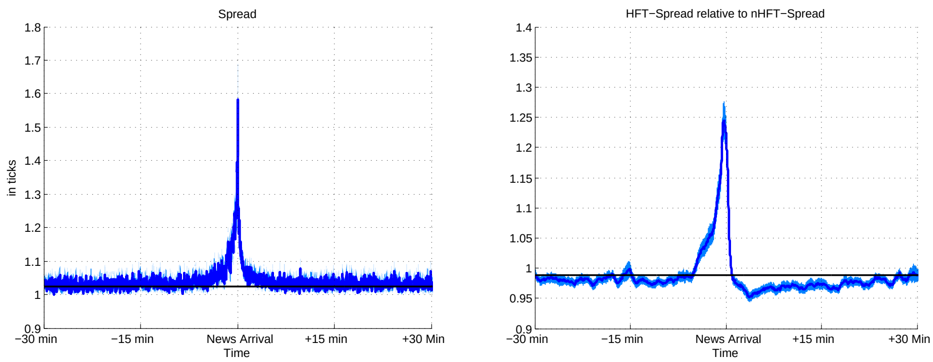
Despite their reduction in liquidity supply around news releases, HFTs still provide more liquidity than they consume it. This is indicated by the HFT "demand ratio", computed as the volume of *HFT-initiated* transactions to their total traded volume, as shown in Figure 4. Overall, the ratio is around 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 4 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 announcements. 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.

We can 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, HFTs, however, significantly reduce liquidity supply. In this way, they behave similarly to a "classical" (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 nearly instantanteously and (due to their dominating role) 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 designated market makers and can undermine market making functionalities. These effects are amplified by a simultaneous increase in HFT liquidity demand, which is likely due to rising activity of speculative (and mostly aggressive) HFTs, and inventory management of passive HFTs. At this point, HFTs draw liquidity from the market, further thinning out depth.

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 market re-stabilization. In Section 5, however, we will demonstrate that during turbulent market periods of high uncertainty, such as after the U.K. Brexit, such phases of increased HFT aggressiveness, momentum trading and reduced market making functionality can persist significantly longer.

3.2. The Costs and Accessibility of HFT Liquidity

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, $QS = Ask - Bid$, i.e., the costs a market maker would earn if he continuously offers (best) quotes on both sides of the market. 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 of HFT and nHFT liquidity supply.



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

Figure 5: 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 release.

Figure 5 shows the across-event averages of the quoted spread and the corresponding HFT/nHFT spread ratio around the 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 release. In general, 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. Panel (b) in Figure 5 shows that 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.

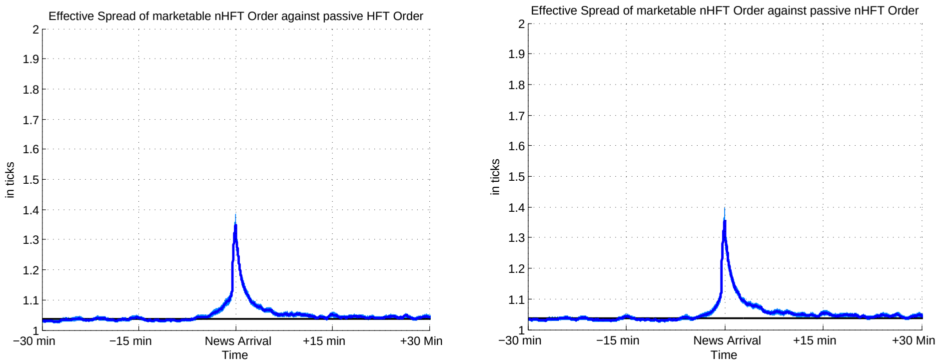
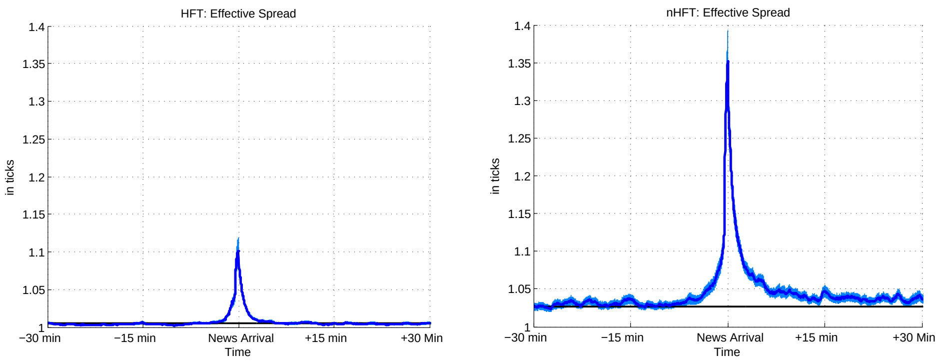


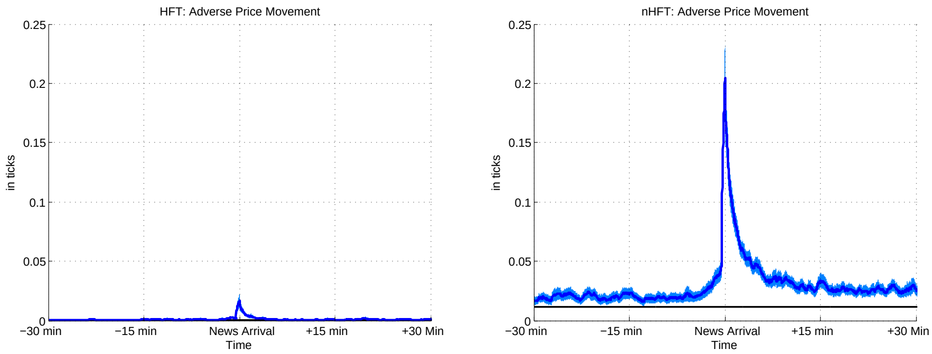
Figure 6: Effective Spreads of Marketable nHFT Orders executed against HFT and nHFT Orders. The effective spreads are computed whenever an nHFT order is executed against an HFT order (left) or nHFT order (right), respectively. Across-event averages of smoothed one-minute averages as described in Section 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.

To analyze to which extent the liquidity offered by HFTs is actually accessible by *non-*HFTs, we re-compute the effective spreads based on quotes which are ultimately matched. Figure 6 shows the effective spreads evaluated whenever an nHFT order is executed against an HFT order 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.[12] 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.

[12]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.



(a) Effective Spread



(b) Adverse Price Movement (APM)

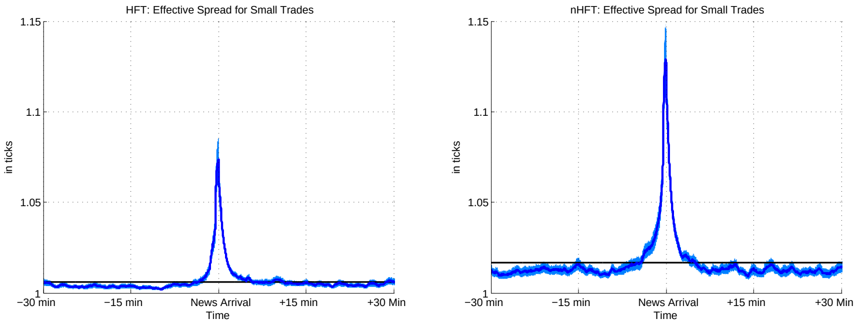
Figure 7: Effective Spread and Adverse Price Movement. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles, while the solid lines are the overall means across all trading days *excluding* a one-hour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

The findings revealed by Figure 5, however, obviously do *not* tell us that nHFTs generally face lower trading costs than HFTs themselves. In fact, Figure 7 shows the average spreads *paid* by HFTs and nHFTs around news arrivals. In this context, we compute the *effective* spread, defined 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 according to Figure 7 effective spreads faced by HFTs are only slightly lower (approx. 2%) than those faced by nHFTs, this picture significantly changes during periods of news arrivals. In particular, during these periods we find that HFTs face effective spreads, which are more than 20% (approximately 0.2 ticks) lower than effective spreads faced by nHFTs. Possible reasons might be better market monitoring capabilities of HFTs (i.e., they supply liquidity when it is expensive and demand it when it is cheap, see, e.g., 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.

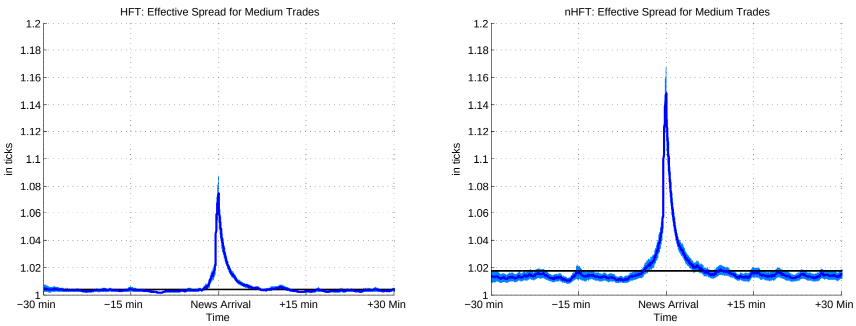
In order to distinguish between these effects, we compute the so-called *adverse price movement (APM)*, defined as the difference between the effective spread and the quoted spread, $APM = (TPrice - Ask)$ for buy trades and $APM = (TPrice - Bid)$ for sell trades. It equals zero if the marketable order 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 by Panel (b) in Figure 7, HFTs manage to widely avoid APMs and actually face no costs induced by orders "walking up" the book during "normal" trading periods. Only during a very short interval closely to the news release, we observe costs induced by APMs of around 0.02 ticks. In contrast, nHFTs face significantly higher costs induced by order matching beyond the first level. Particularly around the new release, these costs are approximately 10 times higher (around 0.2 ticks) than for HFTs.

To check 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" as trades with a trade size of less than or equal to three contracts, "medium trades" as trades with a trade size between 4 and 10 contracts, "large trades" as trades with a trade size between 11 and 100 contracts, and "very large trades" as trades with a trade size above 100 contracts.

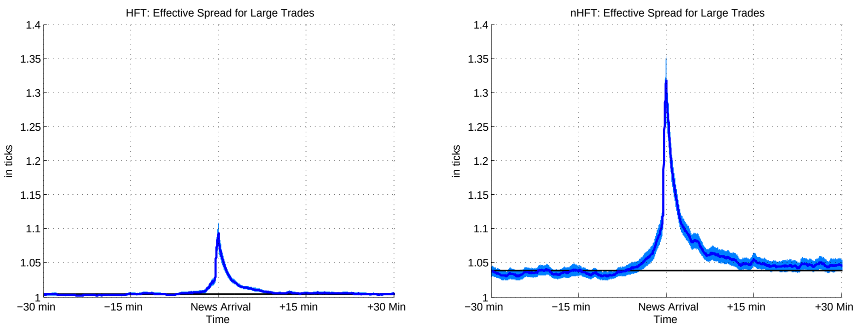
Figure 8 shows the effective spreads for the different trade size groups. In fact, we observe significant differences between the effective spreads paid by HFTs and nHFTs within the *same* trade size group. We therefore conclude that the lower transaction costs paid by HFTs originate from superior market monitoring capabilities rather than from a choice of smaller trade sizes.



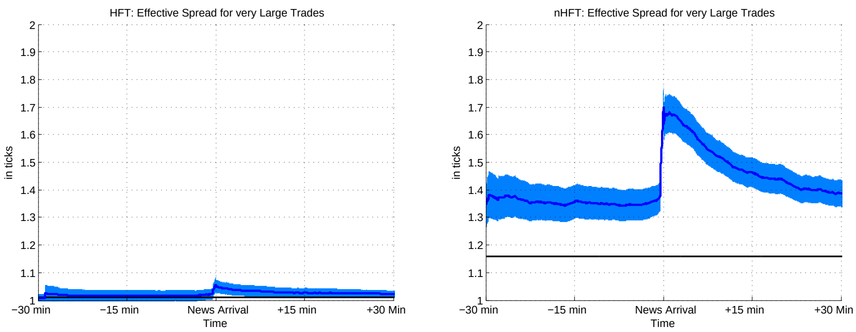
(a) Small trade (trade size <= 3 contracts)



(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 8: 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.

In summary, we show that the costs of HFT-induced liquidity supply are widely widely similar to the costs of liquidity supplied by nHFTs. Prior to the announcement, HFTs react in the same way as designated 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 on the Buy and Sell Side

While the two previous sections focus on the volume and the costs of liquidity supply and demand, in this section, we analyze on *which side* of the market HFTs are active in periods of market uncertainty. In fact, situations, where liquidity supply becomes very unbalanced and one side of the market dries out, can strongly threaten market stability. We therefore study the *net trading* activities of HFTs and nHFTs, defined as the contracts bought minus contracts sold per second. Here, we differentiate between the liquidity demanding and liquidity supplying side of a trade as well as the sign of the underlying price movement.

Figure 9 shows the cumulative net trading of liquidity demanders (i.e., trade initiators) during periods starting 30 minutes before the announcement. We observe that both nHFTs and HFTs actively trade in the direction of the news. Accordingly, their net trading is negative for falling markets and positive for rising markets. This is consistent with other papers providing evidence of HFTs trading on information conveyed by macroeconomic announcements (e.g. Brogaard *et al.*, 2014). 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.

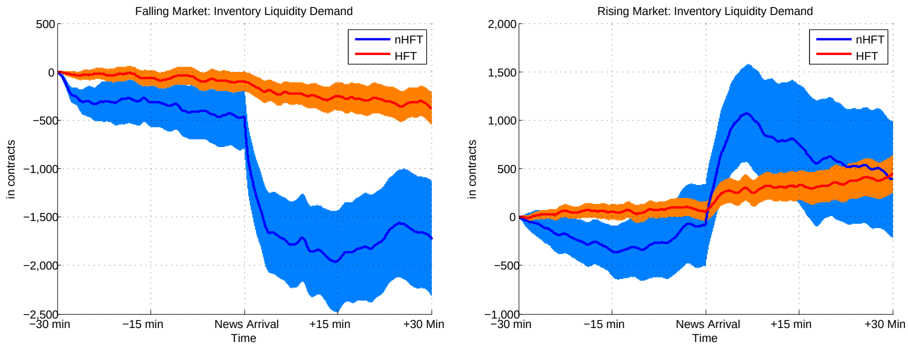


Figure 9: Cumulative Net Trading Through Liquidity Demand. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

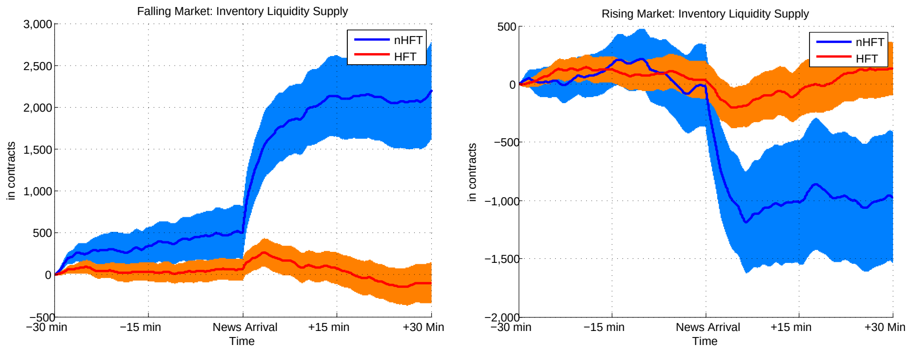


Figure 10: Cumulative Net Trading Through Liquidity Supply. Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

Figure 10 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 withdrawing liquidity in the direction of the market.

The analyses above therefore show that liquidity supply (very) close to news releases is pre-dominantly 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 reduce their liquidity supply in these periods and manage to keep their net positions widely balanced. Hence, in phases of high uncertainty, HFTs tend to avoid risks of adverse selection and inventory imbalances. At the same time, they require a considerable premium to overcompensate their costs (and risks). In these situations, market making services by nHFTs gain a greater importance than those by HFTs.

The result that HFTs widely avoid directional strategies around macroeconomic announcements is striking. This effect is presumably due to the fact that even for HFTs, the window of opportunity to benefit from news trading is comparably short and the risk of being on the wrong side of the market is too high. In fact, in Section 4 we show that in these situations excessive news trading is highly unprofitable (on average) and HFTs strongly benefit from liquidity provision. In Section 5, however, we will show that there are situations when HFTs give up their well-balanced positions but follow directional strategies and build up considerable inventory positions.

4. Trading Profits of HFTs

HFT profits within very short time periods can vary considerably and are highest during highly volatile market periods (cf. WSJ, 2015a). 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.* (2015). In order to gain insights into trading profits and their origins during extreme periods 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 calculated 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

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

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.

Accordingly, the last two terms sum up to the so-called *"net spread"*, the spread earned minus the spread paid. It is earned by passive liquidity supplying orders and paid by 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 fixed costs or transaction fee rebates, such as costs for the connection to Eurex or for data feeds.[13]

As discussed by Menkveld (2013), the decomposition into the *"positioning profit"* and the *"net spread"* helps distinguishing between two different sources of profit: 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.

[13] 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).

Figure 11 shows the total trading gross profit of HFTs and nHFTs. Figure 12 illustrates the decomposition into *Positioning Profits* and *Net Spreads* under the assumption of a zero inventory at the beginning of the trading day. We observe that during the hour around the news release, HFT profits continuously increase while nHFT profits continuously decline. The decomposition in Figure 12 shows that the *Net Spread* component represents a major part of the profits. By overcompensating most variations in the positioning profits, the net spread is the major driver for the profits of HFTs and nHFTs.

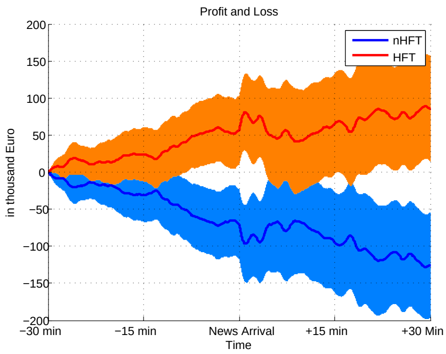


Figure 11: Total Profits (Real Inventory Through the Day). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

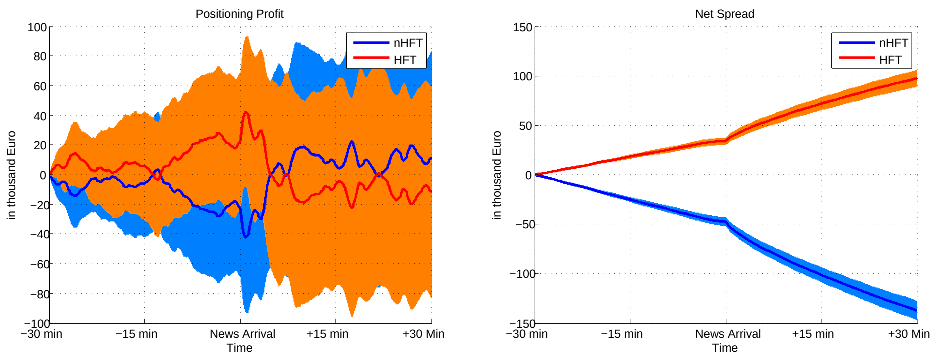


Figure 12: Positioning Profits and Net Spread (Real Inventory Through the Day). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

The trading profits can be separately computed for liquidity demanders as

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

and for liquidity suppliers as

$$\pi_{i,supp} = \underbrace{\sum_{j=1}^{n_i} Inv_{i,j-1} \cdot \Delta p_{i,j}}_{PositioningProfit} + \underbrace{\sum_{j=1}^{n_i^S} V_{i,j}^S \cdot \left(\frac{ES_{i,j}}{2} - \tau\right)}_{NetSpread=SpreadEarned}. \tag{3}$$

Figure 13 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.[14] 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 likely to be 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 any 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 (on average) incur 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.

[14]This assumption is necessary as inventory based solely 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.

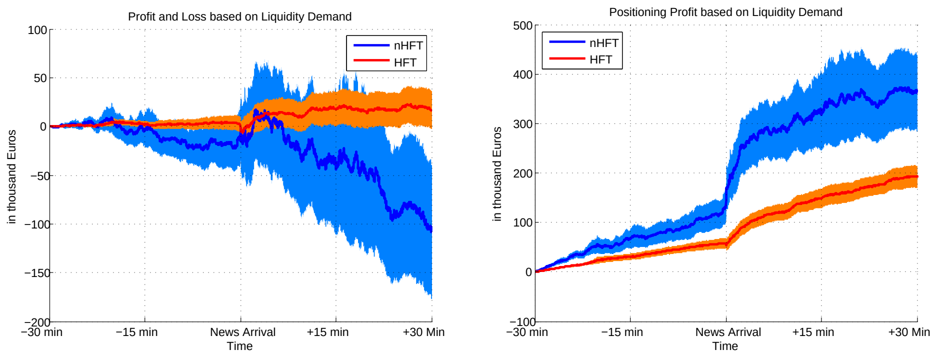


Figure 13: Total Profits and Positioning Profits from Liquidity Demand (Real Inventory Through 30 Minutes). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

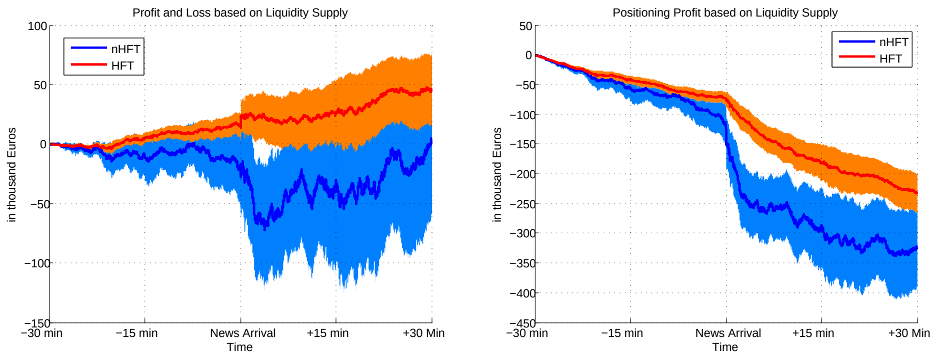


Figure 14: Total Profits and Positioning Profits from Liquidity Supply (Real Inventory Through 30 Minutes). Across-event averages of smoothed one-minute averages as described in Section 3. Shaded areas indicate the corresponding cross-event 2.5% and 97.5% quantiles.

Figure 14 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. Different from the common notion that the highest profits can only result from aggressive trading, we show that 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 market orders more strategically (and thus cost-efficiently) than nHFTs.

5. HFT Liquidity around Extreme Events

In the previous sections, we focused on periods around the scheduled announcements of new macroeconomic information causing market uncertainty and having long-lasting effects on prices. In this section, we aim at analyzing turbulent periods after (widely) unforeseeable events which have recently shaken financial markets. Prominent examples are 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 in the case of a scheduled news announcement.

For regulators and practitioners, it is nevertheless important to gain insights into the role of HFT during such abnormal market conditions. In line with the general research question underlying this paper, we aim at analyzing to which extent the findings of the previous chapters carry over to these situations. We therefore analyze all three events by applying the same HFT identification as in Section 2.3. In contrast to the previous sections, however, we apply these criteria only locally based on order activities on the event day and the day before. To benchmark the used liquidity and trading cost measures on these days with corresponding measures on "normal" trading days, we moreover compute the corresponding statistics for all trading days in the sample *excluding* one-hour windows around all announcements according to Table A2.

We present the most distinct event, the U.K. Brexit announcement, in detail and report the results of the other two events in a more compact way by summarizing some findings in Appendix B.

5.1. E.U. referendum in the U.K. (Brexit announcement), 24 June 2016

On Thursday, 23 June 2016, the U.K. held a referendum whether to remain or to leave the European Union. The result was announced early Friday morning, 24 June 2016, with the result that the U.K. voted to leave the E.U. (so-called "Brexit"). The unexpected results to leave the E.U. sent the pound sterling into a 30-year low and the FTSE 100 lost almost 9% at market opening, although some of the losses were recovered during the day. While most international markets were affected by the sudden fall in the currency and equity markets, 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 discussed in Section 2, events which have negative consequences for the German and global economy are expected to cause pressure on FGBL prices. Accordingly, as shown in

Figure 15, 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. Trading volume steeply increased to around 400,000 traded contracts until 11:30 a.m., corresponding to approximately 50% of the total daily volume.

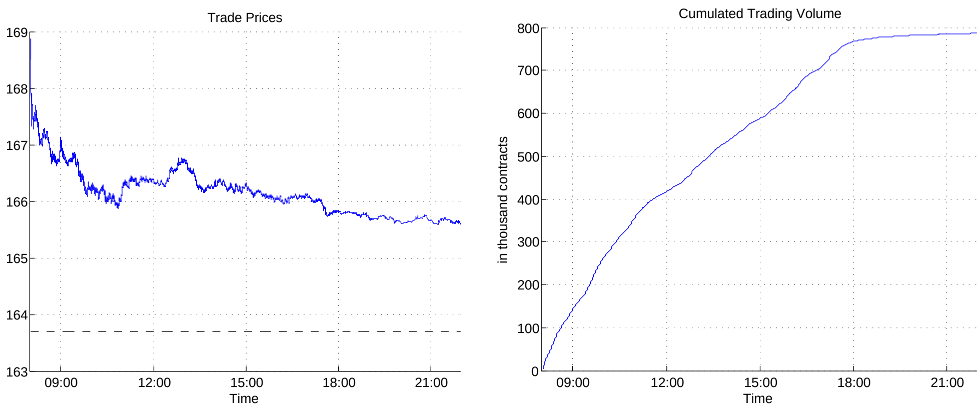


Figure 15: Prices and Trading Volumes on June 24, 2016. The dashed line represents the previous day's closing price of 163.69. The opening price is 168.50.

Figures 16 shows the market depth and the corresponding HFT participation rate on top of the book (i.e., on the first order book level). Compared to the (average) level on "normal" days, the market is generally less liquid on the Brexit day, with the first-level depth being approximately 25-30% lower and the spread being approximately 10% higher. According to Figure 16, 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 (average) macro-announcement days. The increasing importance of HFT liquidity is confirmed by the HFT participation in *traded* liquidity supply, as shown in Figure 17. Likewise, the HFT to nHFT spread ratio tend to be even lower than on days of news releases, indicating cheaper HFT than nHFT liquidity (see Figure 18). Specifically, HFT spreads are on average around 20% below nHFT spreads. We thus have evidence that on a day with an extreme event such as the Brexit announcement, liquidity supply of HFTs seem to play an even more important role than during periods of scheduled news releases.

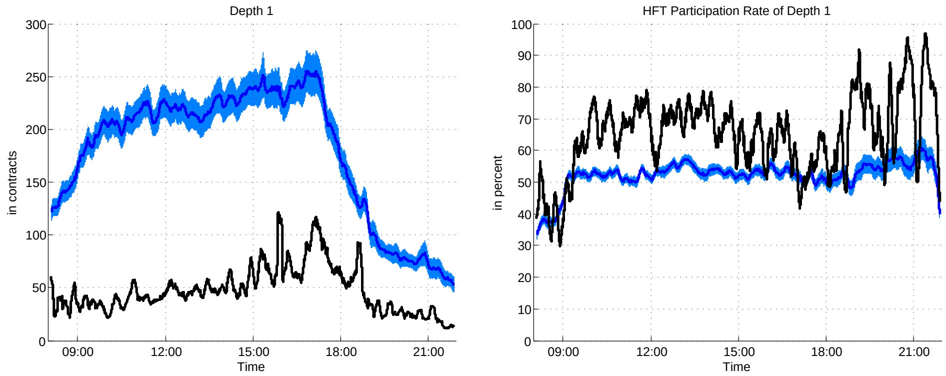


Figure 16: Market Depth and HFT Participation Rate at Level 1 on June 24, 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minutes as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

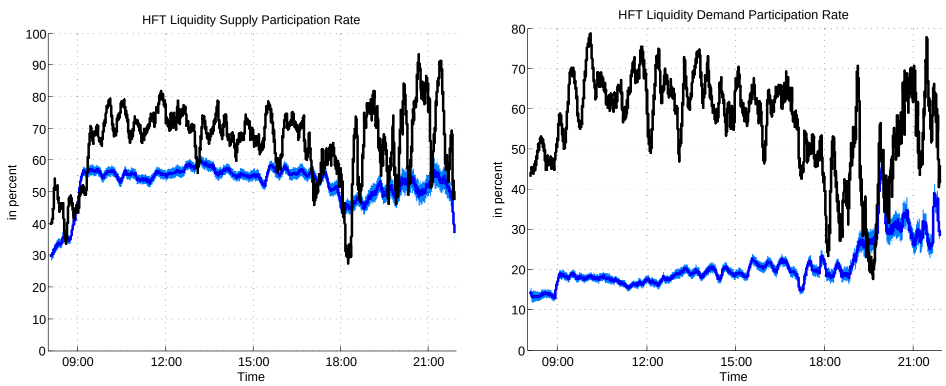
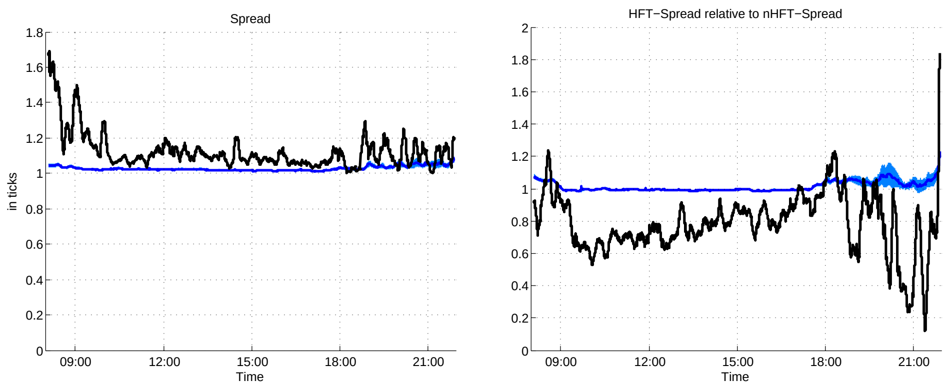


Figure 17: HFT Participation Rate in Liquidity Supply and Demand on June 24, 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minutes as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

A more dominant role of HFTs, however, is also observed in liquidity *demand*. Figure 17 shows that the HFT participation rate in liquidity demand is considerably higher than on normal days and on days with scheduled news releases. In fact, HFTs generate more than 50% of the liquidity demand in most trading periods through the day. Similarly, the HFT demand ratio in Figure 19 illustrates that liquidity demand makes up around 50% of the total HFT trading volume. We therefore find that on the Brexit day, HFTs dominate both liquidity supply and demand and cause around 60-70% of the total trading activity. These results clearly differ from corresponding findings for days of (scheduled) news releases. Hence, during such extreme periods, rather than withdrawing from the market, HFTs are actually more active and tend to be more aggressive than in (more short-lived) periods around news releases.



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

Figure 18: 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.

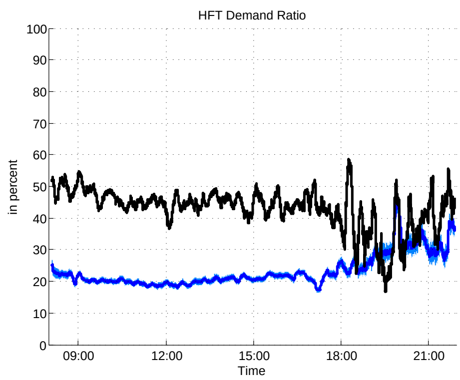


Figure 19: HFT Demand Ratio on June 24, 2016. The blue lines presents the averages across normal trading days, smoothed over 10 minutes as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

Both HFTs and nHFTs build up significant net positions over the course of the trading day (see Figure 20). As shown in the previous chapters, this behavior is nontypical, particularly for HFTs, and clearly differs from behavior observed in periods around news releases. In particular, HFTs exhibit extensive selling behavior in line with the downward price correction through the day. Separating between inventories resulting from liquidity demand and supply

(Figure 21), we find that both liquidity demanding HFTs and nHFTs cumulate a large negative inventory throughout the day. 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.

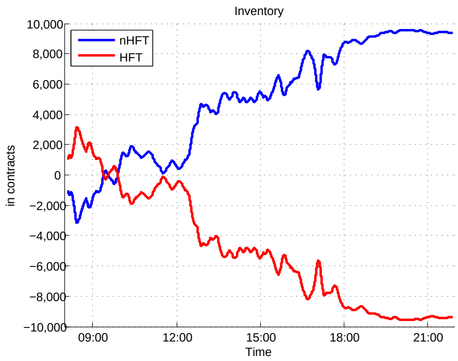


Figure 20: Cumulative Net Trading Volume on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

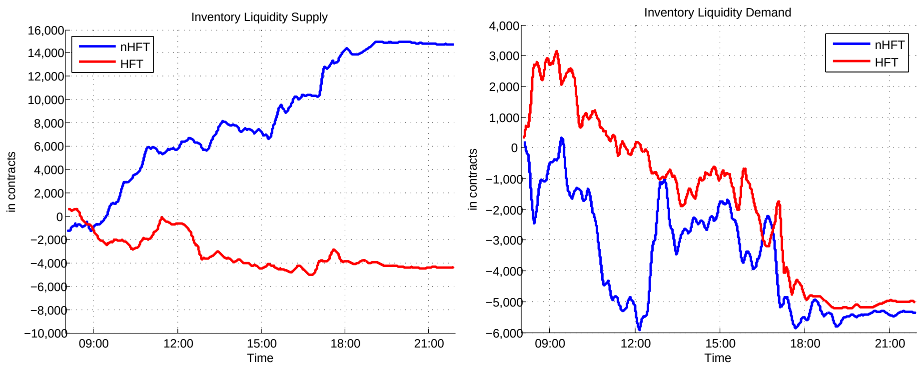


Figure 21: Cumulative Net Trading Liquidity Supply and Demand on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

We further analyze whether these directional trading activities of HFTs result in trading profits. In fact, Figure 22 shows that the overall HFT profits are approximately EUR 4 Mio, whereas nHFTs lose nearly EUR 5 Mio by the end of the trading day. Figure 23, however, shows a major difference in the origins of HFT profits compared to news release days as studied in the previous sections: We find that HFTs make only moderate gains from the net spread component, but considerable benefits 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 24, 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 through and only earning approximately EUR 500,000 through 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.

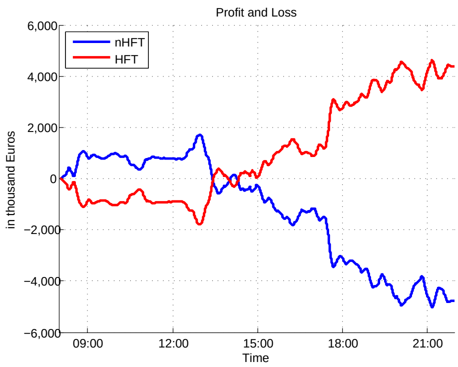


Figure 22: Total Profits on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

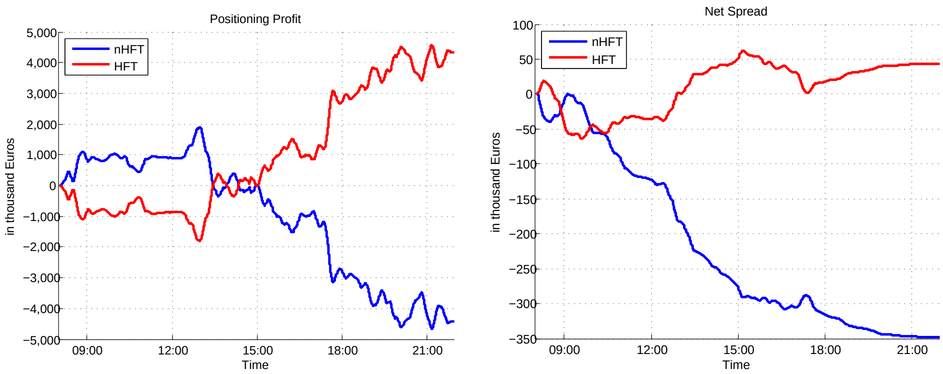


Figure 23: Positioning Profit and Net Spread on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

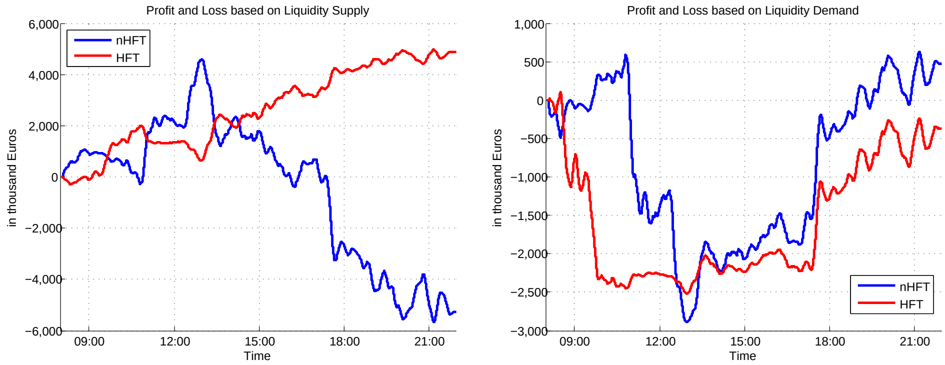


Figure 24: Total Profits from Liquidity Supply and Demand on June 24, 2016. Smoothed over 10 minutes as described in Section 3.

5.2. Greek Debt Crisis, 29 June 2015

The Greek debt crisis reached a worrying climax with the failure to make an IMF loan repayment on 30 June, 2015. After the proposals of the Greek government were rejected by Eurozone members, the Greek government broke off negotiations on Friday evening, 26 June 2015, and called in a referendum on the 5 July 2015 to approve or reject the Troika's proposal from 25 June 2015 (see, e.g., WSJ (2015b)). 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, 29 June 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 (Reuters, 2015).

Figure 33 in the Appendix shows the developments of FGBL prices and cumulative trading volume on 29 June 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.

Since the liquidity effects on this day are found to be similar to the corresponding effects on the Brexit day, we report the corresponding figures for depth, spreads, and liquidity demand and supply participation rates in Appendix B.1. As on the Brexit day, liquidity is generally lower than on “normal” days. Figure 34 in the Appendix reports that depth on the best price level amounts to on average around 50 to 100 contracts, compared to 200 to 250 contracts on “normal” days. Likewise, the quoted spread is approximately 10-20% higher than the average on “normal” days.

We can summarize the following findings for this extreme event: First, the HFT participation rate in liquidity supply fluctuates around 50%-60% (cf. Figure 34). Second, as on the Brexit day, spreads are generally higher than on “normal” days, with HFT-implied spreads being lower than nHFT-implied spreads (cf. Figure 35). Third, the HFT participation in liquidity *demand* is significantly higher than on "normal" days and news-release days. HFTs nevertheless still provide approximately twice as much liquidity as they demand (cf. Figure 36). Thus, also on this distinct day after the Greek referendum announcement, we observe that HFTs play an important role on both sides of the market, contributing to around 60% of liquidity supply and 40% of liquidity demand.

Fourth, unlike nHFTs, HFTs do *not* strongly trade in the direction of the market, but try to keep a relatively balanced inventory position resulting from liquidity demand (cf. Figure 25). This is different from the behavior on the Brexit day and might be due to the fact that price movements after the Greek referendum are less distinct, which causes HFTs being more reluctant to strongly engage in liquidity demand. 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 they build up significantly higher long positions opposite to market movements than on the Brexit day. Hence, on this day, it seems to be more difficult for HFTs to avoid adverse selection risks.

Fifth, the profit analysis shows that the day after the Greek referendum is an example where HFT (despite its strong contribution to daily trading and quoting activities) does not generate any profits. In particular, Figure 26 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 27). 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 28). It is nevertheless positive for HFTs (around EUR 600,000) and negative for nHFTs (around EUR 900,000).

Hence, we can conclude that – as in all cases discussed before – HFT liquidity supply is more dominant and profitable than HFT liquidity demand. Moreover, as on the Brexit day but unlike on days of scheduled news announcements, profits and losses predominantly originate from positioning profits rather than from earning the spread. Finally, in contrast to the Brexit day, however, HFTs are not successful with strategically placing limit orders but face significant losses.

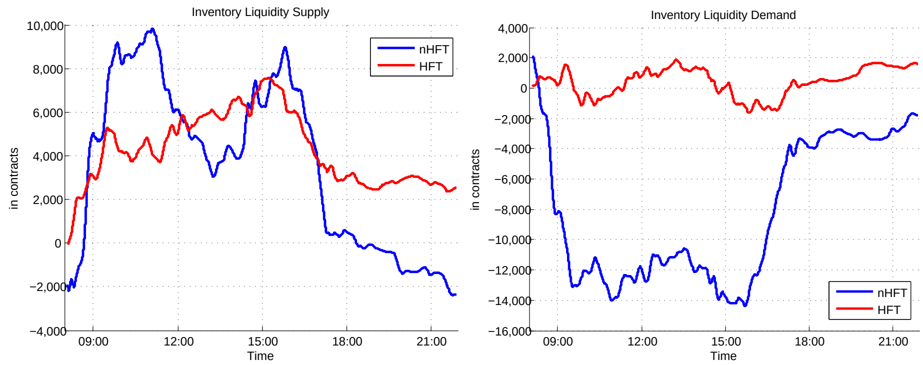


Figure 25: Cumulative Net Trading Liquidity Supply and Demand on 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

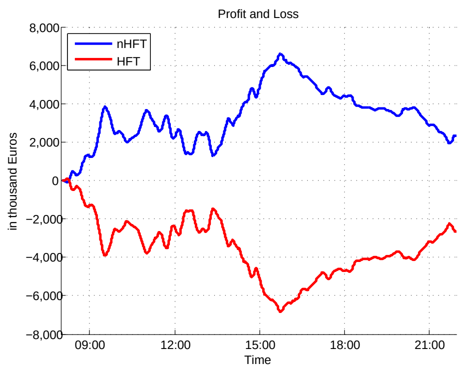


Figure 26: Total Profits on June 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

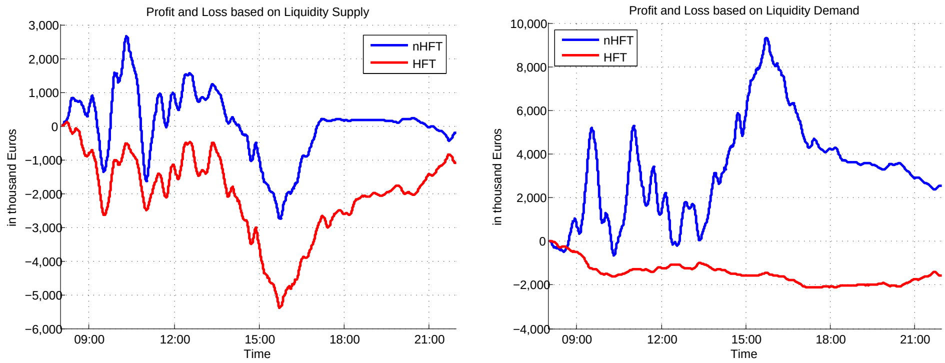


Figure 27: Total Profit from Liquidity Supply and Demand on 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

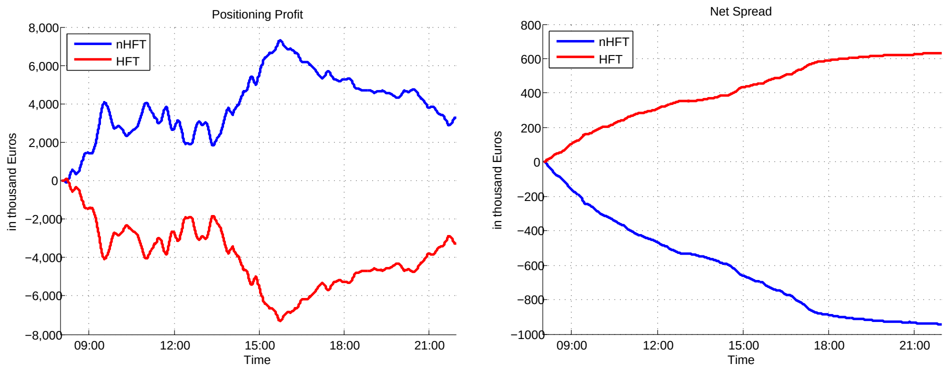


Figure 28: Positioning Profit and Net Spread on 29 June 2015. Smoothed with 10-minute averages as described in Section 3.

5.3. China Black Monday, 24 August 2015

After a stock market rally at the beginning of 2015 which was fueled by margin financing, the Chinese stock markets suffered a decline from the end of May 2015. Major drops occurred on 28 May and 26 June. The Chinese central bank responded with an interest rate cut on 27 June 2015, but the slide in stocks continued. On 23 August 2015, China's government allowed pension funds to invest in stocks. The Shanghai Composite Index, however, still plunged by 8.5% on 24 August 2015, corresponding to the largest one-day percentage loss since 2007 and commonly called China's Black Monday, see, e.g., Bloomberg (2015a). Global markets were affected by the crash, with the Dow Jones Industrial Average losing an unprecedented 1,000 points at market opening.

Figure 37 in the Appendix shows the price development and the cumulative trading volume on China's Black Monday. Similarly to the the Monday after the announcement of the Greek referendum, 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 market opening in the U.S. around 3.30 p.m., as the U.S. market was 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.

While China's Black Monday is the event with the weakest effect on the market, we can still report comparable results for liquidity supply, demand, and trading profits. The corresponding figures are found in Appendix B.2. We again find that the HFT-induced liquidity supply participation rate is higher than on normal days, with HFT spreads being lower than nHFT spreads, and liquidity demand being generally higher. Comparable to the events studied before, HFTs participate in around 65% of all liquidity supplying and 50% of all liquidity demanding activities on that particular day.

As on the day after the Greek referendum announcement, HFTs manage to keep their inventories resulting from liquidity demand and supply more balanced than nHFTs, but nevertheless build up significant positions through the day (see Figure 29). Figure 31 confirms previous results that HFTs are more profitable on the liquidity supply side than on the liquidity demand side (though still less profitable than nHFTs). More specifically, profits of around EUR 1.5m result from liquidity supply and losses of around EUR 1m result from liquidity demand. As in the two other events discussed above, profits and losses are strongly triggered by the positioning components (cf. Figure 32). The relative contribution of the net spread component, however, is higher than on the Brexit day or the day after the Greek referendum and makes approximately one third of the HFT profits and 50% of the nHFT losses (who predominantly lose due to liquidity demand). On this day, HFTs therefore seem to focus more on market making activities.

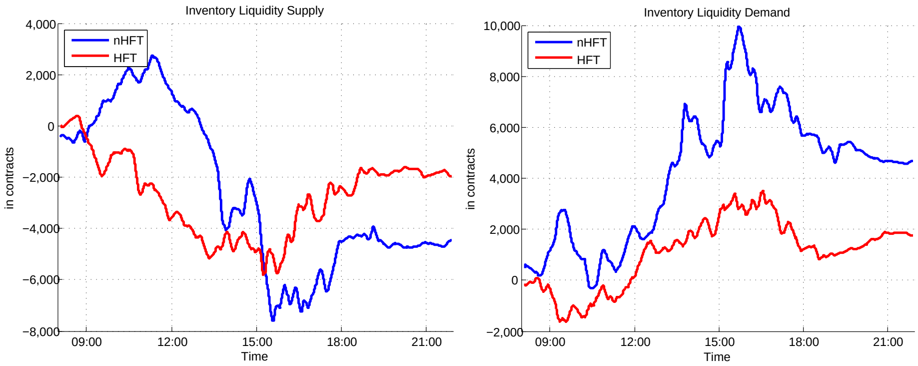


Figure 29: Cumulative Net Trading Liquidity Supply and Demand on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

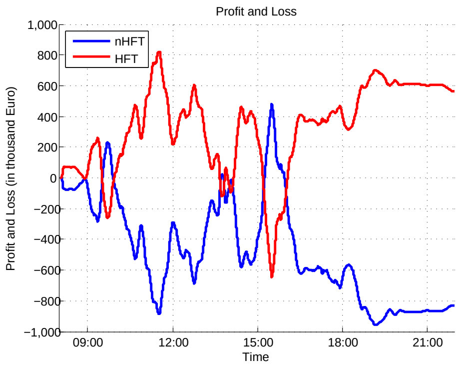


Figure 30: Total Profit (Real Inventory) on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

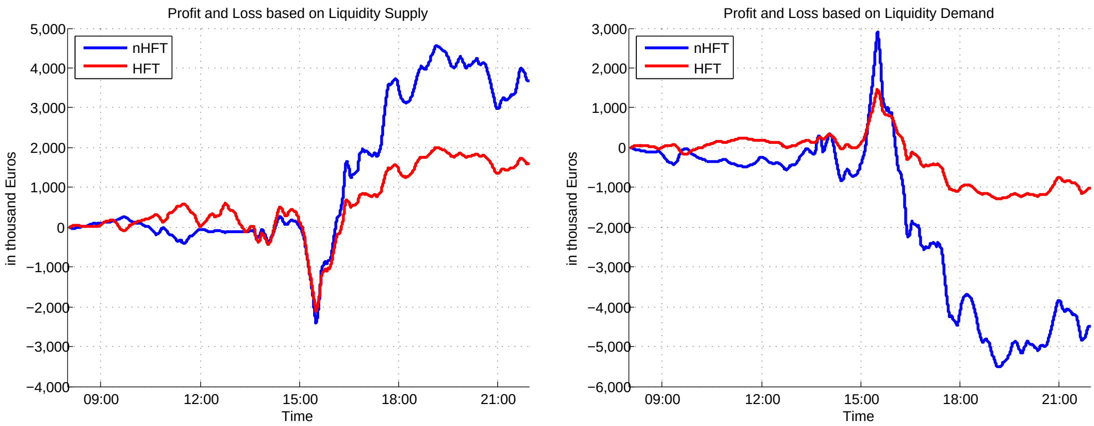


Figure 31: Total Profit from Liquidity Supply and Demand on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

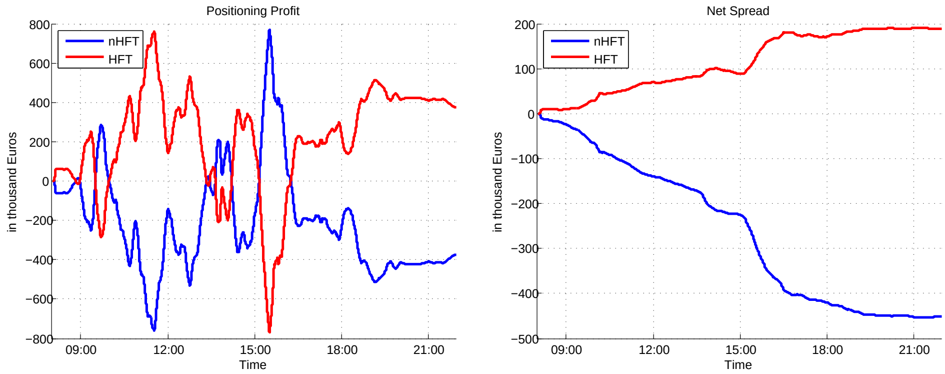


Figure 32: Positioning Profit and Net Spread on August 24, 2015. Smoothed with 10-minute averages as described in Section 3.

5.4. Summary

From the analysis above, we can conclude that also on distinct days of high uncertainty, HFTs serve as important liquidity providers in the market. In line with the findings in Sections 3 and 4, HFTs provide a major part of liquidity on both sides of the market and quote spreads which are on average lower than those quoted by nHFTs.

However, we identify an important difference between HFT behavior on days of scheduled news announcements and distinct days with extreme events and local price adjustments as analyzed above. While HFTs widely refrain from directional strategies around news releases, they position themselves more strategically on extreme 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, HFTs make considerable positional profits and reveal behavior which is significantly different from that of a classical market maker. These results confirm the findings by Kirilenko *et al.* (2017) who find evidence for "stale quote sniping" during the Flash Crash on May 6, 2010, trading behavior which is not in line with classical market making.

The reason why this behavior is not observed to the same extent during periods around news releases is probably due to the fact that these news events are published under strict lock-up conditions. Accordingly, prices adjust very quickly and even for HFTs the time window of opportunity for directional trading is very short. In fact, as illustrated in Section 3, the aggressiveness of HFTs strongly increases (and peaks) 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 clearly higher.

An important result from this study is that HFTs indeed can (and do) operate very much as classical 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. Nevertheless, our results show that HFTs do not necessarily benefit from these trading strategies but, as on the day after the Greek referendum, can face significant losses. According to our evidence, these losses predominantly result from liquidity demanding strategies. In all cases studied in this paper, HFT strategies on the liquidity supply side are (clearly) more beneficial than on the liquidity demand side. Potential reasons are that liquidity *demanding* strategies obviously suffer from costs originating from the bid-ask spread and that 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 resulting market stability. We show that in the Eurex Bund Futures trading, the behavior of HFTs comply to a large extent with traditional market makers. Even in periods of large news-implied price changes, HFTs continuously provide a significant amount of liquidity, but make less than 25% of liquidity demand. They widely refrain from trading aggressively in the direction of news, but tend to evenly buy and sell after a news release. Thus, we document an important stabilizing and intermediary role of HFTs in this market.

In extreme periods, however, this functionality can be severely limited. One important difference between HFT-induced market making and traditional market making by designated specialists is that the latter would stand ready to offer liquidity whenever it is needed and compensate themselves for varying risk by adjusting the bid-ask spread. HFTs on the other side can withdraw (nearly instantaneously) a significant amount of liquidity from the market and refrain from trading until uncertainty is resolved. In these situations, liquidity dries out, transaction costs increase, and HFTs operate as liquidity demanders which benefit from positioning profits. We observe such behavior in periods of high uncertainty and extreme market distress. In our sample, these are time intervals before the arrival of news releases and periods after distinct news shocks, such as the Brexit announcement in June 2016. Liquidity dry-ups shortly before news announcements, however, are only short-lived with liquidity being replenished quickly after the release. In this sense, HFTs tend to stabilize markets as soon as uncertainty is resolved.

Another major difference is that HFTs rapidly shift their strategies from passive market making to aggressive directional trading whenever it appears to be profitable. Such behavior is observable during periods of gradual price adjustments as after the Brexit announcement. In these situations, HFTs absorb liquidity and exploit their speed advantage in order to make positional profits to the disadvantage of slower traders.

These findings have important policy implications as the main goal of most regulators is to "maintain fair, orderly, and efficient markets" (e.g. SEC (2013)). 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 more restrictions 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 and indicate 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 profit from this intermediation, i.e., market making, rather than from positional gains.

Some regulators suggest more restrictions for market makers and specifically HFTs in general, 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 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 disincentivize HFTs to perform such strategies. Stricter regulation in this direction might have detrimental effects on overall liquidity and market stability. The Markets in Financial Instruments Directive II (MiFID II) increases the requirements on HFTs acting as market makers (i.e., liquidity supply on bid and ask prices thoroughout more than 50% of the trading period) by forcing them into a formal market making agreement with the respective trading venue. (cf. ESMA, 2014). MiFID II, however, does not impose any obligations on *aggressive* HFTs, which perform strategies other than market making.

Regulation should rather aim at keeping the benefits of HFTs providing market making services while reducing their incentives to perform more aggressive (e.g., directional or cross-market) trading strategies. Introducing "speed bumps" by removing speed advantages beyond a given threshold (e.g., 350 microseconds as on the U.S. exchange IEX, see Financial Times (2016)) appears to be a viable option achieving both objectives and mitigating ongoing technological arms races for speed advantages. Moreover, safeguards such as trading pauses (see, e.g., Hautsch & Horvath (2017)) and smart market monitoring tools are inevitable in order to protect investors from flash crashes and ensuring a certain level of market stability in extreme periods.

Appendix A. Additional Tables

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. The *Quoted Spread* 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
Trading 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
Quoted Spread	#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 a.m. - 9:00 a.m.	9:00 a.m. - 3:30 p.m.	3:30 p.m. - 5:30 p.m.	5:30 p.m. - 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
Quoted Spread	#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: 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 B. Extreme Event Results

B.1. Greek referendum announcement

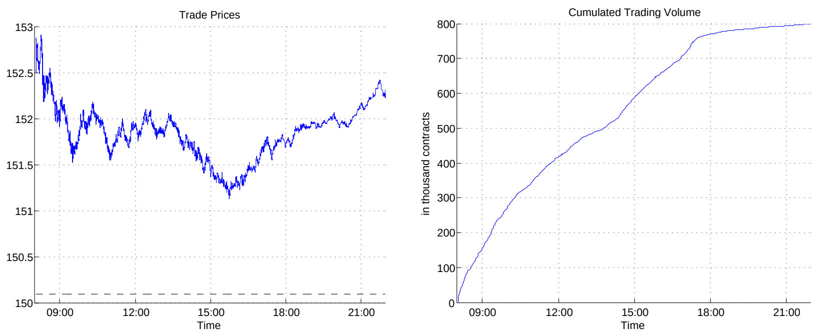


Figure 33: Price and Cumulative Volume on 29 June 2015. The dashed line represents the previous days closing price of 150.09. The opening price is 152.53.

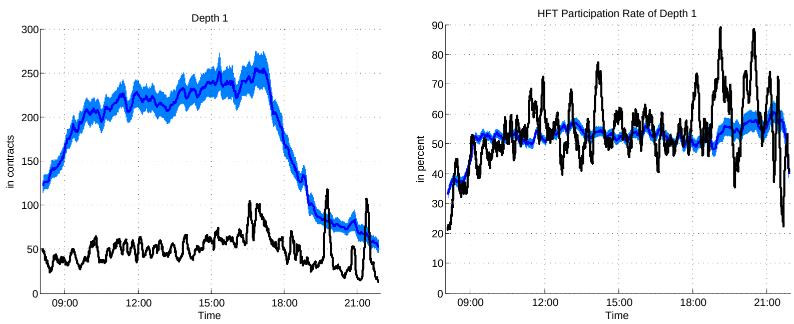
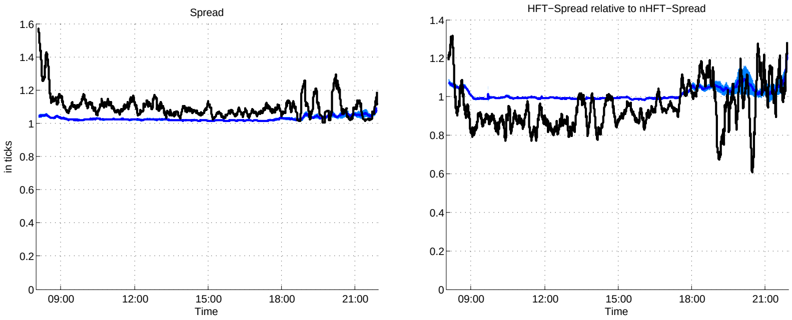


Figure 34: Market Depth and HFT Participation Rate at Level 1 on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.



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

Figure 35: 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.

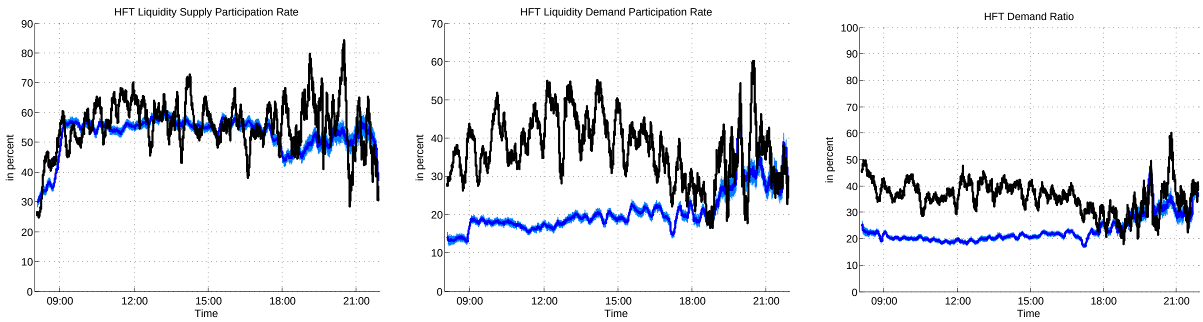


Figure 36: HFT Participation Rate in Liquidity Supply and Demand and Demand Ratio on 29 June 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

B.2. China's Black Monday

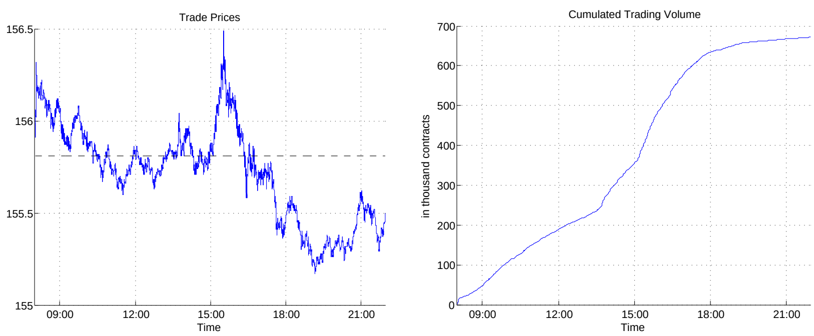


Figure 37: Price and Cumulative Volume on August 24, 2015. The dashed line represents the previous day's closing price of 155.81. The opening price is 155.99.

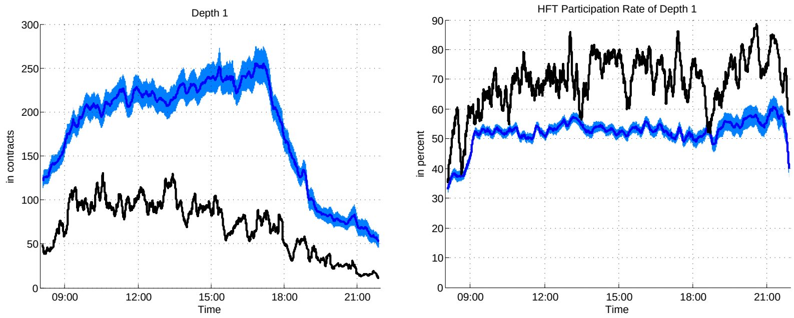
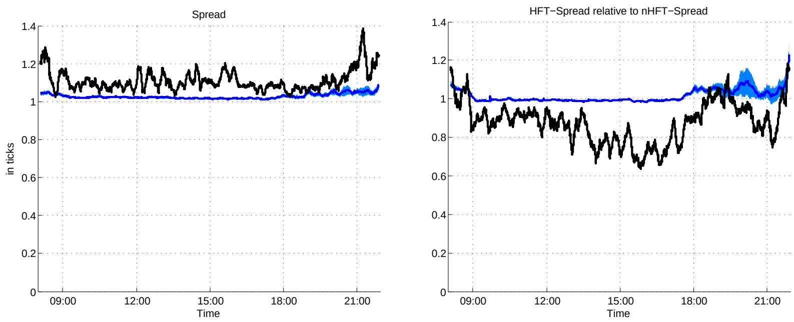


Figure 38: Market Depth and HFT Participation Rate at Level 1 on August 24, 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.



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

Figure 39: 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.

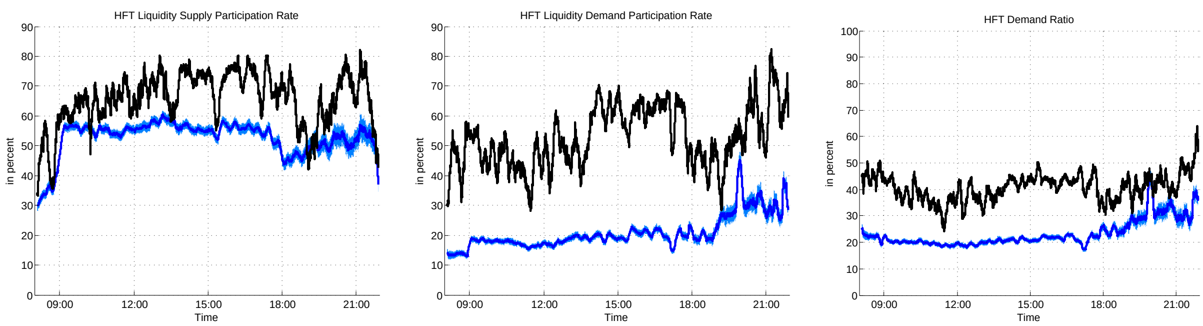


Figure 40: HFT Participation Rate in Liquidity Supply and Demand and Demand Ratio on August 24, 2015. The blue lines presents the averages across normal trading days, smoothed over 10 minute averages as described in Section 3. Shaded areas indicate the corresponding 2.5% and 97.5% quantiles for normal trading days.

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