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High-frequency trading in the Bund futures market

Kathi Schlepper

Editorial Board:

Daniel Foos
Thomas Kick
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Christoph Memmel
Panagiota Tzamourani

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet <http://www.bundesbank.de>

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Non-technical summary

Research Question

This study examines the role of high-frequency trading (HFT) in the German Bund Futures market. The main focus of this work is to analyze how the reaction of high-frequency traders (HFTs) to new information affects market prices and price volatility. Another important aspect of this study is the relationship between HFT and liquidity in this market. More specifically, the question whether HFTs continue providing liquidity also during phases of higher market stress or whether they increasingly withdraw from markets is investigated.

Contribution

Using a new and extremely high-frequency dataset, this study examines how HFTs react to important news announcements. News announcements in this study refer to the publication of macroeconomic data (labor market data in the US and ECB interest rate decisions).

Results

The results suggest that liquidity-taking HFTs trade in the direction of the market trend and are more active in phases of high volatility. Accordingly, they are also more active around the release of macroeconomic news than usual. In these situations, HFTs benefit from their speed advantage and trade according to the news surprise in a fraction of a second and immediately realize their trading profits. Their trades improve the price discovery process. However, the faster reflection of news in prices comes at the cost of short-term excessive volatility, which increases the risk of market disruptions. Moreover, my results show liquidity-providing HFTs increasingly withdraw from markets when volatility rises, either expectedly following macroeconomic news or unexpectedly due to rising risk aversion.

Nichttechnische Zusammenfassung

Fragestellung

In diesem Papier wird untersucht, welche Rolle der Hochfrequenzhandel am Markt für Terminkontrakte auf Bundesanleihen (Bund Futures) spielt. Insbesondere soll analysiert werden, wie die Reaktion von Hochfrequenzhändlern auf neue Informationen die Kurse verändert und sich auf die Kursschwankungen (Volatilität) auswirkt. Ein weiterer Aspekt ist der Zusammenhang zwischen dem Hochfrequenzhandel und der Liquidität auf dem Markt, das heißt die Frage, ob Hochfrequenzhändler in turbulenten Marktphasen weiterhin Liquidität bereitstellen oder sich vermehrt aus dem Markt zurückziehen.

Beitrag

Anhand eines neuen Datensatzes mit hoher Frequenz wird analysiert, wie Hochfrequenzhändler auf marktbewegende Nachrichten reagieren. Marktbewegende Nachrichten sind in dieser Studie die Veröffentlichung von makroökonomischen Daten (hier: Neu geschaffene Stellen in den USA und EZB-Zinsentscheidungen).

Ergebnisse

Die Ergebnisse deuten darauf hin, dass liquiditätsnehmende Hochfrequenzhändler grundsätzlich in Richtung des Markttrends handeln und in Phasen hoher Volatilität aktiver sind. Entsprechend partizipieren sie auch um die Veröffentlichung von wichtigen makroökonomischen Nachrichten überdurchschnittlich stark am Handel. Dabei nutzen Hochfrequenzhändler ihren Geschwindigkeitsvorteil aus und reagieren auf die Überraschungskomponente der Nachrichten schneller als andere Marktteilnehmer, sodass kurzfristige Gewinne realisiert werden können. Zwar werden die neuen Informationen dadurch schneller in den Kursen reflektiert, allerdings erzeugt der Hochfrequenzhandel auch kurzfristige zusätzliche Kursschwankungen, was die Gefahr von Marktverwerfungen erhöht. Die Ergebnisse zeigen außerdem, dass sich liquiditätsbereitstellende Hochfrequenzhändler sowohl in Phasen überraschender Volatilität infolge steigender Risikoaversion als auch infolge der Veröffentlichung von makroökonomischen Daten zurückziehen. Dies zeigt sich daran, dass sie in solchen Phasen mehr Handelsaufträge löschen als neue generieren.

High-Frequency Trading in the Bund Futures Market*

Kathi Schlepper
Deutsche Bundesbank

Abstract

In this work, I study the impact of high-frequency trading (HFT) on price discovery and volatility in the Bund futures market. Using a new dataset based on microseconds, the focus of the study is on the reaction of high-frequency traders (HFTs) to major macroeconomic news events. I show that through their fast and strong reaction to news, HFTs contribute more to price discovery compared to Non-HFTs, but also add a higher share to noise than to permanent volatility. Moreover, I find evidence that HFTs tend to supply less liquidity after an unexpected rise in market volatility and prior to upcoming macroeconomic news events. These findings suggest that in times of high market stress, HFT behavior may exacerbate intraday price volatility and amplify the risk of market disruptions in fixed income markets.

Keywords: High-Frequency Trading, Price Discovery, Volatility

JEL classification: G10, G12, G14

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1 Introduction

High-frequency trading (HFT) has become a dominant tool in many liquid financial markets, such as equity and futures markets. Being considered a subcategory of Algorithmic trading (AT), high-frequency traders (HFTs) typically invest in technological infrastructure that allows them to process a variety of trading signals and send orders to marketplaces in a fraction of a second. In 2012, HFT accounted for about 40% of the activity on European and over 50% of US equity markets (see, e.g., [TABB Group \(2012\)](#)).

Their speed advantage enables HFTs to react to new information faster than other traders (see, e.g., [Foucault, Hombert, and Rosu \(2015\)](#), [Zhang \(2013\)](#)). However, a common point of criticism is that HFTs overreact to important news announcements and thereby generate excessive short-term volatility. Such episodes of extreme volatility can even induce so-called “flash events”, characterized by a rapid and strong fall or rise in asset prices followed by a reversal in a matter of minutes or seconds. Especially since the US equity flash crash on 6 May 2010, HFT has attracted the attention of academics, regulators and policy makers around the globe. Recently, similar flash events could also be observed in fixed income markets. In particular, the Flash rally on 15 October 2014 in US treasury markets and the Bund tantrum in the German government bond market in April/ May 2015 have initiated discussions about the resiliency of fixed income markets and the impact of new market participants like HFTs ([BIS \(2016a\)](#)). Moreover, since the implementation of unconventional policy measures, such as the broad-based asset purchase programs in Europe or the US, many observers fear an increased vulnerability of fixed income markets. Hence, the question whether HFTs’ trading strategies pose an additional risk to market functioning is especially relevant nowadays. Against this background, different regulatory institutions and central banks have investigated the evolution and potential causes of events like the US Flash rally ([Joint Staff Report \(2015\)](#)) and the Bund tantrum ([BIS \(2016a\)](#), [BIS \(2016b\)](#)) in detail. The debate has mainly focused on the impact HFT has on liquidity, price discovery and excessive volatility. To the extent that HFT affects these features of market quality, it also has implications for financial stability ([Benos and Sagade \(2013\)](#)). Therefore, policy makers and regulators, especially in the US but lately also in Europe, have been discussing whether stricter regulation should apply to the HFT practice. However, the market impact HFT and AT activities have during those events remains difficult to establish and also depends on the strategies followed by the respective HFT firm ([Joint Staff Report \(2015\)](#)).

Based on a very recent and unique dataset from Deutsche Börse on a microsecond frequency, I study the role of HFTs in the price discovery process in the Bund futures market. Since macroeconomic news announcements usually have a strong impact on bond

prices (see, e.g., [Altavilla, Giannone, and Modugno \(2014\)](#)), I investigate whether HFT aids or hinders the market's incorporation of such news into asset prices. If HFTs trade on information faster than other traders, they should contribute to price discovery by accelerating the speed at which new information is impounded into prices. However, a common point of critique is that the fast reaction by HFTs to news may also be associated with prices overshooting, leading to noise that cannot be related to information about fundamentals ([Benos and Sagade \(2013\)](#)). Using the methodology by [Hasbrouck \(1991b\)](#) to decompose the price in its transitory and permanent components allows me to study this question in detail. Another recent point of criticism is that HFTs supply liquidity when volatility is low but withdraw from markets when volatility rises ([ESMA \(2011\)](#), [ASIC \(2012\)](#)). This might pose an additional risk for financial stability because if a market shock induces HFTs to suspend their liquidity provision, the shock may be amplified. Hence, in the final part of this work, I study the behavior of liquidity-providing HFTs considering two different types of volatility. I distinguish between phases of unexpected increases in market volatility due to higher risk perception by market participants and phases of anticipated volatility that follow from macroeconomic news releases in order to find out whether HFT behavior depends on the nature of volatility.

This paper represents the first study on the impact of HFT on price discovery and volatility in European bond markets. The few existing fixed income studies are limited to US Treasury markets ([Jiang, Lo, and Valente \(2013\)](#), [Liu, Lo, Nguyen, and Valente \(2014\)](#)) but suffer from less granular data. The present study is based on a new Bund futures dataset from 2013 to 2014 which is in contrast to existing empirical work that mostly rely on US stock market data (e.g., [Gao and Mizrach \(2013\)](#), [Zhang \(2013\)](#) [Brogaard, Hendershott, and Riordan \(2013\)](#)) with some exceptions for FX data ([Chaboud, Chiquoine, Hjalmarsson, and Vega \(2012\)](#)) that are already several years old. Although there might still be some useful conclusions to be drawn on the effect of HFT using older data, HFT activity has developed strongly in the last years. Particularly the dimensions of speed and latency have changed substantially over the last decade, supporting the need for data timeliness. A unique HFT flag assigned by Deutsche Börse makes it possible to distinguish the trading behavior of HFTs from that of other market participants, which is not available in most other studies. The existing literature often relies on proxies for AT or HFT based on certain data characteristics like reaction times typical for HFT (e.g., [Jiang et al. \(2013\)](#), [Hendershott, Jones, and Menkveld \(2011\)](#), [Zhang \(2010\)](#)). Moreover, the data are based on microseconds, which enables a more granular and deep analysis than in other empirical HFT studies that are at most based on milliseconds (e.g., [Brogaard et al. \(2013\)](#), [Gao and Mizrach \(2013\)](#), [Zhang \(2013\)](#)). Given the improvement in trading speed over the last years, the extremely high frequency of the Bund futures data

is of particular value and helps to understand the reactions of HFTs to major macroeconomic news on a tick-by-tick basis. Since macroeconomic news has been proven to be a crucial driver of bond price movements on a lower data frequency (see, e.g., [Altavilla et al. \(2014\)](#), [Jones, Lamont, and Lumsdaine \(1998\)](#)), the analysis of the HFT price impact around important news releases reveals new insights about HFT strategies in these highly volatile market episodes. Also, to my knowledge the contribution of HFT trading to the noise- and information-related determinants of the variance has not been studied around the publication of macroeconomic news before. Moreover, investigating the liquidity supply by HFTs in two different volatility environments, i.e. after macroeconomic news releases and in times of higher risk aversion, allows new insights into HFT market making behavior. While most existing studies rely on trading volume data to measure liquidity provision ([Brogaard et al. \(2013\)](#), [Chaboud et al. \(2012\)](#)), this study focuses on order deletion activity, which is often associated with HFT behavior (e.g., [ESMA \(2014\)](#)). The major advantage with this approach is that order deletions can be directly related to volatility, whereas any causal link between trading volume and volatility is hard to establish as the two variables cannot be considered separately from each other.

In the first part of this work, I study the behavior and trading strategies of liquidity-taking (active) and liquidity-providing (passive) HFTs and Non-HFTs (NHFTs), using one week of increased and one week of low volatility defined as the positive and negative deviation of the German implied volatility index (VDAX) from its average historical level. I find that active HFTs tend to follow momentum strategies, implying that they trade in the direction of the market return, which can increase intraday price movements. In contrast, passive HFTs appear to dampen excessive volatility using contrarian trading strategies. During the high-volatility week, active HFTs initiating momentum trades dominate over passive HFTs such that overall HFTs exacerbate price trends when volatility is already at an increased level. Moreover, the results show that both active and passive HFTs trade more in times of high volatility, which is broadly consistent with the findings by [Boehmer, Fong, and Wu \(2012\)](#) and [Benos and Sagade \(2013\)](#). In particular, the share of active HFTs in the traded volume rises to above-average levels in the highest 3% of market volatility in both weeks. A possible explanation for this result is that active HFTs prefer phases of high volatility since their trading strategies are most beneficial in these times. An alternative explanation is that HFT trading simply generates high volatility. By contrast, slower traders deem these phases too risky and rather withdraw from markets.

In the second part, I analyze the trading behavior of HFTs around macroeconomic news releases using a vector auto-regression (VAR) model based on return and order flow time series on a second-by-second and tick-by-tick data frequency. Here, the most

influential US and European macroeconomic news, namely the US Nonfarm Payrolls (NFPs) and ECB rate decisions (Schopen and Missong (2011), Chaboud et al. (2012)), are taken into account. The exogeneity of the macroeconomic news (Chaboud et al. (2012)) and the granularity of this analysis allow to study the link between HFT trading and volatility more precisely. The results show that liquidity-taking HFTs are the most active trading group around the release of macroeconomic news and dominate overall HFT activity, whereas slower active traders rather withdraw from markets a couple of seconds prior to the news announcement. Active HFTs benefit from their speed advantage and trade in the direction of the news release within the first second after publication and thereby pick off the standing limit orders of NHFTs. Analyzing the effect of HFT and NHFT trading on prices on a tick-by-tick-basis, I find that HFT contributes about five times more to the price formation process of the Bund futures return in the millisecond environment following the news release compared to NHFTs, which is similar to previous findings (e.g., Hendershott and Riordan (2011), Benos and Sagade (2013), Brogaard et al. (2013)). Applying variance decomposition methods to the permanent and transitory price components, my results show that HFT contributes more to noise than to permanent price volatility, which is in line with an overshooting behavior. This is a new finding in the empirical literature and implies that the trading by active HFTs adds significantly to price discovery but also generates disproportionately high short-term volatility through their fast and aggressive trading in response to macroeconomic news. Given that most of the HFT news reaction occurs within the first second, the ultra-high frequency data are uniquely suited for this part of the study.

The above results suggest that different active HFT strategies dominate in different market environments. While in times of rising unexpected volatility active HFTs tend to follow momentum strategies, around the release of macroeconomic news they pursue news trading strategies and react independent of previous price movements.

In the last part, I examine the market making activity of passive HFTs and NHFTs in times of high and low unexpected volatility as well as around macroeconomic news releases. The results suggest that deletion activity depends on the nature of uncertainty. Passive HFTs tend to delete more orders than they submit after market volatility has risen suddenly, since they fear higher risks to their market making activity. By contrast, passive NHFTs delete fewer orders than average when volatility rises unexpectedly. Against this evidence, HFTs and, to a lesser extent, also NHFTs already tend to withdraw from markets several minutes before an upcoming macroeconomic news event. This is because they anticipate increasing market volatility following macroeconomic news releases and want to minimize their risk exposure. Even though passive HFTs still participate significantly in the traded volume following sudden increases in volatility, my findings suggest

that overall a significant part of the liquidity supplied by HFTs disappears quickly as soon as market uncertainty rises, either expected or unexpected. Also, one can conclude that NHFTs supply liquidity more continuously than HFTs and are not as sensitive to changes in the market environment as HFTs.

The present study allows for a better understanding of the role HFT plays in different phases of the market and offers useful implications for market stability. According to [Biais and Foucault \(2014\)](#), short-term volatility reflects the impact of liquidity demand to a certain extent. Hence, the finding that under increased market stress HFTs reduce their liquidity supply and consume more liquidity at the same time suggests that, overall, HFT trading exacerbates extreme price movements in those periods. This may in turn increase the risk of flash events that have been observed more frequently in the recent past, particularly in fixed income markets. Therefore, regulators and policy makers should indeed think about appropriate tools to strengthen market quality, especially liquidity supply in phases of increased market stress.

The paper is organized as follows. Section 2 contains a literature review, Section 3 describes the data used in this study and explains different characteristics of the data. Section 4 presents the results on the trading strategies of HFTs and their activity related to market volatility. Section 5 provides the empirical analysis of HFT trading around news releases and its contribution to price discovery. Section 6 discusses the role of passive HFTs as liquidity providers during different phases of market volatility. Section 7 concludes.

2 Literature Review

Analyzing the impact of HFT in the government bond market is a very new field of research. The bulk of empirical HFT studies are based on the US stock market, with some exceptions on FX markets. Given the scarcity of recent high-frequency data, especially for markets outside the US and for asset classes other than equity, new empirical evidence is limited. I am aware of only two papers focusing on fixed income markets which both examine the role of HFT in the US Treasury bond markets ([Jiang et al. \(2013\)](#), [Liu et al. \(2014\)](#)). Similar to my work, [Jiang et al. \(2013\)](#) study the effect of HFT on bond market quality aspects around major macroeconomic news announcements from 2004 to 2007. The authors show that HFT increases market volatility during pre- and post-announcement periods. Before the news release, HFT has an adverse effect on market liquidity and does not enhance the price efficiency of US Treasury securities. But after the information's arrival, HFT narrows bid-ask spreads and has a positive effect on price efficiency. [Liu et al. \(2014\)](#) examine the impact of HFT on expected returns of US Treasury

bonds and document a significantly positive relationship between bond expected returns and a factor capturing HFT intensity in the market.

Empirical research on the role of HFT around news events is generally sparse. Closely related to my work is the paper by [Chaboud et al. \(2012\)](#), who investigate the impact of AT in the foreign exchange market around macroeconomic news releases from 2003 through 2007. Using a VAR model they find that AT contributes to a more efficient price discovery process through the elimination of arbitrage opportunities and the faster incorporation of news into prices. However, human-initiated trades add a larger share to the variance in exchange rate returns than AT-initiated trades. Although computer trades tend to be correlated, they find no evidence that AT causes excessive volatility. Focusing on news events in the stock market, [Zhang \(2013\)](#) examines the role of HFTs in reacting to extreme price changes as well as to firm-specific news in US equity markets from 2008 to 2009. By testing whether HFT order flow has a significant influence on stock returns relative to NHFT order flow, she finds that HFT orders dominate price discovery in the short run. In the longer run, however, NHFTs contribute more to price discovery than HFTs.

Some other recent studies address the role of HFT in the price discovery process in a broader context. [Brogaard et al. \(2013\)](#) use a state space model to decompose price movements for 120 US stocks from 2008 to 2009 into permanent (information) and temporary (pricing errors) components and to relate changes in both to HFT. The authors find that HFT trades improve price efficiency by trading in the direction of permanent and in the opposite direction of transitory price changes, both on average and on the highest volatility days. [Benos and Sagade \(2013\)](#) analyze the behavior of HFTs and their impact on market quality for four UK stocks in a randomly selected 1-week period from 2010-2011. They find that higher price volatility causes HFT activity to increase. Finally, the authors provide evidence that while HFTs have a higher information-to-noise ratio than NHFTs, there are instances in which the contribution to information by HFTs is accompanied by a large absolute noise contribution. The study is one of the few exceptions that analyze HFT in European financial markets. The bulk of empirical literature on HFT are based on US markets using data from the NASDAQ exchange (e.g., [Gao and Mizrach \(2013\)](#), [Zhang \(2013\)](#) and [Brogaard et al. \(2013\)](#)). Other studies on European markets comprise the work by [Breckenfelder \(2013\)](#), who investigates the impact of HFT competition on market quality in the Swedish stock exchange in 2009 using the OMXS Index obtained from the NASDAQ OMS Nordic, or the paper by [Menkveld \(2013\)](#), which is based on data on Dutch local index stocks from 2007 through 2008 and examines the trading strategy of a large HFT. There is, however, no work so far on European bond markets.

Information on whether trades or orders are placed by a HFT or not is usually scarce.

Therefore, a large part of empirical work on HFT uses proxies of HFT and AT, which are often based on certain data characteristics like reaction times and other properties typical for HFTs (e.g., [Hendershott et al. \(2011\)](#), [Zhang \(2010\)](#)). For example, [Jiang et al. \(2013\)](#) and [Liu et al. \(2014\)](#) infer HFT trades and orders on the basis of the reaction time between order placement and subsequent modification and cancellation that exceeds human ability. Datasets including AT and HFT identifiers have become available only recently. For example, the NASDAQ dataset from 2008 to 2009 used by [Gao and Mizrach \(2013\)](#), [Zhang \(2013\)](#) and [Brogaard et al. \(2013\)](#) includes an HFT flag which identifies 26 HFT firms. However, it cannot identify all HFTs, e.g., those that also act as brokers, but only independent proprietary trading firms. The dataset used by [Chaboud et al. \(2012\)](#) exhibits a distinction between humans and computers behind each trade. While this might have been an appropriate classification scheme during the study period from 2003 to 2007, a pure distinction between humans and computers would no longer be appropriate nowadays. Not only has the trading volume of HFTs in US stock markets increased dramatically (from 30% in 2005 to more than 50% in 2012, according to a study by [TABB Group \(2012\)](#)), but also speed and latency have developed strongly in the last decade. Today, most trades are carried out electronically on highly liquid financial markets, and many business units apply AT strategies which cannot be classified as HFT, however, given their specific characteristics, particularly their lower speed. Only very little empirical work is based on datasets including the identities of the HFT firms. Among these few exceptions are the studies by [Benos and Sagade \(2013\)](#) and [Breckenfelder \(2013\)](#), which are based on trade data. However, the datasets including an HFT identifier can often only identify specific HFT firms, as in the work by [Benos and Sagade \(2013\)](#), where only the largest HFT firms are identified.

3 Data and Descriptive Statistics

3.1 Bund Futures Dataset

This study is based on Bund futures data from Deutsche Börse's subsidiary Eurex and comprises two different datasets. The first dataset consists of one week of relatively high volatility from 6 to 13 March 2014 and one week of relatively low volatility from 3 to 10 June 2014.¹ Each of the 12 trading days consists of all order book activities, including modifications, executions, and deletions, that occurred between 8 a.m. and 10 p.m. CET. The different volatility episodes are defined using the VDAX, which is the implied

¹Given the extremely high frequency of the data and the focus on rather short-term aspects of HFT trading strategies, two weeks of data seem sufficient to draw conclusions on HFT trading behavior in high and low volatility environments.

volatility index based on equity options on the German DAX index. In March 2014, when the Krim crisis induced a period of increased risk aversion on European financial markets, the VDAX reached a level of close to 20, with an average of 17.2 during the 6 days in March compared to an average level of 14.1 in the previous 6 months. In the low-volatility period in June, the DAX attained a new all-time high of more than 10,000 points and the VDAX was at an average level of 13.4 during the 6 days of June compared to an average level of 16.7 in the previous 6 months. The second dataset comprises single trading days between July 2013 and June 2014 on which major macroeconomic news was released. More specifically, I use the entire trading days of the Bund futures contract from 8:00 a.m. to 10 p.m. when the Nonfarm Payrolls for the US (first Friday of each month) and ECB rate decisions (first Thursday of each month) were published. These are the most relevant US and European macroeconomic news (e.g., [Schopen and Missong \(2011\)](#) and [Chaboud et al. \(2012\)](#)) which also have the strongest impact on bond market prices.

A large number of studies are based on trade data (e.g., [Brogaard et al. \(2013\)](#), [Benos and Sagade \(2013\)](#), [Breckenfelder \(2013\)](#)), while the dataset used in this study comprises the full order book information. Hence, besides best bid and ask prices, limit and market orders submitted and any order activity including cancellations or modifications are available. This allows to follow each order from its submission to its execution or deletion. Moreover, depending on the size of a marketable order, in addition to the best bid/ask price, further limit orders may be executed, too. This is especially relevant for large orders that often occur after important macroeconomic news releases. Thus, the information on all limit orders enables to see how deeply an order hits the order book.

Trade and order timestamps are given in microseconds and ranked within each microsecond. This high data frequency allows for a more granular analysis than in other empirical HFT studies that are, at most, based on milliseconds (e.g., [Brogaard et al. \(2013\)](#), [Gao and Mizrach \(2013\)](#), [Zhang \(2013\)](#)). Given that trading speed has improved steadily in the last years and latency has become more and more important, the extremely high frequency of the Bund futures data is of particular value and allows to appropriately study the information processing of prices and the role HFTs play therein.

Furthermore, the dataset includes a dummy variable for HFT. This dummy is based on a methodology developed by Deutsche Börse (see [Appendix A.1](#)). The idea is to test whether the order submission sequencing of a business unit, i.e. the branch of a firm that submits the order, exhibits patterns that are typical for HFT participants. More specifically, the theoretical random sequencing is calculated by the expected mean arrival rate of incoming transactions.² The deviation of the observed transactions from the

²The theoretical random sequencing is derived from the following formula: $f(t) = \frac{1}{\mu} e^{-\frac{t}{\mu}}$, where μ is the mean arrival rate and t the time interval.

expected sequencing is used as selection criterion for being classified as a latency-sensitive business unit (HFT). So if the transactions carried out by a specific business unit exhibit a latency-sensitive behavior, all orders of this business unit will be classified as HFT. The methodology is updated on a continuous basis. One limitation of the data is that they do not include the identity of the order initiator.

3.2 Characteristics of the Dataset

In the following, several ratios related to the orders submitted by HFTs and NHFTs are presented.

First, I want to find out whether HFTs or NHFTs submit more orders on an absolute and relative basis and thereby add liquidity to the market. For this purpose, I estimate the total number of submitted orders as well as the **order submission ratio**, defined as the ratio of submitted orders to all activities, including modifications, deletions and executions. A typical characteristic of HFT is its speed of trading. Hence, in the second step, I measure the life-time of each order given by the **execution time** and the **deletion time**, i.e. the time that elapses from the order submission to its execution or its cancellation. Next, I measure the **modification time**, which is the time difference between an order submission and subsequent modifications. Furthermore, I calculate the **deletion ratio** and the **modification ratio**, given by the average number of deletions and modifications relative to the added orders, respectively, as well as the **number of modifications**, defined as the average number of modifications per order. A typical observation of HFT activity is the frequent submission and cancellation of limit orders. Hence, I also calculate the **order-to-trade ratio**, which reflects the overall quoted volume divided by all real transactions. In this study, volume is measured as the number of Bund futures contracts.

The following results are based on the six trading days of high volatility in March and the six low-volatility days in June. This allows me to compare the HFT activity in two different market environments. Table 1 displays the calculated numbers and ratios. According to the first row, both trading groups, i.e. HFTs and NHFTs, submit more orders in the week of relatively higher volatility than in the low-volatility week on an absolute basis. Relative to other order book activities, HFTs submit more orders than NHFTs. This ratio is nearly constant across the two weeks. Also, the results show that during a more volatile market environment it takes, on average, longer for both HFTs and NHFTs to execute or modify an order. Regarding latency, which is an important factor of HFT strategies, I find evidence that the life-time of an order is much shorter in the case of HFTs, i.e. it is executed or deleted on average almost twice as fast as for NHFTs. Other studies focusing on European markets (e.g., [ESMA \(2014\)](#)) also highlight the great importance of order deletion for HFTs. For example, [Hasbrouck and Saar \(2009\)](#) argue

Table 1: Descriptive Statistics

Variable	Measure	A: High Volatility		B: Low Volatility	
		HFT	NHFT	HFT	NHFT
Orders submissions	Number (million)	1.700	1.352	1.379	1.146
	Ratio in %	40.91	33.73	39.65	33.04
Execution time	Median	2.04	3.94	1.75	3.13
	Mean	185.70	370.24	152.60	288.60
Deletion time	Median	2.57	3.66	2.43	3.92
	Mean	253.15	511.51	286.61	468.16
Deletion ratio in %	Mean	73.51	67.63	68.56	71.25
Modification time	Median	3.07	2.01	1.74	1.11
	Mean	115.18	66.66	93.70	61.12
Modification ratio in %	Mean	36.55	90.68	43.62	95.65
Number of modifications	Mean	14.99	130.14	76.54	160.34
Order-to-trade ratio	Mean	2.85	2.32	2.50	2.29

This table includes different measures describing the characteristics in the trading behavior of HFTs and NHFTs. Most measures are given as the mean or median value for the 6 trading days in March (high volatility) and June (low volatility). Time is displayed in seconds.

that over one-third of limit orders are canceled within two seconds in the US equity market and name those “fleeting orders”. The calculated median deletion time of 2.5 seconds is close to their findings. This result suggests that the supplied liquidity by HFTs is rather short-lived.

As Table 1 shows, the median modification time is smaller for NHFTs than for HFTs. This might seem surprising at first. But due to technical properties of the exchange’s trading infrastructure, it generally takes more time to modify an order than to delete it. Therefore, a high number of modifications is not typical for HFTs, who focus on the very short term, but rather for slower algorithmic traders, who are not dependent on extremely low latency strategies. The much higher average number of modifications for NHFTs provides further evidence for the different trading approaches. Remarkably, the discrepancy is even higher during the highly volatile market phase, i.e. NHFTs modify their orders almost 10 times more often than HFTs. Hence, HFTs seem to prefer canceling over modifying orders when volatility rises to above-average levels. The order-to-trade ratio is higher for HFTs in both market phases, implying that the ratio of submitted orders which lead to a real execution is lower. The difference is more pronounced in the

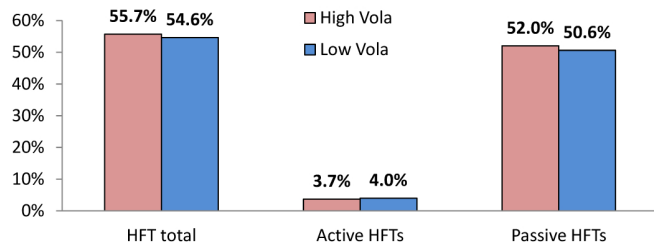


Figure 1: This figure depicts the HFT activity as measured by participation in the overall orders.

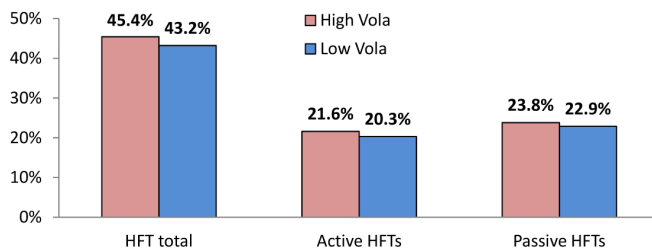


Figure 2: This figure depicts the HFT activity as measured by participation in the overall traded volume.

high-volatility phase, underlining the higher deletion activity by HFTs relative to real transactions in these times.

Second, I classify the HFT identifier variable further and distinguish between active and passive HFTs and NHFTs (liquidity taker and provider). I define the liquidity-providing part of the transaction as being the limit order in the order book that was hit by a marketable order, i.e. a market or another more recent limit order that takes the opposite side of a trade. The liquidity taker is the market participant that enters the marketable order. The order of the liquidity taker is immediately executed when it enters the order book. The sum of active and passive HFTs (NHFTs) constitutes the total number of HFTs (NHFTs). This classification is the same as in, e.g., [Brogaard et al. \(2013\)](#) or [Brogaard \(2011\)](#). It is important to mention, however, that the division in active and passive market participants just refers to the cross-section of trades. Hence, unlike [Benos and Sagade \(2013\)](#), who group traders based on their overall liquidity taking/providing activity, in the present study the composition of the trading groups (active and passive HFTs and NHFTs) can vary over time. Thus, a trade from an HFT firm who mostly places “aggressive” orders can still be classified as passive at a specific point in time if the firm places a limit order that is not immediately executed.

According to [Figure 1](#), in March total HFT participation of all orders is over 50%, but only 3.7% of HFT orders are submitted by active HFTs. However, when considering the total traded volume ([Figure 2](#)), active HFTs contribute with a much higher share of 21.6%. In contrast, the traded volume by passive HFTs is much smaller than their share

in the submitted orders, which again reflects the significant role of order deletions in HFT activity. In June, during the low-volatility market period, both HFT order submission activity and trading volume participation is slightly lower than in March.

One can conclude that HFTs seem to be slightly more active and delete significantly more orders in highly volatile market periods. Although HFTs contribute to a larger share of the traded volume in these periods, a smaller share of their submitted orders leads to a real transaction as shown by the order-to-trade ratios. The speed advantage of HFTs is reflected in the overall lower execution and deletion time compared to NHFTs.

4 HFT Trading Strategies

4.1 Momentum vs. Contrarian Strategies

In this section, the overall trading behavior of active and passive HFTs and NHFTs in periods of high and low market stress is investigated. The week in March captures the high-volatility period and the week in June the low-volatility period.

In the first subsection, the question whether HFTs amplify or dampen excessive price movements by trading in the direction of or opposed to the market return is analyzed. In the second subsection, I study the relationship of active and passive HFT and NHFT trading activity and volatility within the two market environments. To investigate whether HFTs rather follow momentum or contrarian strategies and thereby exacerbate or reduce short-term volatility, I follow the work by [Breckenfelder \(2013\)](#), who proposes several measures to capture momentum strategies. The measure I apply is given by

$$Mom_d = \frac{1}{T} \sum_{t=1}^T r_{d,t} \frac{Vol_{buy,d,t}^j - Vol_{sell,d,t}^j}{Vol_{d,t}}, \quad (1)$$

where $r_{d,t}$ represents the log mean return over time interval t , $Vol_{buy,d,t}^j$ denotes the trading volume from buy trades for trading group j , where $j = 1, \dots, 6$ (HFT, NHFT, active HFT/NHFT, passive HFT/NHFT), in time interval t , $Vol_{sell,d,t}^j$ captures the trading volume from sell trades for trading group j in t , and $Vol_{d,t}$ is the total volume traded in the futures contract within the same time interval t . The momentum measure constitutes the sum over the 1-minute intervals for each trading day d and is calculated separately for each trading group j . It becomes positive when the trading group, e.g., HFTs, buy (sell) on average with an increasing (decreasing) futures price, and negative when they trade in the opposite direction of the price movement. Hence, a positive sign signals a momentum strategy, whereas a negative one would be interpreted as a contrarian strategy. The average momentum measure is calculated for both weeks to obtain an indication of

Table 2: Momentum Measure

A: High Vola					
Active HFT	Active NHFT	Passive HFT	Passive NHFT	HFT	NHFT
0.5541***	0.4654***	-0.3658***	-0.6776***	0.1362***	-0.1306***
(0.0211)	(0.02174)	(0.0140)	(0.0212)	(0.0183)	(0.0182)
B: Low Vola					
Active HFT	Active NHFT	Passive HFT	Passive NHFT	HFT	NHFT
0.4394***	0.5763***	-0.4093***	-0.6621***	-0.1229***	0.0175
(0.0310)	(0.0259)	(0.0209)	(0.0311)	(0.0067)	(0.0209)

This table shows the results of the momentum measure, which is the product of the return and the signed net order flow relative to the traded volume, for active HFTs and NHFTs, passive HFTs and NHFTs as well as overall HFTs and NHFTs. It is calculated as the mean over all 1-minute time intervals for the week in March and the week in June, multiplied times 100,000. Positive values indicate momentum, negative values indicate contrarian strategies. Standard errors are given in parentheses and * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%.

the strategies applied by HFTs and NHFTs in phases of high and low volatility.

Table 2 summarizes the results for all six trading groups. As the results show, the momentum measure for active HFTs exhibits a significantly positive coefficient in both market environments, implying that active HFTs tend to trade in the direction of price changes. In contrast, passive HFTs on average trade in the opposite direction of contemporaneous price movements, as indicated by their significantly negative coefficient. Using one lag of the return variable does not change the results which implies that active (passive) HFTs also trade in the direction of (opposed to) past price movements. The results are in line with [Benos and Sagade \(2013\)](#) and [Brogaard et al. \(2013\)](#), which points to consistent patterns of HFTs' trading behavior across different markets. While the measure for active HFTs (NHFTs) is higher (lower) during the high-volatility week than in the low-volatility week, passive HFTs and NHFTs do not exhibit any adjustment of their strategies to the market environment. Interestingly, the overall HFT ratio is significantly positive in March and negative in June. This implies that, on average, HFTs follow momentum strategies on high-volatility days and contrarian strategies on low-volatility days.

One can conclude that overall HFT activity varies with different market environments. In highly volatile market periods, HFTs overall trade in the direction of the market trend, while they act as liquidity-providers in periods of low market stress. At the same time HFTs' share of the traded volume is higher in volatile market phases. Hence, by trading in the direction of the market return, active HFTs may amplify intraday price variation, especially in times of high market uncertainty. Although the contrarian strategies by

passive HFTs tend to dampen excessive price fluctuations, they are dominated by momentum trades of active HFTs in those times. Thus, liquidity-providing strategies by HFTs mainly prevail in tranquil market phases. The question whether active and passive HFTs trade in the direction of or opposed to the market movement is also analyzed in the context of macroeconomic news releases in Section 5.

4.2 HFT and Volatility

In the next step, I want to find out how the trading behavior of HFTs is related to market volatility. In order to obtain proper volatility measurements on short time scales, one must take into account the high variation of tick-by-tick market activity within specific time intervals. One of the most common measures in the context of high-frequency data is the realized variance, which is the sum of squared incremental returns. [Zhang, Mykland, and Ait-Sahalia \(2005\)](#) propose a method to estimate the realized variance consistently for predefined subsamples in the presence of microstructure noise. The idea is to divide a time span, e.g. one day, into non-overlapping time intervals of the same length. Based on this approach, the realized variance for each 1-minute time interval is given by

$$Real_Var_t = \sum_{i=1}^N r_{t,i}^2, \quad (2)$$

where N is the number of observations in time interval t and r is the log Bund futures return. In order to link the volatility measure to HFT activity, I build 100 volatility percentiles based on the realized variance per 1-minute interval for the week in March and the week in June and calculate the excess HFT and NHFT trading participation ratio per percentile. The ratio reflects the traded volume of active and passive HFTs and NHFTs divided by the overall trading volume per time interval. Excess trading participation is defined as deviation of the trading participation ratio per 1-minute interval from the average ratio of the traded volume over all time intervals for each week.

Figures 3 and 4 depict HFT and NHFT trading activity for the highest 50 volatility percentiles.³ For the week in March (Figure 3) one can see that active and passive HFT trading activity is positively related to volatility. This positive relationship is also statistically significant and in line with the findings by [Brogaard et al. \(2013\)](#). In contrast, both active and passive NHFT trading activity co-moves negatively with volatility. While HFTs trade more the higher the volatility, NHFTs trade less compared to their average share at the overall traded volume. This is in contrast to the results for the week in June,

³To get a clearer picture of the relationship between HFT trading and increasing volatility, I have only included the highest 50 percentiles. Also, the question whether HFTs are more active in times of high market stress is at the core of this study. There is no clear relationship between HFT trading and volatility for the lower 50 percentiles, anyway.

where no clear relationship between the volatility percentiles and the HFT and NHFT trading can be identified (see Figure 4). However, in the highest 3 volatility percentiles the ratio of active HFT exhibits a sudden jump, which shows that above a certain volatility level liquidity-taking HFTs suddenly trade more. At the same time, active NHFTs scale back their trading activity dramatically. Against this evidence, trading by passive HFTs and NHFTs does not change with varying volatility levels.

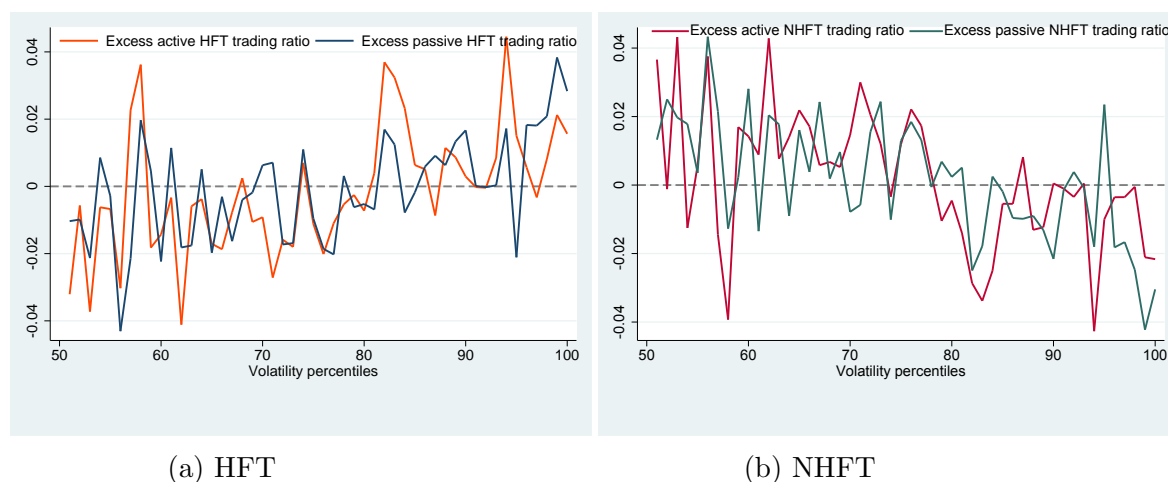


Figure 3: These figures depict the HFT and NHFT excess trading ratios for the highest 50 volatility percentiles in March.

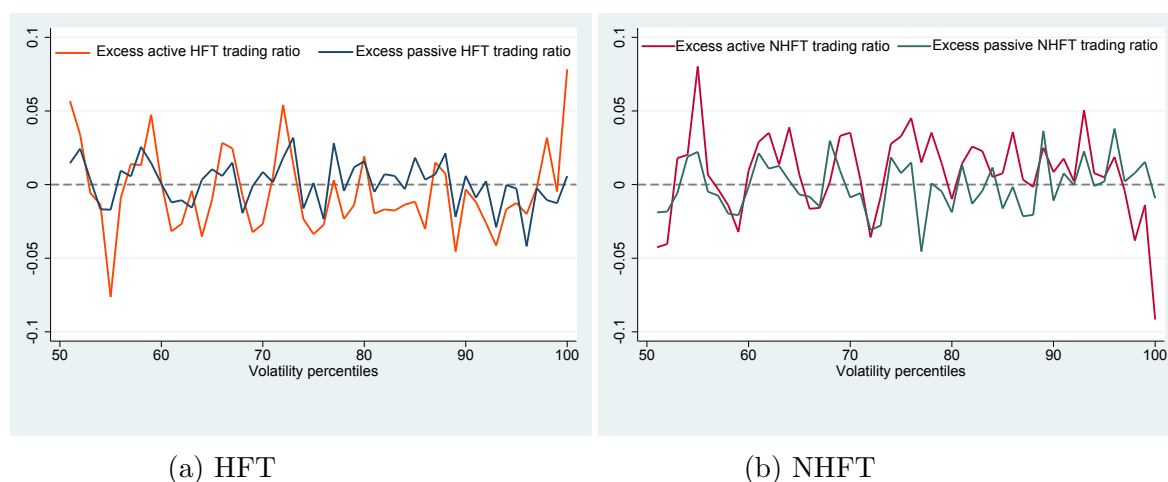


Figure 4: These figures depict the HFT and NHFT excess trading ratios for the highest 50 volatility percentiles in June. Excess trading ratio is calculated as the difference between the active and passive HFT trading volume participation and the average trading volume ratios over the entire week. The volatility percentiles are based on 1-minute time intervals.

The results imply that in the most volatile market episodes, liquidity-taking HFTs seem to trade more, while active slower traders withdraw increasingly from markets. The evidence is more pronounced for the high-volatility week and is in line with prior work

(e.g., [Zhang \(2010\)](#), [Boehmer et al. \(2012\)](#) and [Chaboud et al. \(2012\)](#)). For liquidity-providing participants, the results depend on the week considered. In the low-volatility week, none of the passive trading groups are sensitive to volatility changes. In the week of higher market stress, passive HFTs trade more the higher the volatility, while slower traders again rather withdraw from the market. However, a certain part of this positive relationship between passive HFTs and volatility can be due to mechanical reasons: a limit order is more likely to be executed when volatility is high ([Benos and Sagade \(2013\)](#)).

To conclude, the findings of this section suggest that active HFTs dominate in high-volatility periods and trade more than usual when volatility exceeds a certain level. By trading in the direction of market movements, they may exacerbate extreme volatility episodes. In contrast, NHFTs trade less the higher the volatility in a market environment that is already volatile. On low-volatility days, volatility-dampening passive strategies dominate overall HFT trading activity. The above results only provide evidence that excess trading of active HFTs coincides with highly volatile market environments. Based on this analysis, a conclusion on causality between HFT activity and volatility cannot be drawn. To establish a causal link between HFT trading and volatility requires appropriate instruments, which are generally hard to find ([Biais and Foucault \(2014\)](#), [Benos and Sagade \(2013\)](#)). Hence, it could be that HFT trading induces stronger price fluctuations. But it is also likely that HFTs are rather attracted by higher volatility. The reason may be that HFTs engage in trading strategies that are most beneficial when volatility is high ([Benos and Sagade \(2013\)](#)), which allows them to quickly generate short-term profits. Hence, in order to obtain a more precise idea about the relationship between HFT activity and volatility, the following analysis will focus on specific market episodes, namely the period around macroeconomic news releases, which constitute a source of high volatility. As macroeconomic news can be considered as exogenous variables ([Chaboud et al. \(2012\)](#)) and are announced at a specific time, the impact of HFT trading on volatility following the news is easier to establish, especially when the analysis is carried out at a very granular level.

5 HFT around Macroeconomic News Announcements

5.1 HFT Trading around Macroeconomic News

It is well known that macroeconomic news releases receive especially strong attention in government bond markets. Among the most relevant macroeconomic news for European bond markets are the US Nonfarm Payrolls (NFPs), released every first Friday of each month, and the ECB rate decision, released every first Thursday of each month (e.g.,

Schopen and Missong (2011), Chaboud et al. (2012)). In the following, I analyze the impact of these macroeconomic news announcements on HFT activity in the Bund futures market within a one-year period from July 2013 to June 2014. The NFPs are usually reported at 2:30 pm and ECB rate decisions at 1:45 pm (CET). In order to avoid small deviations in the actual report time, the time stamp of the first news announcement from Bloomberg is used, which usually corresponds to one second after the anticipated publication time. A positive macroeconomic data surprise occurs when the announced number is greater than the analysts' survey median forecast as reported by Bloomberg, and a negative one if it is smaller than the forecast median.

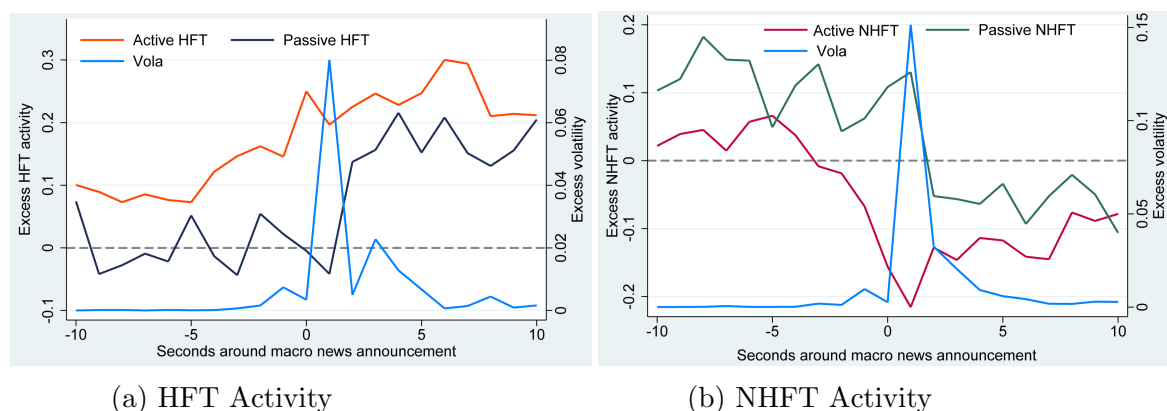


Figure 5: These figures illustrate the average excess HFT activity and the volatility of the Bund futures around the release of the monthly NFPs including 12 news events from July 2013 to July 2014.

In the first step, I graphically examine HFT trading activity around the publication of NFPs compared to their average activity on that particular trading day.⁴ In the second step, the reaction of HFTs and NHFTs to both NFPs and ECB rate decisions is examined in an econometric approach.

Figure 5 depicts the trading behavior of active and passive HFTs and NHFTs from 10 seconds prior to 10 seconds after the NFPs release. Apparently, the excess volatility of the Bund futures return increases strongly immediately after the news release, but already reaches its normal level of zero after five seconds. As Figure 5 (a) shows, there is a clear difference in the activity of active and passive HFTs. While active HFTs already increase their trading activity significantly several seconds before the data become public where the first peak is reached exactly at the second of the announced publication time, passive HFTs only increase their trading share to an above-average level one to two seconds after the news release. However, even 10 seconds after the data are announced, both active and passive HFTs remain highly active. In contrast, as shown in Figure 5 (b), active and

⁴In the graphical analysis, I focus only on NFP releases, since the distinction between positive and negative surprises is more clear-cut in the case of macroeconomic data than for ECB rate decisions.

passive NHFTs trade less after the NFP release compared to their average trading activity over the entire trading day. Interestingly, active NHFTs strongly scale back their activity already a few seconds before the macroeconomic news is published. A possible reason for this could be that NHFTs are aware of their disadvantage in speed and their lower chances of generating gains from short-term trading on the news compared to HFTs.

Next, I analyze whether HFTs trade in or against the direction of the market return around news events and whether the reaction depends on the nature of the news surprise, i.e. a positive or a negative deviation of the NFPs from the market expectation. A positive (negative) macroeconomic news surprise usually implies rising bond yields and falling bond prices due to higher interest rate and inflation expectations. Figures 6 and 7 depict the HFT and NHFT signed net order flow and the return in 1-second intervals around positive and negative NFP releases. The figures show that immediately after the news is released ($t = 0$), the return jumps in the direction of the surprise, stabilizes shortly afterwards and finally reaches a level close to the pre-announcement value. As one can see in Figure 6 (a), the trading of active HFTs co-moves very closely with the price movement, especially when news releases are positive.⁵ This picture suggests that active HFTs sell Bund futures contracts on positive and buy on negative news releases, which is in line with the findings by Brogaard et al. (2013) for the US stock market. The opposed order flow evolution of passive NHFTs suggests that their trades are picked off by active HFTs (see Figures 6 and 7 (b)). In contrast, passive HFTs do not change their trading activity significantly around the news releases: their buy and sell trades remain balanced, which corresponds to a net order flow of nearly zero. Therefore, overall HFT order flow is positively related to the market return, meaning that HFTs, on average, take liquidity after macroeconomic news releases. This result contradicts the empirical evidence by Brogaard et al. (2013) that overall HFTs trade in the opposite direction of macroeconomic news and so dampen excessive price movements.

5.2 HFT Price Discovery around Macroeconomic News

While the graphical analysis above was helpful to obtain a broad idea of HFT trading behavior around macroeconomic news events, I study this issue in more detail next. First, I investigate the impact of macroeconomic news releases on HFT trading behavior in clock time and then go over to tick time in order to exploit the high granularity of the data. Second, I analyze the role of HFT in price discovery and its contribution to information and noise on a tick-by-tick-basis.

⁵The results for the negative news releases are biased because of a large HFT trade on one day immediately before the news release. Given the small number of negative news surprises of only five, this effect distorts the results.

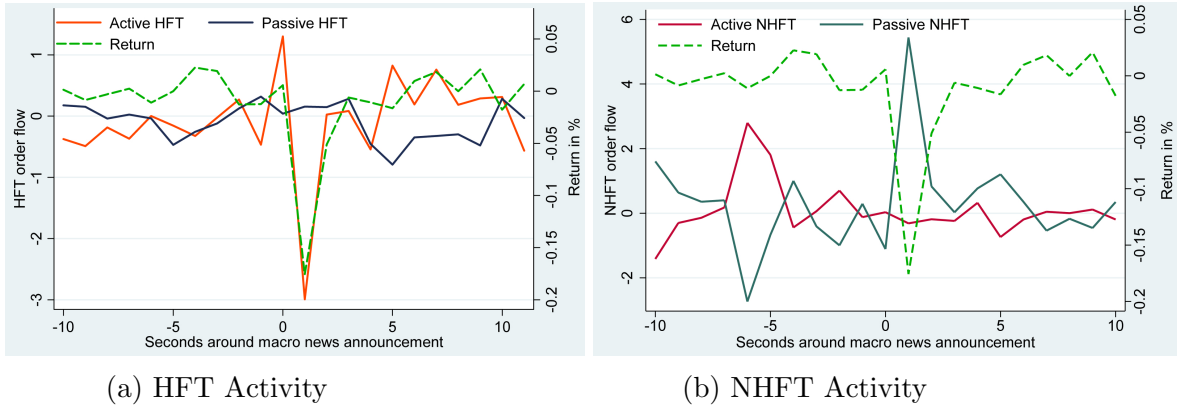


Figure 6: These figures depict the HFT and NHFT order flow as well as the log return within 1-second intervals around the release of positive NFPs from July 2013 to July 2014, including seven positive news events. Positive news announcements occur when the actual NFP number is higher than the median forecast of NFPs. Order flow is calculated as the difference between execution quantities from buy trades and sell trades.

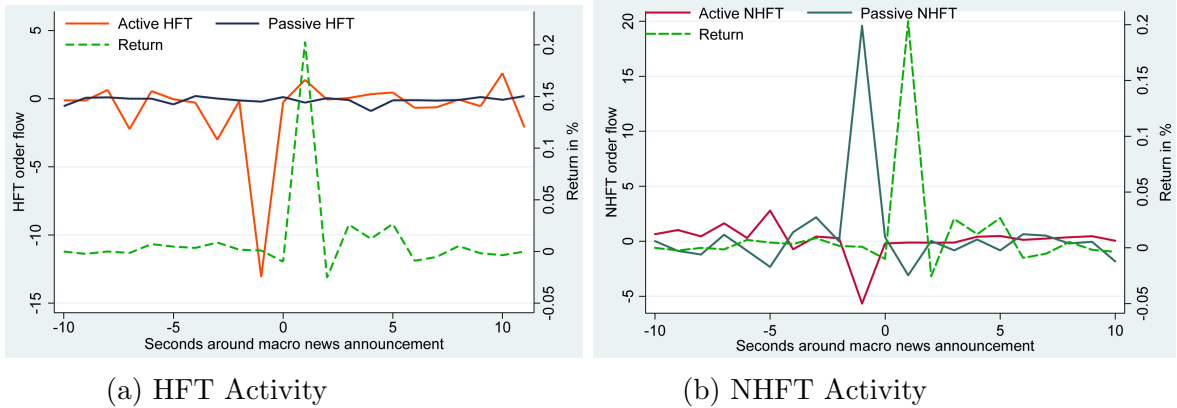


Figure 7: These figures depict the HFT and NHFT order flow as well as the log return within 1-second intervals around the release of negative NFPs from July 2013 to July 2014, including five negative news events. Negative news announcements occur when the actual NFP number is lower than the median forecast of NFPs. Order flow is calculated as the difference between execution quantities from buy trades and sell trades.

Analysis in clock time

For the clock time analysis, I build 1-second intervals and calculate the immediate ($t = 0$) and the long-term effect ($t = 10$) of NFP and ECB news announcements on the order flow of active and passive HFTs and NHFTs. Therefore, I estimate a structural VAR with excess HFT and NHFT order flow as well as excess return within the 10-minute interval of the news releases (five minutes prior to five minutes after the news releases) using 10 lags, as in [Hendershott and Riordan \(2011\)](#) and [Benos and Sagade \(2013\)](#). Excess order flow and return are calculated as the difference between the order flow of the 10-minute interval and the average values on the entire trading day excluding the event window.

This results in the following VAR model including the macroeconomic news as exogenous variable similar to [Zhang \(2013\)](#) and [Chaboud et al. \(2012\)](#).

$$\begin{aligned}
r_t &= \alpha + \sum_{i=1}^l \beta_i OF_{t-i}^{hft} + \sum_{i=1}^l \gamma_i OF_{t-i}^{nhft} + \sum_{i=1}^l \delta_i r_{t-i} + \sum_{i=0}^l \psi_i D_i + \epsilon_{1t} \\
OF_t^{hft} &= \kappa + \sum_{i=1}^l \eta_i OF_{t-i}^{hft} + \sum_{i=1}^l \lambda_i OF_{t-i}^{nhft} + \sum_{i=1}^l \nu_i r_{t-i} + \sum_{i=0}^l \phi_i D_i + \epsilon_{2t} \\
OF_t^{nhft} &= \zeta + \sum_{i=1}^l \rho_i OF_{t-i}^{hft} + \sum_{i=1}^l \tau_i OF_{t-i}^{nhft} + \sum_{i=1}^l \upsilon_i r_{t-i} + \sum_{i=0}^l \pi_i D_i + \epsilon_{3t},
\end{aligned} \tag{3}$$

where t denotes the 1-second time interval, OF is the signed net order flow (buyer-initiated minus seller-initiated volume), r is the log return per time interval, and D is the dummy variable indicating the macroeconomic news. The latter is equal to 1 when news is released and 0 otherwise. In contrast to most existing HFT literature (e.g., [Hendershott and Riordan \(2011\)](#), [Benos and Sagade \(2013\)](#), [Zhang and Riordan \(2011\)](#)), instead of using the mid-price based on quote updates and transactions, I use execution prices as in [Hasbrouck \(1993\)](#). The reason for this is the following. The density of transactions is extremely high following certain news events such as the NFP releases, and often a large number of transactions occur within the same microsecond. In these instances, the bid-ask spread usually widens substantially due to some very large trades which can often only be partially executed, so that the execution price adjusts until the limit price of the large order is reached. Therefore, the execution price varies strongly, while the mid-price remains constant. Hence, using the mid-price would imply significant information loss, especially around the publication of important macroeconomic news. Moreover, instead of using the trade direction as in [Benos and Sagade \(2013\)](#) or [Hendershott and Riordan \(2011\)](#), I include the signed net order flow to account for the fact that large orders might have a stronger impact on prices than small trades. This seems reasonable given the above evidence of some large trades, especially by HFTs after major news releases.

The above representation is based on the restriction that NHFT order flow does not contemporaneously affect HFT order flow or vice versa, which would not be intuitive. Therefore, one does not need to assume a specific ordering of the order flow time series in the VAR. As a robustness check, I switch the orderings of the two order flow time series, which yields almost identical results. The above VAR model is estimated separately for active and passive trading participants. In order to capture the impact of the macroeconomic news on the order flow variables, in the first step I calculate the dynamic multipliers using the macroeconomic news as impulse and the order flow variables as responses. In the second step, I estimate the impact of the HFT and NHFT order flow

on return and the respective impulse responses. To generate dynamic multipliers and impulse responses, I invert the above VAR model and apply a Cholesky decomposition on the variance-covariance matrix Σ to obtain a vector moving average (VMA) form with orthogonalized error terms

$$\begin{pmatrix} r_t \\ OF_t^{hft} \\ OF_t^{nhft} \end{pmatrix} = \begin{pmatrix} a(L)b(L)c(L) \\ d(L)e(L)f(L) \\ g(L)h(L)k(L) \end{pmatrix} \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix} + \begin{pmatrix} q(L) \\ r(L) \\ u(L) \end{pmatrix} \begin{pmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \end{pmatrix}, \quad (4)$$

where the error terms $e_{i,t}$ are mutually orthogonal with $\mathbf{e}_t \mathbf{e}_t' = \mathbf{I}$. This allows for causal statements about shocks to one element of \mathbf{e}_t without considering correlations with the other variables. The lag polynomials $a(L)$ to $k(L)$ represent the impulse response functions of the three variables to shocks, while $q(L)$ to $u(L)$ are dynamic multipliers that capture the cumulative impact of macroeconomic news on the three variables. The impulse response functions for HFT and NHFT order flow are $b(L)$ and $c(L)$, respectively, and can be interpreted as an estimate of the permanent price impact of a trade innovation.

Table 3: Impact of News Shocks on Order Flow - Clock-based Analysis

	Active HFT	Active NHFT	Passive HFT	Passive NHFT	HFT	NHFT
<i>SR</i>	-0.247* (0.152)	-0.046 (0.159)	-0.007 (0.136)	0.463*** (0.157)	-0.240 (0.159)	0.398*** (0.159)
<i>LR</i>	0.170 (0.383)	-0.012 (0.458)	-0.397 (0.384)	0.498 (0.466)	-0.249 (0.487)	0.578 (0.486)
<i>LR - SR</i>	0.417 (0.412)	0.034 (0.485)	-0.390 (0.407)	0.035 (0.492)	-0.05 (0.512)	0.18 (0.511)

This table shows the results of the VAR analysis including the macroeconomic news dummy as exogenous variable. The analysis is carried out on a 1-second frequency. *SR* denotes short-run effect, which is the immediate impact of the news dummy on the order flow of the different market participants, *LR* is the cumulative effect after 10 seconds and (*LR - SR*) the difference between the two. The analysis is carried out for active and passive HFTs and NHFTs as well as overall HFTs. Standard errors are given in parentheses and * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%.

Table 3 summarizes the results of the impact of NFP and ECB events on the order flow of active and passive HFTs and NHFTs, given by $r(L)$ and $u(L)$, respectively, based on 1-second intervals. As the graphical analysis already showed (Figures 6 and 7), only active HFTs and passive NHFTs exhibit a significant reaction to the news release. The negative *SR* effect ($t = 0$) of active HFTs implies that overall they net sell Bund futures contracts on macroeconomic news releases in the first second following the announcement. Given the majority of positive news events and the stronger reaction of HFTs to positive surprises we have seen above, the negative coefficient of active HFTs implies that overall

they trade in the direction of the market. While their initial reaction is quite strong, active HFTs already tend to reverse their trading positions right after the *SR* reaction (in $t = 1$), leading to a positive cumulative net trading effect after 10 seconds (Table 3).

As a robustness test, I performed the analysis accounting for positive and negative news surprises.⁶ Since this alternative specification yields very similar results, I do not explicitly show them.

The above results reflect the typical HFT trading behavior around news events. HFTs are aware of their advantage in speed and trade on the macroeconomic news surprise faster than other traders. Given the generally strong market impact of NFP and ECB news announcements, HFTs can be certain that other traders will also trade according to the surprise component of the news, but only with a delay. Hence, in case of a positive news surprise, HFTs are among the first traders who sell Bund futures contracts at a still relatively high price. As soon as slower market participants also react to the news announcement by selling futures contracts, which amplifies the downward price pressure, HFTs buy back the contracts at a much lower price and realize short-term trading gains. This effect is called information arbitrage. [Hirschey \(2013\)](#) provides further support for this explanation, even though not directly linked to news. The author shows that HFTs anticipate NHFTs' future buying and selling pressure and trade ahead of them to profit from the NHFTs' subsequent price impact. According to the results, on the other side of the trades are usually passive NHFTs, indicated by a significantly positive coefficient. When the news is announced, aggressive HFT orders hit their bid limit orders to sell the Bund futures contract within one second. NHFTs cannot withdraw their limit orders as fast as HFTs react to the news; this is called adverse selection risk. Hence, traders who post standing limit orders that do not yet reflect the price changes implied by news lose to HFTs.

As Table 3 shows, the *LR* effect (after 10 seconds) is not significant overall. This supports the graphical evidence (see Figures 5 to 7 (a)) that HFTs execute their trading strategies within a few seconds and mostly even within the first second following a news release.

My results are not fully in line with the findings by [Brogaard et al. \(2013\)](#), who show that mainly passive HFTs are adversely selected by active HFTs around macroeconomic news releases using 1-second intervals. The different results might be due to the fact

⁶The dummy variable equals 1 for positive news surprises and -1 for negative surprises. In the case of the NFPs, a positive news event occurs when the actual employment number lies above the survey median, and vice versa for negative surprises. For ECB news, I apply two different rules. A positive (negative) surprise of the ECB rate decision occurs if the Bund futures return after one tick following the decision is lower (higher) than one standard deviation below (above) its 30-tick rolling mean or if the cumulative return five ticks after the rate decision is lower (higher) than two standard deviations below (above) its mean.

that they look at stock markets, while I study government bond markets, which usually show the strongest reaction to macroeconomic data (Altavilla et al. (2014)). Hence, the reaction of stock returns to such news might differ from that of bond returns. Given that HFTs know that macroeconomic news can create excessive intraday volatility in bond markets, they may anticipate higher risks in this market segment and withdraw from the market before the news is released. Overall, the previous findings highlight very well HFT trading strategies around news events from a human observer’s point of view, but they also suggest that most of the news reactions occur within a few seconds. On some of the NFP days between July 2013 and June 2014, more than 500 transactions are carried out within the first second after the data are published. In order to get a clearer picture of the initial reactions by HFTs that usually occur within milliseconds, which is beyond the scope of human perception, the following analyses are carried out on a tick-by-tick-basis.

Table 4: Impact of News Shocks on Order Flow - Tick Analysis

	Active HFT	Active NHFT	Passive HFT	Passive NHFT	HFT	NHFT
<i>SR</i>	-0.089 (0.304)	0.004 (0.237)	-0.019 (0.160)	0.065 (0.346)	-0.099 (0.292)	0.096 (0.316)
<i>LR</i>	-6.715*** (1.764)	-0.875 (1.228)	0.967 (0.654)	5.686*** (1.890)	-5.892*** (1.704)	5.709*** (1.700)
<i>LR – SR</i>	-6.626*** (1.790)	-0.879 (1.251)	0.986 (0.673)	5.621*** (1.921)	-5.793*** (1.729)	5.613*** (1.729)

This table shows the results of the VAR analysis including the macroeconomic news dummy as exogenous variable. The analysis is carried out on a tick-by-tick basis. *SR* denotes the short-run effect, which is the immediate impact of the news dummy on the order flow of the different market participants, *LR* is the cumulative effect after 10 ticks and (*LR – SR*) the difference between the two. The analysis is carried out for active and passive HFTs and NHFTs as well as overall HFTs. Standard errors are given in parentheses and * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%.

Analysis in tick time

In the present dataset, the number of ticks within the first 10 seconds after the news release varies between five trades for one ECB rate decision and 1330 for a specific NFP event. Applying a fixed time window does not appropriately account for the strong variability of trades after a news release, while it allows for a chronological analysis of the news events, which has been particularly useful in gaining an initial idea of the trading reactions by HFTs and NHFTs. In a second approach, I replace seconds with number of ticks, i.e. the *SR* effect equals the first tick after the news is published and the *LR* effect is set to 10 ticks. This enables me to account for each event that takes place after the news release

and complements the above clock time analysis. The time period of the first 10 ticks varies strongly among the single event days and ranges between 60 milliseconds for NFP events and 12 seconds for some ECB rate decisions. Order flow and return variables are standardized using mean and standard deviation of the respective Bund futures trading day.

The estimated effects of the news shocks on HFT and NHFT order flow, i.e. $r(L)$ and $u(L)$, based on ticks are given in Table 4. Within the first 10 ticks, active HFTs trade exactly in the direction of the market and the cumulative effect expands the more ticks are considered. The coefficient is significant from the second tick on. Comparing the results of the clock-based and the tick-based analysis shows that the significance levels of the effects are higher overall when using ticks. Particularly, the coefficient after 10 ticks has a higher explanatory power than the coefficient for the first second in the clock-based analysis. This confirms the presumption that active HFTs already realize their profits by reversing their positions within the first second following the news, which is likely the reason for the overall weaker impact in the initial 1-second interval. Also, the effect that passive NHFT orders are hit by active HFT trades is stronger than in the clock-based analysis. This supports the hypothesis that estimating the trading behavior of HFTs and NHFTs after news based on trading events rather than time intervals captures the initial trading reaction more precisely. Performing the analysis using 20 ticks yields similar results.

In the next step, I calculate the impulse responses for HFT and NHFT order flow on return, given by $b(L)$ and $c(L)$, again for the first 10 ticks. Similar to [Hendershott and Riordan \(2011\)](#) and [Chaboud et al. \(2012\)](#), I limit the analysis to active trading participants, since they initiate the trades around the news release and thereby mainly contribute to price discovery. Results are given in Table 5 Panel A. They show that both HFT and NHFT order flow have a significant positive immediate effect on the return. Based on the first tick, the impact of NHFT trading is even slightly greater. While the positive impact expands for HFTs over the subsequent 10 events, it diminishes slightly for NHFTs. This result is also shown in Figure 8, which depicts the cumulative impulse response functions and their 95% confidence intervals of a positive shock to HFT and NHFT order flow on return from the initial response to 10 steps in the future. The impulse response function for HFTs after 10 ticks is around five times as high as for NHFTs. This implies that an innovation in HFT trading induces a 400% greater price change than an innovation in NHFT trading, suggesting that HFT trades contain more information than NHFT trades, which is also confirmed by the significantly positive difference between HFT and NHFT impulse responses. Moreover, the subsequent adjustment ($LR - SR$) is significantly positive only for HFT trading. As a robustness test, I performed the analysis for 20 ticks. The results are very similar to the analysis for 10 ticks (see Appendix A.2).

Table 5: Price Impact of Active HFT and NHFT - Tick Analysis

Panel A: Single IRFs

	Active HFTs	Active NHFTs	Active HFT - NHFT
SR	0.069** (0.031)	0.081*** (0.032)	-0.012 (0.045)
LR	0.607*** (0.063)	0.120* (0.067)	0.486*** (0.092)
$LR - SR$	0.538*** (0.070)	0.039 (0.074)	0.498 *** (0.102)

Panel B: Contribution to Permanent and Transitory Variance

	Active HFTs	Active NHFTs	Public information
Permanent variance	0.092*** (0.016)	0.004 (0.017)	0.905*** (0.031)
Transitory variance	0.334*** (0.037)	0.023 (0.065)	0.643*** (0.088)
Information-to-noise ratio	0.274*** (0.056)	0.158 (0.855)	1.408*** (0.199)

Panel A of this table shows the results of the impulse responses from active HFT and NHFT order flow on returns using 10 ticks, based on the VAR analysis including the macroeconomic news dummy as exogenous variable. SR denotes the short-run effect, LR is the cumulative effect after 10 ticks and $(LR - SR)$ the difference between the two. Panel B includes the result of the variance decomposition for the permanent and transitory price components. It shows the shares of the variance of active HFTs and NHFTs relative to the efficient and transitory variance, as well as the information-to-noise ratio after 10 ticks. Standard errors are given in parentheses and * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%.

The above results are consistent with news trading strategies by HFTs that rely on speedy and aggressive trades and are close to the existing empirical evidence: e.g., [Jiang et al. \(2013\)](#) also find that HFT trades are more informative than NHFT trades for US Treasury bond returns after the announcement of important macroeconomic news. Independent of news releases, [Hendershott and Riordan \(2011\)](#) find similar results for different German stocks, and [Benos and Sagade \(2013\)](#) for UK stocks. Also, [Brogaard et al. \(2013\)](#) show that while both active HFTs and NHFTs trading are positively correlated with permanent price movements, HFT trades are the more informed ones. However, the above finding that HFT trades contain more information than NHFT trades relates to milliseconds. Hence, the improvement in price efficiency simply reflects the fact that through aggressive HFT trading on the surprise component of the news, the new information is

reflected into prices by fractions of a second faster than without the presence of HFTs.

To conclude, HFT plays an important role in the price discovery process on a micro-perspective. Through their advantage in speed that enables them to react faster to news compared to other traders, HFT trading improves price efficiency. The incremental economic benefit of this achievement is difficult to assess, however. Regarding market efficiency, it is worth noting that these order flow anticipation strategies pursued by HFTs might discourage NHFTs to participate in the market during those times. Also, [Shorter and Miller \(2014\)](#) state that while most empirical literature shows that HFT helps in price discovery (see also [SEC \(2014\)](#)), order anticipation and momentum ignition strategies pursued by HFTs can potentially exacerbate slower investors' transaction costs and can contribute to extreme volatility events. In the next subsection, I will analyze how the above identified fast and strong reaction by active HFTs to news contributes to price volatility. Since volatility can have both a short-term noise and a permanent information-related character I will look at both volatility types separately.

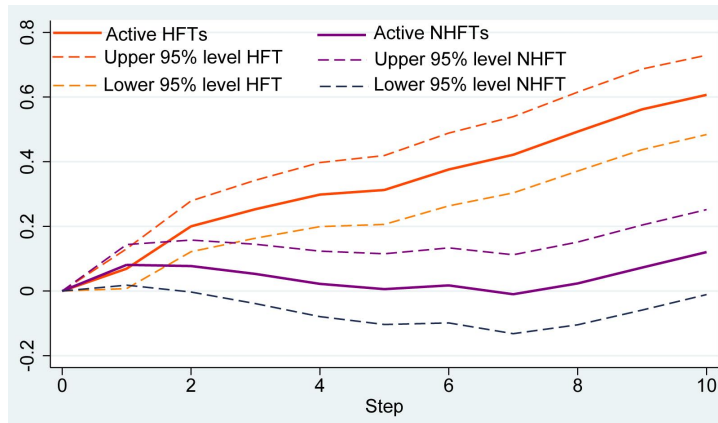


Figure 8: This figure shows the cumulative impulse response functions of active HFTs and NHFTs for 10 steps as well as the lower and upper confidence levels at 5%.

5.3 HFT Contribution to Information and Noise

In the following, I apply the variance decomposition method proposed by [Hasbrouck \(1991b\)](#) to assess the impact of HFT and NHFT trading on the fraction of information and noise. The method is based on the idea that the observed price has a permanent and a transitory component and is given by

$$p_t = m_t + s_t. \quad (5)$$

The permanent price m_t follows a random walk $m_t = m_{t-1} + \omega_t$, where $E\omega_t = 0$, $E\omega_t^2 = \sigma_\omega^2$ and $E\omega_t\omega_s = 0$ for $t \neq s$, and s_t denotes the transitory component, which is assumed

to have no long-term impact on prices. Given the assumption that the efficient price follows a random walk, s_t can be referred to as noise, which holds true for any stationary deviation from a random walk process (Benos and Sagade (2013)). According to the above decomposition, the return can be expressed as

$$r_t = p_t - p_{t-1} = \Delta m_t + \Delta s_t. \quad (6)$$

Similar to the original approach by Hasbrouck (1993), I use actual transaction prices to calculate return and variance. Using equations (3) and (4), the permanent price impact is given by

$$\Delta m_t = \left(\sum_{i=0}^{\infty} a_i \right) e_{1t} + \left(\sum_{i=0}^{\infty} b_i \right) e_{2t} + \left(\sum_{i=0}^{\infty} c_i \right) e_{3t}. \quad (7)$$

Based on 10 lags, the variance of the permanent price impact can be approximated by

$$\sigma_{\omega}^2 = \left(\sum_{i=0}^{10} \hat{a}_i \right)^2 \hat{\sigma}_{e1}^2 + \left(\sum_{i=0}^{10} \hat{b}_i \right)^2 \hat{\sigma}_{e2}^2 + \left(\sum_{i=0}^{10} \hat{c}_i \right)^2 \hat{\sigma}_{e3}^2. \quad (8)$$

Since the error terms are mutually orthogonal, the variances are equal to one. The first two terms are trade-correlated and capture the proportions of the permanent price innovation related to HFT and NHFT trading activity, while the last term is the contribution to price discovery that is not related to trading and can be interpreted as public information (see Hasbrouck (1991a)).

Next, I assess HFT contribution to noise, i.e. the transitory part of the observed price. Following Hasbrouck (1993) and Benos and Sagade (2013), noise is assumed to evolve according to a moving average (MA) process of the residuals of the VMA form

$$s_t = \left(\sum_{i=0}^{\infty} \tilde{a}_i \right) e_{1t} + \left(\sum_{i=0}^{\infty} \tilde{b}_i \right) e_{2t} + \left(\sum_{i=0}^{\infty} \tilde{c}_i \right) e_{3t}. \quad (9)$$

The noise process parameters can be estimated as follows:

$$\tilde{a}_j = - \sum_{v=j+1}^{\infty} a_v, \quad \tilde{b}_j = - \sum_{v=j+1}^{\infty} b_v, \quad \tilde{c}_j = - \sum_{v=j+1}^{\infty} c_v. \quad (10)$$

Using 10 lags, the estimate for the transitory variance⁷ is given by

$$\sigma_s^2 = \left(\sum_{i=0}^{10} \hat{\tilde{a}}_i \right)^2 \hat{\sigma}_{e1}^2 + \left(\sum_{i=0}^{10} \hat{\tilde{b}}_i \right)^2 \hat{\sigma}_{e2}^2 + \left(\sum_{i=0}^{10} \hat{\tilde{c}}_i \right)^2 \hat{\sigma}_{e3}^2. \quad (11)$$

⁷Due to the specific identification method of this model, which is based on Beveridge and Nelson (1981), the estimate represents a lower bound for σ_s . For details, see Hasbrouck (1993).

According to [Hasbrouck \(1993\)](#), the variance of the transitory component can be interpreted as a measure of market quality, i.e. the lower the transitory variance, the greater the price efficiency. In order to assess the informational efficiency of HFT and NHFT trading, each trader group's contribution to the overall permanent and transitory variance, σ_{ω}^2 and σ_s^2 , respectively, are estimated based on the above decomposition.

According to the results in [Table 5 Panel B](#), active HFTs contribute a much higher share to permanent volatility than NHFTs, whose contribution is basically zero. Since HFTs' share relative to the traded volume is about twice as high as for NHFTs around macroeconomic news, HFTs also add more to the permanent volatility in relative terms. The result is consistent with the findings by [Chaboud et al. \(2012\)](#) and [Hendershott and Riordan \(2011\)](#), who show that HFTs explain more of the variance of returns than NHFTs in the FX and the US equity market, respectively. However, the present findings also indicate that HFT trades add a large amount to noise, which is about 33% after 10 ticks. In contrast, NHFTs make no statistically significant contribution to noise. The information-to-noise ratio for HFTs is far below 1, indicating that HFTs' fast trading after the news release contributes much more to transitory volatility than to information. Similar to my results, [Benos and Sagade \(2013\)](#) find that HFTs both contribute a higher share to information and to noise than NHFTs. However, they obtain information-to-noise ratios greater than one for the majority of stocks they analyze. [Brogaard et al. \(2013\)](#) show that HFTs trade in the direction of the permanent and opposed to the transitory price component which they see as evidence for an improvement in price discovery. My results are not as conclusive given the large noise contribution of HFT trades. However, it is important to note that these two studies do not look at macroeconomic news releases, which is likely an environment where excessive volatility is more common than usual and where HFTs are more active than on average. Using 20 ticks instead of 10 results in a higher share of the transitory volatility for HFTs (around 45%) and of the permanent volatility as well (13%). For NHFTs the contribution to both information and noise is small and still insignificant (see [Appendix A.2](#)).

The above results are consistent with HFTs following news trading strategies. Since this requires fast and aggressive trading according to the surprise component of the news, HFT trades amplify both the beneficial and the harmful determinants of price volatility around such events. Due to the fast reaction of HFTs, the overall improvement in price discovery goes hand in hand with an even higher amount of excessive volatility. One reason for the high noise generation could be that HFTs process the signals they receive very quickly and overreact to these signals or even interpret them wrongly implying that their trades may not be entirely informative.

6 HFT Liquidity Supply

While in the previous chapter the trading strategies by active HFTs were analyzed, the final part of this study focuses on liquidity-providing (passive) HFTs. A rising concern among regulators and practitioners has been that HFTs who act as market makers and supply liquidity only do so in quiet market phases, and tend to withdraw from markets in stress periods when liquidity is sparse (ESMA (2011), ASIC (2012)). The issue is crucial for market stability in the sense that if a market shock induces HFTs to suspend their liquidity provision, this shock might be amplified (Ait-Sahalia and Saglam (2014)).

In the following, I address this topic by studying changes in HFT liquidity supply in different market environments. More specifically, I introduce two measures of liquidity supply and relate these to periods of unexpected volatility due to a rise in risk aversion and to periods of anticipated volatility around macroeconomic news releases. I use the term liquidity supply instead of liquidity provision in order to distinguish the order book activities, such as quoting and cancellations, from the traded volume by passive HFTs, studied in the previous sections. In the existing literature, the notion “liquidity provision” also mostly refers to the traded volume (e.g., Chaboud et al. (2012), Brogaard et al. (2013)), but is also used to analyze quoting and order cancellations, as done by Ait-Sahalia and Saglam (2014).

To account for changes in the volume of quoted orders, I estimate an order deletion ratio, which I define as the volume of order cancellations relative to the volume of submitted orders. This ratio gives an indication of the change in the overall liquidity supplied by passive HFTs and NHFTs. If the ratio is greater than 1, the liquidity supply in a specific time interval is reduced.⁸ To study whether passive HFTs submit fewer orders during phases of increased volatility than usual, I also calculate the order submission ratio. The latter is defined as the volume of added orders by trading group divided by the volume of all activity types, including transactions, modifications and deletions.

The depth of the data is of particular value in this part of the analysis. Most of the existing studies that address liquidity supply in different market environments are limited to transaction data (e.g., Chaboud et al. (2012), Brogaard et al. (2013)). Hence, as in the previous part of this study, they focus on liquidity provision, calculated as the traded volume by passive market participants. However, as pointed out by, e.g., Benos and Sagade (2013), a positive relationship between the volume of executed limit orders and volatility could also be due to mechanical reasons. In times of stronger market movements,

⁸The deletion ratio captures the overall supplied liquidity independent of the distance to the current best bid and offer price. In a more sophisticated approach one could account for this distance and attain a higher weighting to those orders that are closer to the last price. However, in order to proxy for the changes in the supplied liquidity in different market environments, this measure should also provide useful insights on a relative basis.

limit orders are more likely to be executed. This potential disruption of the results does not occur when using order deletions and submissions. Another important benefit of using deletions and submissions is that there are no endogeneity issues when studying the impact of volatility on changes in liquidity supply by HFTs. Yet, as discussed by [Chaboud et al. \(2012\)](#), it is not possible to regress the traded volume by passive market participants on volatility since the two variables cannot be considered separately from each other.

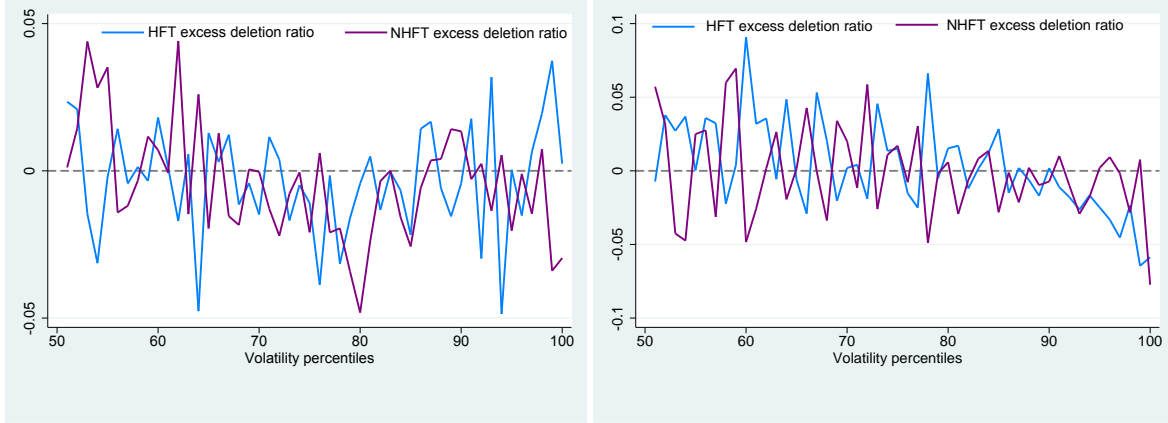
In this section, I proceed as follows. First, I look at the deletion ratio for passive HFTs and NHFTs as aggregate ratio for both trading weeks and per time interval. Second, I calculate the volatility per 1-minute interval and generate volatility percentiles based on the intervals. From this, the deletion and submission ratios per percentile can be computed. Finally, the excess deletion and submission ratios for five minutes prior to five minutes after the NFP releases based on 1-second intervals are calculated.

According to the descriptive statistics in [Table 1](#), the aggregate deletion activity of passive HFTs is, on average, significantly higher in the high-volatility week in March (77% versus 72% in June). Also, the deletion ratio in March is slightly higher for HFTs than for NHFTs, while in the week of June it is the opposite, although the difference is smaller than in March. In contrast, NHFTs exhibit the same deletion behavior in both market phases; they even delete slightly less in the high-volatility week. This highlights the fact that, on average, HFTs acting as liquidity suppliers indeed tend to withdraw from markets more than NHFTs when volatility increases unexpectedly. At the same time, both HFTs and NHFTs seem to submit more orders on an absolute scale in the high-volatility week, while the ratio relative to all activities is the same in both weeks. Since the deletion ratio is computed relative to the submitted orders, the deleted volume exceeds the volume of orders submitted, however.

Next, the deletion ratio per time interval is calculated. Overall, there is a positively significant relationship between the absolute number of deletions both for HFTs and NHFTs and volatility per minute, which is intuitive since market makers have to adjust their orders more often when prices vary more frequently. At the same time, absolute order submission by both trading groups exhibits a positive relationship with volatility as well. Moreover, in both weeks HFTs exhibit a significantly higher deletion and submission ratio than NHFTs on a minute-by-minute basis.

[Figure 9](#) shows the excess HFT and NHFT deletion ratios for the highest 50 volatility percentiles out of 100 percentiles for March and June. For both weeks, there is no clear relationship between the excess deletion ratios and volatility for HFTs and NHFTs. Similar to the results for the trading participation ratios, I find a stronger deviation from 0 in both weeks for the highest volatility percentiles. Thereby, HFTs delete more in March

and less in June in the most volatile market phases compared to the average deletion ratios. In contrast, NHFTs delete less than average in the highest three percentiles in both weeks. Excess submission ratios are not depicted since they do not show any evidence of a relationship with volatility.



(a) March - High Volatility

(b) June - Low Volatility

Figure 9: These figures depict the HFT and NHFT excess deletion ratios for the highest 50 volatility percentiles in March and June. The excess deletion ratio is calculated as the difference between the deletion ratio in a specific time interval t and the average deletion ratio over the entire week. The volatility percentiles are based on 1-minute time intervals.

Since the graphical results do not provide a clear relationship between liquidity supply and volatility, a statistical analysis is carried out next. I therefore create a dummy variable which equals 1 when the deletion (submission) ratio per time interval is higher than the mean deletion (submission) ratio over the entire week for HFTs and NHFTs. In order to test whether the probability of deleting orders increases when volatility picks up suddenly, I regress the dummy variable on the lagged volatility for the 1-minute intervals. The same is done for order submissions. Results are given in Table 6.

Apparently, in March HFTs are likely to delete more orders when volatility rises, while NHFTs tend to delete fewer orders. At the same time, HFTs tend to submit more orders when volatility rises, while NHFTs are less active. In June, when overall volatility is lower, both HFTs and NHFTs are likely to delete fewer orders after volatility has risen in the previous minute. There is weak statistical evidence that order submission also declines slightly for HFTs when volatility rises.⁹ Given that overall volatility was very low during the week of June, an increase in market stress during this time was not a reason for HFTs to withdraw from markets. The fact that they delete significantly more orders in the highest volatility percentiles in March suggests that there are volatility thresholds above which HFTs consider the market too risky. Also, in these phases HFTs do not have any

⁹Results are similar when carrying out the regressions without a time lag.

Table 6: Order Deletions and Submissions

Panel A: March		
Probit regression	HFT	NHFT
Deletion	578.18*** (120.40)	-293.44*** (109.45)
Submission	576.97*** (119.95)	-746.43*** (126.34)
Panel B: June		
Probit regression	HFT	NHFT
Deletion	-1815.34*** (266.48)	-1113.57*** (254.70)
Submission	-185.17* (113.33)	27.092 (27.211)

This table shows the probit regression results of a dummy variable indicating an above-average deletion (submission) ratio on the first lag of the 1-minute volatility. The analysis is carried out for passive HFTs and NHFTs. Standard errors are given in parentheses and * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%.

informational advantage over NHFTs. This implies that they suddenly withdraw from markets when a certain level of market stress is reached to avoid increased hedging costs of market making (BIS (2014)). The above results are similar to those by Ait-Sahalia and Saglam (2014). In a theoretical approach the authors show that HFTs provide plenty of liquidity in quiet market periods but suddenly decrease their liquidity supply when volatility rises. I find that both deletion and order submission by HFTs rise in times of higher market stress. However, given that the deletion ratio is calculated with respect to added orders, the volume of order cancellation seems to rise disproportionately strongly.

Next, excess order deletions around NFP releases are analyzed. As shown by Figure 10, both HFTs and NHFTs cancel more orders than on average in the minutes before the NFP event. However, while for HFTs the deletion activity is highly pronounced during the entire five minutes before the macroeconomic news release, NHFTs' deletion activity increases immediately before the event. The difference between the HFT and NHFT excess deletion ratio is positively significant during this episode as well. There is no statistical relationship between excess volatility and deletions, however. Figure 11 shows the excess order submission by HFTs and NHFTs around the NFP news releases. One can see a divergent movement in the order submissions between HFTs and NHFTs. While HFTs seem to submit more orders than usual a few minutes before the news release, they scale back their supplied liquidity strongly within the minute before the news is released. This is supported by a weakly significant negative relationship between order submission and volatility for HFTs. At the same time, NHFTs submit many more limit orders

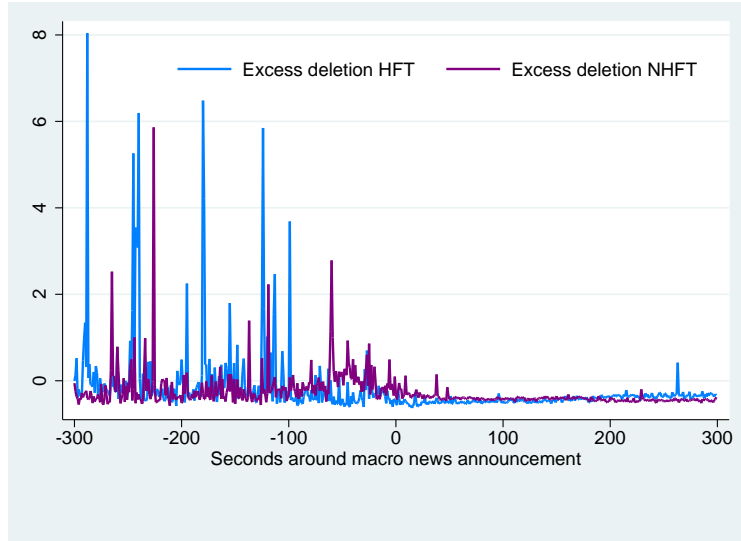


Figure 10: This figure depicts the HFT and NHFT excess deletion ratios per second around the NFP news releases.

immediately before the NFP release. Similarly, [Chaboud et al. \(2012\)](#) find that HFTs do not increase liquidity provision as much as human traders in the minute following the macroeconomic news announcement in terms of traded volume.

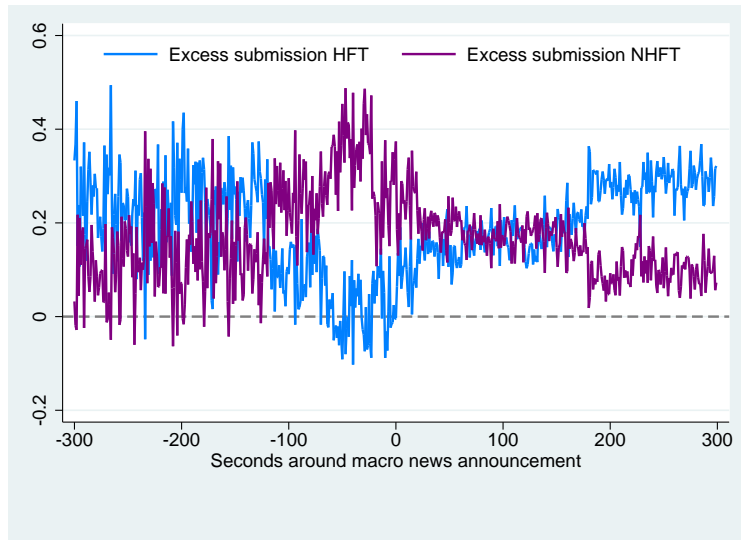


Figure 11: This figure depicts the HFT and NHFT excess submission ratios per second around NFP news releases.

To conclude, the above analysis yields slightly different results for HFT and NHFT liquidity supply depending on whether anticipated volatility due to previously announced macroeconomic news or unpredicted market stress as, e.g., in the week of March is considered. While passive HFTs tend to delete more limit orders as soon as market volatility rises suddenly, they know that macroeconomic news releases usually create high market

volatility and therefore already withdraw from markets several minutes before the event due to the risk of being adversely selected. Nonetheless, under both types of stress, HFTs overall supply less liquidity. By contrast, liquidity-providing NHFTs do not show a clear reaction to increased market stress.

7 Conclusion

In this study, I examine the impact of HFTs for price discovery and excessive volatility around major macroeconomic news releases. I further analyze HFTs' trading behavior and their role as market makers during episodes of high and low market stress. Within this work, I distinguish between two sources of volatility: unexpected volatility that is due to increasing risk aversion and expected volatility that follows from important macroeconomic news announcements.

The first part of the analysis looks at HFT trading behavior during a week of unexpected high volatility and a week of low volatility in a rather general setup. The results show that liquidity-taking (active) HFTs overall tend to follow momentum strategies. In times of high market stress they dominate over liquidity-providing (passive) HFTs who trade in the opposite direction of the market. But similar to active HFTs, the trading participation by passive HFTs is higher than usual when volatility rises unexpectedly. Against this evidence, slower traders overall withdraw from markets in phases of increased volatility since they deem the market too risky.

The core part of this paper addresses the trading behavior of HFTs around the release of major macroeconomic news such as the NFPs and ECB rate decisions. Since these news releases are known in advance, they constitute a second source of market stress which is anticipated by market participants to a certain extent ("expected volatility"). My results show that active HFTs are more dominant than any other trading group during the release of important macroeconomic news. They benefit from their speed advantage by trading according to the news surprise in the fraction of a second when the news is published. As soon as other slower traders buy or sell on the news, they close their positions and realize their trading profits. Limit orders of slower traders are usually picked off during these events. Analyzing HFT trading activity on a tick-by-tick basis, I find evidence that active HFTs substantially contribute to price discovery around macroeconomic news events. More specifically, in the milliseconds following the news release HFT trades contain more information than NHFT trades. Decomposing the variance into a permanent and a transitory component indicates a much larger contribution by active HFTs to transitory than to permanent volatility. Hence, the benefit of higher market efficiency through HFT trading comes at the cost of short-term excessive volatility, which is the result of

the fast information processing and aggressive trading in response to news events. The above findings suggest that overall HFTs consume liquidity in times of higher volatility, either expected as a result of macroeconomic news announcements or unexpected due to higher risk aversion of investors. However, the strategies pursued by active HFTs seem to depend on the market environment. While in times of rising unexpected volatility active HFTs overall follow momentum strategies, around the release of macroeconomic news they apply news trading strategies and react independent of previous price movements.

Finally, I address the question whether passive HFTs increasingly disappear from markets when uncertainty rises or whether they continue supplying liquidity. I find that in response to an unexpected rise in market volatility, passive HFTs cancel more orders than they submit. The opposite holds true for passive NHFTs, who are probably not as fast or well enough informed to quickly withdraw from markets during those stress episodes. Nevertheless, given that passive HFTs contribute strongly to the traded volume when volatility rises suddenly, a large number of them still seem to provide liquidity when it is needed. Around macroeconomic news events, passive HFTs increasingly cancel limit orders already several minutes before the data are released and scale back their order submission activity at the same time due to the known risk of being adversely selected.

The results of this study provide useful implications for academics, market participants and regulators. The finding that HFTs overreact to news and thereby contribute more strongly to noise than to information implies a higher risk of excessive volatility around important news events which can even cause flash events. Therefore, regulators should think of potential measures to incentivize HFTs to generate more informational trades. The results that passive HFTs provide less liquidity during macroeconomic news events amplifies the risk of market disruptions through the fast and strong reaction by active HFTs. In the future, slower market participants might be less willing to provide liquidity during those times given their inability to quickly withdraw from markets and the risk of being adversely selected, which could be additionally harmful for market stability. Hence, finding ways to guarantee liquidity provision even during stress episodes is of particular importance.

A Appendix

A.1 Classification methodology of technical transactions by latency-sensitive market participants

Deutsche Börse Group applies a methodology in order to classify technical transactions by latency-sensitive market participants for internal purposes. Based on the assumption that for transactions arriving randomly the non-correlated intervals between single transactions constitute an exponential distribution, one can represent their ratios relative to each other as a linear function when using the log of the number of observations per time interval.

The observation of a significant accumulation of transactions within very short time intervals ($< 500 \mu s$) of all transactions by a specific business unit relative to all transactions by all other market participants provides an indication that these transactions have been initiated by a latency-sensitive participant. The results based on the application of this methodology are used exclusively for internal purposes in order to classify and analyze latency-sensitive activities. Neither the methodology nor the classification are publicly available.

This methodology is not entirely consistent with common classification approaches such as, for example, those applied for regulatory purposes in order to identify high-frequency trading strategies. The aim of this methodology is the practicability and stability that guarantee the independence of third parties and transparency for the trading participants themselves.

A.2 Price impact of active NHFTs and NHFTs for 20 ticks

Table 7: Price impact of active HFT and NHFT - tick-based analysis 20 ticks

Panel A: Single IRFs			
	Active HFTs	Active NHFTs	Active HFT - NHFT
<i>SR</i>	0.053* (0.032)	0.084*** (0.032)	-0.031 (0.045)
<i>LR</i>	0.717*** (0.080)	0.185** (0.086)	0.532*** (0.117)
<i>LR - SR</i>	0.664*** (0.086)	0.101 (0.092)	0.563*** (0.126)

Panel B: Contribution to permanent and transitory variance			
	Active HFTs	Active NHFTs	Public information
Permanent variance	0.129*** (0.021)	0.000 (0.022)	0.862*** (0.032)
Transitory variance	0.453*** (0.109)	0.040 (0.091)	0.506*** (0.118)
Information-to-noise ratio	0.285*** (0.082)	0.010 (0.533)	1.703*** (0.403)

Panel A of this table shows the results of the impulse responses from active HFT and NHFT order flow on returns using 20 ticks, based on the VAR analysis including the macroeconomic news dummy as exogenous variable. *SR* denotes the short-run effect, *LR* is the cumulative effect after 20 ticks and (*LR - SR*) the difference between the two. Panel B includes the result of the variance decomposition for the permanent and transitory price components. It shows the shares of the variance of active HFTs and NHFTs, relative to the efficient and transitory variance, as well as the information-to-noise ratio after 20 ticks. Standard errors are given in parentheses and * denotes significant at 10%, ** denotes significant at 5%, *** denotes significant at 1%.

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