Does Speed Matter? The Role of High-Frequency Trading for Order Book Resiliency

Benjamin Clapham, Martin Haferkorn and Kai Zimmermann
Chair of e-Finance
Goethe University Frankfurt

Abstract

This paper explores limit order book resiliency following liquidity shocks in the presence of high-frequency trading firms. Based on a unique data set that enables the identification of orders submitted by algorithmic traders and subscribers of co-location services, we study whether high-frequency traders are involved in the reconstruction of the order book. We analyze order submission and deletion activity before and after a liquidity shock initiated by a large market order. Our results show that exclusively high-frequency traders reduce the spread within the first seconds after the market impact making use of their speed advantage. However, liquidity recovery in terms of order book depth takes significantly longer and is accomplished by human traders' submission activity only.

Keywords: Germany, High-Frequency Trading, Liquidity, Securities Markets, Market Quality, Resiliency

JEL Classification: G14, G15, G18, G28

Introduction

Since the emergence of highly automated trading desks and fully electronic securities markets in the last decade, academics, regulators, and trading firms argue about the direct and indirect consequences of this technological evolution on modern securities markets. Among the most controversially discussed issue is the speed of trading at which especially High-Frequency Trading (HFT) participants act and react within the open limit order book. In particular, proponents argue that automated decision making and low-latency infrastructure favors liquidity provision and order book resiliency as information evaluation and subsequent trading reaction is conducted more efficiently which subsequently may reduce implicit transaction costs. Especially in times of market distress or liquidity shocks, HFT traders may react quicker and more precisely in accomplishing the recovery of market liquidity thereby fostering order book resiliency. Accordingly, Brogaard, Hendershott, and Riordan (2014) show that HFT firms are more likely to participate in the order book when bid-ask spreads are wide, trading volume and price volatility are high, and when the order book depth is low. Likewise, Hasbrouck and Saar (2013) also find decreasing bid-ask spreads caused by HFT participants using data from 2007. Further is has been shown that HFT provides liquidity when spreads are wide and vice-visa (Carrion, 2013). This supports the findings of Hagstroemer and Norden (2013) who finds that HFTs mostly use market-making strategies. Considering recent regulatory initiatives where HFT was either directly or indirectly regulated caused an increase of the bid-ask spread in Canada (Malinova, Park, & Riordan, 2013) as well as in Germany (Haferkorn & Zimmermann, 2015). These results suggests that HFT resolves temporal imbalances in the order flow by providing liquidity if the public supply is insufficient and therefore provides a valuable service during periods of market uncertainty.

However, order book activity of HFT users is likewise found to be specifically adapted for the speed of modern trading systems minimizing especially their own market risk. Hence, HFT liquidity providers may use their superior latency to suddenly retreat from the order book in situations where market conditions are unclear. Indeed, related literature that focuses on the trading characteristics of HFT traders finds overall liquidity provision to be highly transitory due to the fact that their trading behavior is associated with an increase in order deletions, short order resting times as well as overall small trading sizes. Jarnecic and Snape (2014) examine liquidity supply by HTF firms versus non-HFT participants in the limit order book in 2009. The authors claim that low-latency trading activity focuses on the use of small aggressively placed orders in combination with rapid cancellations. When submitting non-marketable limit orders, high-frequency participants make use of short order durations. Further, the cancellation probability increases if the order was submitted at the bid-ask spread. Hence, transient liquidity provision biases the transparency of the open limit order book and increases the trading complexity for non-HFT participants. Subsequently, the quality of HFT liquidity provision depends on the utilization of latency advantages especially during liquidity shocks where such strategies bridge liquidity gaps and foster order book resiliency.

Therefore, this paper examines the quality of order book resiliency in the presence of HFT. Based on the depicted debate about the role of HFT for liquidity provision, this paper determines the contribution of this trader faction in contrast to non-HFT participants following liquidity shocks to the open limit order book. During and after such shocks, low-latency traders can maximize their speed advantages and benefit from the widened bid-ask spreads respectively the low order book depth. Given HFTs follow such strategies, other market participants may profit from the increased order book resiliency. Therefore, we apply a data sample of large market orders that hit the open order book and clear several order book levels. In particular, we focus on the order submission behavior of HFT and non-HFT traders around these market order shocks to add further evidence on this highly controversial topic. We therefore rely on a proprietary data set provided by Deutsche Boerse where HFT as well as Algorithmic Trading (AT) activity is explicitly indicated. Thus, we are able to provide detailed insights into the order book resiliency dynamics in the presence of HFT participants.

In particular, we find HFT participants significantly contributing to the recovery of the open limit order book. Especially HFT using co-located machines are found to be the driving force in reestablishing tight spreads with superior speed and precision. In contrast, AT participants that do not rely on low-latency infrastructures need additional time before likewise contributing to the recovery of the bid-ask spread. In total, with the help of HFT and AT participants the bid-ask spread recovers within the first few seconds after the market order shock, while the largest fraction recovers even within the first second. Human traders, although adapting their submission behavior within the very first seconds after the shock, do not significantly affect bid-ask spread recovery. However, considering the resiliency of order book depth besides the bid-ask spread, results strikingly change. HFT and AT participants totally refrain from refitting the order book depth level. This is only achieved by human traders contributing with abnormally high net liquidity provision combined with large order sizes. Therefore, fast and transient liquidity provision of HFTs that is also prevailing after liquidity shocks, represents only a very specific and limited contribution to overall order book resiliency. In order to absorb further liquidity shocks, order book depth levels have to be refitted by manifold orders. As shown in our analysis, this is only achieved with the help of various human traders that persistently stay in the order book and offer a vast amount of non-transient liquidity.

Within section two, the applied data sets are present and descriptively analyzed. Section three addresses the methodological approach as well as the results of the analysis. Finally, section four concludes.

Data

Data Set

Our study focuses on the German blue-chip index DAX30 which comprises the 30 largest and most actively traded German companies. The data set provided by Deutsche Boerse contains all Xetra trading messages for the DAX30 securities within the two-weeks time period from August 31$^{\text{st}}$ to September 11$^{\text{th}}$, 2009, thereby covering 10 trading days. In this time interval, 74.4% of the trading volume of these 30 securities was executed on Xetra, the electronic order book of Deutsche Boerse (Fidessa (2015), for comparison, in March 2015, 55.7% of total trading volume was executed on Xetra). For every messages, the data set available contains a time stamp, the International Securities Identification Number (ISIN) of the respective stock, an order number which allows to identify all other messages related to the same event, the information whether the respective order was a buy or a sell order as well as information about limit respectively price and order size. Moreover, the data set contains several flags which are particularly important for the purpose of this study. An auction trade flag indicates the trading phase in which a specific message occurred. The order type indicates whether an order is a limit, market, iceberg or market-to-limit order. The Modification Reason Code (MRC) illustrates why the observation was generated. A message might be created because of an order submission, an order modification, the deletion of an order by a user, full or partial execution of an order, deletion of an order by the trading system or other system-sided reasons.

The uniqueness of the available data set is caused by an additional AT flag (Algo-flag) that indicates whether a certain message has been triggered by an algorithm (Algo-flag = 1) or not (Algo-flag = 0). The identification of algorithmic traders is possible because Deutsche Boerse implemented a special pricing model for computer generated trades called Automated Trading Program (ATP) in 2005 to increase the transparency of algorithmic trading on its electronic trading system Xetra (Deutsche Boerse, 2004). Buy side customers participating in the Automated Trading Program can take advantage of fee-rebates for transactions that have been triggered by an algorithm if they oblige themselves to exclusively use their Automated Trading User-ID whenever they trade using computer algorithms. In order to be classified as an order triggered by an algorithm, a computer must determine at least two of the following parameters: price (market order or limit order with limit), timing (time of order entry), and quantity (number of securities) (Deutsche Boerse, 2004). Moreover, an electronic system must submit or delete an order independently without manual intervention. Since the rebates increase with a customer's number of algorithmic trades per month, it is rational for banks and brokers to use their Automated Trading User-ID for every order triggered by an electronic system. While the requirements for the Automated Trading Program set by Deutsche Boerse ensure that users are in fact algorithmic trading engines, not all algorithmic traders might participate in the program despite the strong incentives for these traders to do so. However, Hendershott and Riordan (2011) show that the savings associated with the Automated Trading Program are significant for high-frequency trading firms, whose turnover is higher than the amount of capital invested. Therefore, the Algo-flag appears to be highly reliable and the best proxy for algorithmic trading activity currently available. Since Deutsche Boerse extended the fee reduction program to all Xetra orders in November 2009, it effectively ended the possibility to differentiate between algorithmic and non-algorithmic trading (Deutsche Boerse, 2009). Therefore, a more recent data set is not available.

Additionally, a second flag indicates whether the submitter of an order is a subscriber of co-location services (Colo-flag = 1) offered by Deutsche Boerse or not (Colo-flag = 0). Therefore, fast traders using co-location services can be differentiated from relatively slower ones. However, this classification does not ensure that every order flagged as being submitted by a co-located trader has been inserted via a co-located machine since a subscriber of co-location services can still use traditional ways to send orders to the exchange. However, it is highly probable that most orders flagged as co-located have indeed been inserted making use of co-location services since traders who pay for being able to submit orders in high frequency would act irrational if they would not use their speed advantage. All corresponding messages to an order submission such as modification or deletion will have the same Algo-flag respectively Colo-flag as corresponding messages can be identified via the order number by the system. Combining Algo- and Colo-flag, we are able to differentiate four different factions of traders (numbers in parentheses represent Algo-flag/Colo-flag): High frequency traders (HFT, 1/1), non-HFT algorithmic traders (AT, 1/0), human traders (0/0), and traders not using algorithmic trading engines yet having co-location access (0/1). The last category is somewhat difficult to interpret. This faction might include both high frequency traders not participating in the ATP program despite the strong incentive to do so as well as human traders trading via intermediaries that have subscribed for co-location services. As this category possibly is a mixture of different trader factions and due to its rather small size, it will not be considered for further analysis. Using the other three factions, we are able to differentiate between the trading activity of HFT, AT, and humans and can analyze their respective role for order book resiliency.

Table 1 reports descriptive statistics for the 30 DAX constituents between August 31$^{\text{st}}$, 2009 and September 11$^{\text{th}}$, 2009. Stock price and volume related data as well as market capitalization of the stocks are gathered from the website of Deutsche Boerse. Market capitalization is reported per December 31$^{\text{st}}$, 2009 and the standard deviation of daily returns is determined for each stock during the sample period. All other variables are calculated based on 300 observations (30 stocks and 10 trading days). As market capitalization suggests, the 30 stocks included in this data set represent the largest traded German companies. However, the smallest firm Salzgitter AG with a market capitalization of 2.57 billion euro is almost 19 times smaller than the largest company E.ON AG. Also, daily trading volume differs quite significantly. However, the constituents of the DAX are highly liquid securities with a mean daily trading volume of 92.73 million euro.

In order to study the role of HFT, AT, and humans for order book resiliency, we only focus on data created during continuous trading phases since market impacts caused

Table 1: Descriptive statistics of the DAX30 constituents

Variable	Mean	Std. Dev.	Min	Max
Market Cap (euro billion)	17.56	14.92	2.57	48.47
Price (euro)	43.68	25.23	8.75	135.05
Daily Returns (%)	-0.01	2.00	-8.55	10.33
Std. Dev. of Daily Returns (%)	1.89	0.83	0.83	4.78
Daily Trading Volume (euro million)	92.73	76.22	0.99	428.95

by liquidity shocks are less prevalent in high liquid call auctions. The data set contains 1,243,083 messages created during continuous trading, thereof 49.1% submissions, 40.9% deletions by users, 5.2% executions, 2.7% partial executions, and 2.0% modifications. The number of modifications compared to submissions and deletions is rather low because only a reduction of the order's volume leads to a modification while all other changes which affect the price-time-priority of an order lead to the deletion of the order and the insertion of a "new" order with a new time stamp and order number. The remaining 3.2% of all messages represent technical messages such as deletions by the exchange system which are not relevant for the following analysis. Therefore, all messages other than submission, modification, deletion by user, execution and partial execution are dropped from the data set. Moreover, submissions that resulted in a deletion in the same 1/100 second are excluded together with their deletions because they are not liquidity increasing and therefore do not contribute to order book resiliency. These modifications lead to a sample of 1,049,212 messages, where most of them are triggered by HFT. As depicted in Table 2, 64.9% of all messages in the data set at hand are generated by HFT, 15.4% by AT, and only 12.4% by human traders.

Table 2: Proportion of messages triggered by each of the four trader factions

	Colo	Non-Colo
Algo	64.9%	15.4%
Non-Algo	7.3%	12.4%

Market Impact Events

In order to analyze order book resiliency, we have to identify events in which an order results in high market impact meaning that the order leads to an immediate and considerable price change by taking significant liquidity away from the market. Related research investigating order book resiliency typically relies on large orders to classify market impact (e.g. Large (2007), Chlistalla (2011)). However, a relatively large order does not necessarily lead to a notable price and thus market impact. Gomber, Schweickert, and

Theissen (2015), for example, show that large orders are timed which implies that large orders are most often submitted in times of high liquidity to avoid market impact. To circumvent this problem, we directly identify market impact events using a price-based technique as suggested by Biais (1995), who identifies market impact events via aggressive orders that require more liquidity than present at the highest bid/lowest ask. Specifically, we take the data set at hand and count the partial executions that follow a specific market order. As every partial execution represents the volume traded for a certain price, the number of partial executions shows how many order book levels have been cleared respectively affected by an incoming order. We choose market orders instead of limit orders since market orders are executed for any price available while limit orders are only executed as long as the price is above/below a certain limit while the remaining volume rests in the order book.

For our analysis, we take the 10 market orders with the highest number of partial executions (i.e. with the highest market impact) for every stock listed in the German blue chip index DAX30 in the time window available so that we identify 300 market impact events in total. If there are several market orders for an identical stock executed with the same number of partial executions and not all of them can be considered in the sample of 10 events per stock, market orders with higher volume are given preference. Additionally, we did not include any market impact events in our sample that happened 15 minutes before or after an auction as well as circumstances in which two market events follow one another in order to avoid a bias from these special situations. Although the data set provided by Deutsche Boerse contains highly relevant information, no order book data are included although they are necessary to analyze the quality of the order book resiliency. Therefore, we mapped order book data retrieved from Thomson Reuters Tick History (TRTH) to the respective events. Thereby, 33 events were lost in the course of the mapping process because the time stamps of both data sources are not synchronized and the order book impact was not visible in the TRTH data. However, the remaining 267 events could properly be identified and were double-checked manually. The market orders that lead to market impact are almost evenly split between buyer (134) and seller-initiated (133) orders. However, 79.4% of these orders are submitted by human traders while 6.4% are inserted by AT and only 2.2% by HFT. This finding seems reasonable since AT regularly slice large orders into smaller parts using limit orders in order to avoid market impact while human traders might also trade large quantities with market orders, e.g. if they need to fulfill contracts or close positions in a short period of time. Moreover, HFT only operate on the top levels of the order book submitting and deleting limit orders within short durations as shown by Jarnecic and Snape (2014). The following Table 3 depicts the descriptive statistics of the 267 events included in the sample.

Although we have not explicitly searched for the largest orders to identify order book situations with large market impacts, the volume of the market orders that initiated the events covered in this study are on average 12.30 times (median 9.92 times) larger than the respective stock's Standard Market Size reported by the European Securities and Markets

Table 3: Descriptive statistics of events

	Market Impact (euro)	Ordersize (no. of shares)	Volume (euro)	Volume/Standard Market Size
Mean	0.07	8,355	232,741	12.30
Median	0.06	4,030	170,842	9.92
Min	0.01	190	18,623	0.67
Max	0.35	117,700	1,590,104	63.60

Authority (ESMA) for the analyzed time period. Moreover, the mean price impact of 0.07 euro (median 0.06 euro) is quite significant given that we study the most liquid German stocks with tick sizes of 0.01 euro respectively 0.005 euro. The descriptive statistics per stock are given in appendix.

Having identified the market impact events, we drop all partial and full execution messages (95,990 messages in total) because they do not represent trader's activity in a narrower sense since executions are rather system-generated consequences of previous submissions and therefore do not contribute to order book resiliency. Moreover, we do not consider market order submissions and order modifications (24,336 messages in total) for the following analysis since they do not provide liquidity respectively the change in liquidity provision cannot be measured adequately. In order to analyze the resiliency after the order book is hit by a large market order that clears several order book levels, we concentrate on each trader faction's activity before and after the event by investigating their submission (liquidity providing) and deletion (liquidity taking) behavior. In a first step, we show the submission and deletion behavior during the five (ten) seconds before and after the 267 events included in this study. This time frame seems to be appropriate given that we analyze HFT, AT and human trader's activity. Moreover, the time frame is also supported by the findings depicted in Figure 2 in the subsequent chapter. The following Tables 4 and 5 give an impression how the different trader factions react to market impacts.

Table 4: Trading behavior before and after a market impact (five seconds)

Mean	HFT		AT		Humans		Algo=0, Colo=1	
(Median)	-5	+5	-5	+5	-5	+5	-5	+5
Submissions	35.58%	37.75%	5.45%	7.15%	9.64%	9.36%	3.95%	3.94%
	(34.29%)	(38.27%)	(0.00%)	(5.16%)	(5.06%)	(7.94%)	(0.00%)	(2.88%)
Deletions	31.86%	29.63%	5.27%	5.62%	4.29%	3.57%	3.95%	2.98%
	(31.71%)	(30.12%)	(0.00%)	(3.85%)	(0.00%)	(3.03%)	(0.00%)	(2.00%)
Total Activity	67.44%	67.38%	10.71%	12.78%	13.94%	12.93%	7.91%	6.91%
	(65.99%)	(68.39%)	(0.00%)	(9.01%)	(5.06%)	(10.97%)	(0.00%)	(4.88%)

Tables 4 and 5 report the mean and median share of submission and deletion activity

Table 5: Trading behavior before and after a market impact (ten seconds)

Mean	HFT		AT		Humans		Algo=0, Colo=1	
(Median)	-10	+10	-10	+10	-10	+10	-10	+10
Submissions	36.12%	37.74%	6.06%	7.09%	9.39%	8.93%	3.98%	3.90%
	(36.23%)	(38.37%)	(2.47%)	(5.17%)	(6.15%)	(7.41%)	(1.77%)	(2.89%)
Deletions	31.58%	30.28%	5.87%	5.76%	3.59%	3.50%	3.41%	2.89%
	(31.58%)	(30.56%)	(1.37%)	(3.57%)	(1.64%)	(3.08%)	(1.27%)	(1.96%)
Total Activity	67.70%	68.03%	11.93%	12.75%	12.98%	12.43%	7.39%	6.78%
	(67.81)%	(68.93%)	(3.84%)	(8.74%)	(7.79%)	(10.49%)	(3.04%)	(4.85%)

for each faction five (ten) seconds before and after a market impact. Each percentage shown in both tables is calculated as the mean (median) proportion of a faction's submissions (deletions) compared to all factions' submissions and deletions in a certain time interval over the 267 events included in the sample. Total activity is calculated by summing up the submission and deletions percentages for each faction and time interval. The mean pre-event (post-event) percentages of submissions and deletions add up to 100%. The same holds true for total activity in each time interval. Similar to the complete sample analysis presented in Table 2, HFTs are the most active faction in terms of submissions and deletions with around 68% of all messages around market impacts. AT and human traders generate significantly less submissions and deletions ranging from 10% to 14%. Moreover, human traders have more than twice as many submissions as deletions while HFT and AT generate a lot of deletions compared to their submissions. This in turn means that HFT and AT frequently delete their orders before they are being executed. As shown in Tables 4 and 5, all three factions seem to react to the market impact event by changing their submission and deletion behavior. Each faction's percentage of submissions increases after a market impact while the percentage of deletions decreases or remains stable meaning that all groups of traders provide more liquidity after the exogenous shock of a large market order. While total activity of HFT and humans remains relatively stable, it increases slightly for AT.

The increasing commitment of liquidity by all trading factions as suggested by the numbers in Tables 4 and 5 is also supported by the observations reported in Figure 1 which depicts the mean euro order volume of all factions five (ten) seconds before and after the liquidity shock. All traders increase the mean euro order size after the market impact thereby providing additional liquidity. This finding is true for both time time windows analyzed in this study. Additionally, the chart shows that human traders submit orders with on average significantly larger order sizes than AT and HFT. Their mean order size across all 267 events amounts to 23,654 euro (27,216 euro) in the five (ten) seconds interval before the order book is hit by a large market order and 40,614 euro (40,080 euro) in the five (ten) seconds interval after the market impact. ATs submit the smallest mean order sizes of all factions with 7,177 euro (10,499 euro) before and 10,973 euro (11,652 euro) after

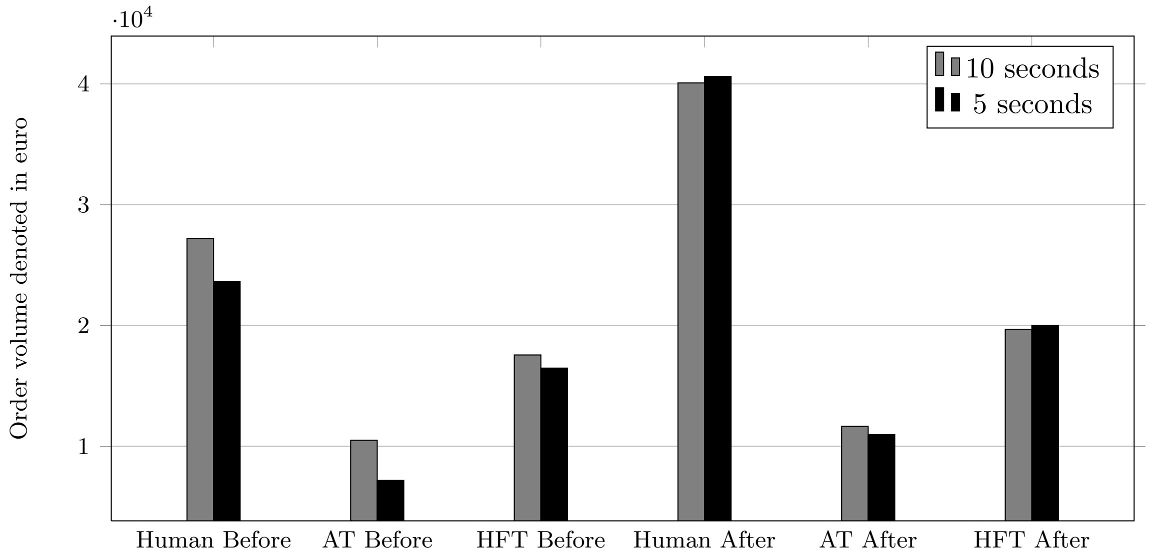

Figure 1. : Order volume of each trader faction before and after our event.

the liquidity shock. This finding seems reasonable since pure ATs often split large orders into smaller sizes to avoid market impact. The mean order sizes of HFTs are in between the ones of the other trader factions with on average 16,475 euro (17,564 euro) before and 20,005 euro (19,686 euro) after the market impact event.

Reactions to Market Order Liquidity Shock

Research Approach

In this section, we summarize our empirical approach directed to evaluate the role of AT and HFT firms for the resiliency of the limit order book. Based on the exogenous shock of a large market order, we analyze the reaction and contribution of each trader faction separately in order to derive distinct patterns that characterize the behavior and commitment of these market participants. Within the next section, we further evaluate each faction's trading activity based on its contribution to the quality of the subsequent order book resiliency dynamic. We start with a general evaluation of each faction's adaption concerning their submission and deletion behavior. We relate the submission to deletion ratio following each shock to the respective pattern in the moment right before the submission of the market order. Therefore, we use two different observation periods in order to obtain robust insights. We rely on a short-term window of five seconds before and after the execution of the market order. Further, we apply a ten seconds time window in order to account for delayed effects. Both time windows are highly relevant for our data sample as indicated by the average second-wise aggregation provided in Figure 2. Figure 2 depicts one second average bid-ask spread as well as the order book depth starting with the spread (depth) situation just after the execution of the market order.

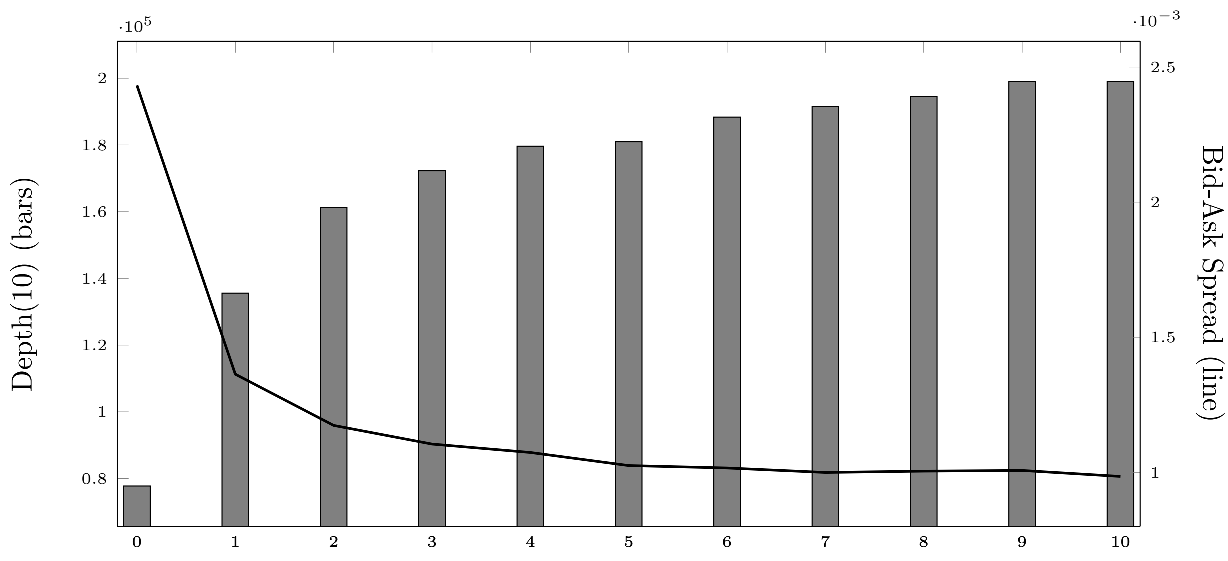

Figure 2. : Aggregated bid-ask spread and Depth(10) recovery ten seconds after the market order shock

Results

Two distinct observations are obviously indicated in this high level aggregation. First, relative bid-ask spreads seem to recover quite fast. While the strongest recovery occurs within the first second after the event, it takes further four seconds until the relative bid-ask spread proceeds without further significant changes. After five seconds following the initial impact, no significant changes in the average relative bid-ask spreads are observable. Second, order book depth needs additional time to reach a similar constant and persistent normal level. Even though the largest recovery contribution is located within the first second, it takes up to eight more seconds to gain a constant level. So far, these results are not based on statistical reasoning and thus only argue in favor of the proposed observation periods. With the five and the separate ten seconds intervals we are able to analyze the entire recovery dynamic of both liquidity dimensions. One might ask whether five seconds are a reasonable time period to analyze trading activity, especially if HFT is the subject of interest. In particular, previous studies confirm that HFT activity takes place in fractions of seconds (Jarnecic & Snape, 2014; Brogaard et al., 2014). However, the methodology we propose does not aim at a millisecond-wise liquidity leader and follower perspective. HFT reacts much faster than AT or human traders based on their superior infrastructure. In contrast, our approach aims at identifying each factions' overall contribution to the entire recovery process that takes into account the whole five respectively ten seconds following the event. Therefore, not only the first second is of special interest for our analysis but also the subsequent resiliency dynamic.

In order to answer whether and how the specific trading factions are reacting to this event, we determine each faction's normal liquidity provision characteristics based on the respective five and ten seconds interval before the shock. Hence, we will not analyze the change in mere trading frequency based on the overall trading activity. These results are shown descriptively the previous section (p. 8). This section focuses on the change in liquidity provision. Liquidity provision is hereby determined by the net effect of all liquidity donating limit order submissions in the respective observation window and all subsequent order book deletions for each faction. Hence, liquidity provision as defined in the context of this study does only involve the net submission or deletion activity in the respective observation window of five and ten seconds. Therefore, net liquidity provision can be negative if a faction is systematically deleting all existing limit orders while simultaneously submitting less new limit orders. Obviously, net liquidity provision is positive in case the respective faction is submitting more orders than it has deleted. As especially HFT-strategies heavily rely on a high deletion ratio, this approach is suited to differentiate between real and transient liquidity provision. Further, as indicated in the previous section, all submissions that resulted in a deletion in the same 1/100 second are excluded together with their deletions. Our net liquidity provision ratio is calculated as follows:

$$NetLiquidityProvision = \frac{(Submissions - Deletions)}{(Submissions + Deletions)} \tag{1}$$

Subsequently, a $NetLiquidityProvision$ of one indicates that the respective trader faction submitted at least one limit order with no deletion within five or ten seconds after the shock. On the other hand, a net liquidity provision of minus one shows that the respective faction has deleted at least one existing order without submitting a new one. If a faction neither submitted nor deleted within five or ten seconds, the measure is set to zero. Further, net liquidity provision ratios of each faction within five and ten seconds before and after the liquidity shock are obtained and analyzed in a cross-sectional regression setup. The estimated regression model is based on the following equation:

$$\begin{aligned} NetLiquidityProvision = \alpha &+ \beta_1 * AT + \beta_2 * HFT + \beta_3 * PrePost * \alpha \\ &+ \beta_4 * PrePost * AT + \beta_5 * PrePost * HFT \\ &+ \beta_6 * Activity + \sum_{n=7}^{45} \beta_n * Controls_n + \epsilon \end{aligned} \tag{2}$$

Therefore, all five (ten) seconds $NetLiquidityProvision$ ratios before as well as after the shock are explained and compared according to their respective characteristics. Consequently, the number of observations is increased by the factor six to 1,602, as each of our 267 events has a pre- and a post-event observation and is calculated for HFT traders, AT traders, and human traders. AT (HFT) is a dummy variable indicating that the liquidity provision ratio contains only submissions and deletions of AT (HFT) firms. Consequently, $PrePost$ is a dummy variable that equals zero if the ratio is measured based on the five (ten) second before the shock. $PrePost$ switches to one, if the ratio measures the submission to deletion ratio after the shock. The interaction terms $PrePost * \alpha$, $PrePost * AT$ and $PrePost * HFT$ subsequently indicate the changes in the respective human, AT and HFT ratios between the ratios before and after the shock. Additionally, we apply control variables capturing further idiosyncratic differences of the different ratios. Foremost important is the overall activity level in terms of the sum of submissions and deletions in the specific five (ten) seconds observation window. Intuitively, the $NetLiquidityProvision$ ratio may systematically be different based on each stock. We therefore apply a dummy variable for each of the 30 different stocks as well as a dummy for each trading day. Finally the estimation provides an overview of the different net liquidity provision ratios of each faction before the market order shock. Most interestingly, the estimated coefficients on $PrePost * \alpha$, $PrePost * AT$, and $PrePost * HFT$ provide indications about a significant and systematic change of each trading faction's behavior in the post-event situation. Table 6 presents the estimates on the five as well as on the ten seconds aggregation.

Table 6: Results on the liquidity provision regression based on equation 2 for the five and ten seconds interval respectively. Heteroskedastic robust variance estimators are applied. t statistics in parentheses;* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1) $NetLiquidityProvision$ 5 seconds	(2) $NetLiquidityProvision$ 10 seconds
AT	-0.193***	-0.231***
	(-5.99)	(-7.33)
HFT	-0.165***	-0.220***
	(-4.59)	(-7.40)
$PrePost * \alpha$	0.178***	0.109***
	(5.51)	(3.75)
$PrePost * AT$	0.143***	0.125***
	(5.19)	(4.48)
$PrePost * HFT$	0.0822**	0.0589**
	(3.16)	(2.71)
$Activity_5$	-0.000496**	
	(-3.27)	
$Activity_{10}$		-0.000283*
		(-2.02)
Constant	0.205***	0.280***
	(3.56)	(5.81)
Observations	1,602	1,602
Adjusted R^2	0.151	0.183

Compared to the descriptive statistics of the previous section, the regressions provide a deeper insight into the change of the specific trader factions' behavior. The constant of the equation (2) represents the average pre-event net liquidity provision ratio of human traders that do not participate in the ATP program and likewise do not connect via a collocated infrastructure. Within the five and ten seconds before the shock, these non-HFT non-AT traders show an average positive net liquidity provision ratio of 0.21 (five seconds) to 0.28 (ten seconds), indicating that this faction submits more limit orders to the order book than it actually deletes. Based on the coefficients, only two out of three limit order submissions are subsequently cancelled. In comparison, AT as well as HFT participants show a significant lower commitment as both faction's net liquidity provision ratios within the pre-event phase is significant lower. The ratio of AT (HFT) participants is on average

0.01 (0.04) percentage points lower in the five seconds observation window compared to human traders. Similar effects can be observed for the ten seconds interval (AT: 0.05; HFT: 0.06). Therefore, the number of submissions of AT and HFT participants equals roughly the number of deletions in the pre-event window. These results are in line with recent academic papers, showing that especially HFT traders rapidly submit and delete orders in order to follow the current order book conditions (Jarnecic & Snape, 2014). Results confirm that traders, relying on automated and autonomous order generation systems follow transient order duration strategies. The change in liquidity provision characteristics after the shock are depicted by the respective coefficients at the $PrePost$ interactions. For each trader faction, the coefficient shows an average in- or decrease of the pre-event average. Starting with the reaction of the human trader faction, the coefficient indicates a significant increase of about 0.18 (0.11) percentage points in the five (ten) seconds after the event. Therefore, human traders nearly double their engagement, i.e. net liquidity provision ratio, in the time following the shock. Likewise, AT as well as HFT participants increase their engagement significantly. As the initial pre-event net liquidity provision ratio is close to zero, the increase in the post-event phase is especially severe. The submission to deletion ratio of AT (HFT) participants rises by about 0.14 (0.08) percentage points within five seconds. Results are similar within the ten second period (AT: 0.12; HFT: 0.06). In total, all trading factions react to the liquidity gap due to the incoming market order. However, the commitment to liquidity provision of the human trader faction remains the highest in both observation periods. That means, human traders submit essentially more liquidity to the order book before and after the event than they consume. On the other hand, liquidity provision of AT as well as HFT participants is more transient as submissions are more regularly accompanied with subsequent deletions. Even though, AT and HFT traders react positively to the liquidity shock since the net liquidity provision ratio significantly increases. Based on the low pre-event ratio, the relative increase in the net liquidity ratio is the most severe. For now, the analysis covered the quantitative change in liquidity provision. In order to give an indication for the qualitative effect of these changes, we have to analyze the resiliency dynamics using order book characteristics within the respective five and ten seconds intervals. This way, we are able to extent the previous analysis to the specific utility of the change in the traders' submission and deletion behavior for order book resiliency.

Order Book Resiliency

Research Approach

Although different in the specific magnitude, each factions' reaction to the market order liquidity shock is considered positive for the resiliency of the order book as more new limit orders are submitted to the order book than deleted by market participants. The actual contribution to order book resiliency is the focus of this subsection. Therefore, we strive to evaluate whether and how the different factions affect order book liquidity resiliency in the post-shock phase. Hence, we propose a very intuitive two step analysis model. First, we determine the quality of the order book resiliency for each event. Subsequently, the quality measure is related to the specific net liquidity provision ratios of each faction within the five and ten second period following the liquidity shock. Thus, we are also able to identify which faction systematically contributes to different dimensions of liquidity recovery.

First, we focus on the measurement of the order book resiliency efficiency for each of our 267 events. Therefore, we assume that resiliency is conducted in a more efficient way, the faster liquidity is restored after the liquidity shock. The most common liquidity dimensions are the relative bid-ask spread in terms of trading cost at the top of the order book as well as market depth as proposed by Degryse, Jong, and Kervel (2011) that covers order book breadth. Both dimensions account for different order book characteristics and, based on the selection of our events and indicated in Figure 2, are affected by the liquidity shock. Hence, the stronger and the fast both measures recover after the shock, the more efficient the resiliency dynamic is assumed. However, we need to find a measure that allows for comparability of this process among all events in order to differentiate faster order book resiliency from slower. We therefore estimate the specific abnormal order book recovery level of each event based on the following regression model:

$$Liquidity_{post} = \beta * Liquidity_{event} + \epsilon \tag{3}$$

$Liquidity_{post}$ denotes the average liquidity (relative bid-ask spread or Depth(10)) within five and ten seconds after the shock excluding the order book snapshot right after the execution of the large market order. Within the five and ten seconds, the average relative bid-ask spread (Depth(10)) incorporates the respective level of liquidity resiliency. Moreover, a sharp or a very fast liquidity recovery will result in a lower (higher) average bid-ask spread (Depth(10)) as recovery takes additional time. Likewise, $Liquidity_{event}$ denotes the single liquidity snapshot (relative bid-ask spread or Depth(10)) following the liquidity shock, i.e. the first order book situation after the execution of the large market order. Thus, β_1 estimates the average rate of liquidity recovery based on all 267 observations. We assume the coefficient to be smaller (larger) than one in the bid-ask spread (Depth(10)) regression, indicating that the average liquidity level following the shock has significantly improved compared to the liquidity situation right after the shock. β_1 is therefore considered the expected liquidity recovery after the liquidity shock. Further, this simple linear relation covers the abnormal order book recovery quality specific for each observation indicated by the error term ϵ. In case ϵ is negative, $\beta_1 * Liquidity_{event}$ is further reduced, i.e. we observe a positive (negative) deviation from the expected bid-ask spread (Depth(10)) recovery as the $Liquidity_{post}$ is smaller (larger) than anticipated in this situation. Subsequently, a positive ϵ indicates that $Liquidity_{post}$ is larger than the expected overall liquidity recovery, i.e. the bid-ask spread (Depth(10)) recovery took longer (shorter) or was less (more) effective within the observed observation windows. The probability distribution of the abnormal order book recovery quality ϵ for five as well as ten seconds are depicted in the appendix.

Within the next step, we relate the abnormal order book recovery quality ϵ to the respective $NetLiquidityProvision$ measure of the AT, HFT and human participants in the same five and ten seconds after the shock. If a positive or negative expected overall liquidity recovery of a distinct liquidity measure can regularly be associated with the contribution of one specific trader faction, then a regression setup can estimate such a significant relation. Otherwise, if a specific trader faction is regularly contributing via a high submission rate but abnormal order book recovery quality remains negative, the quality of those submission must be doubted. The regression is performed in the following way:

$$\begin{aligned}\epsilon = \gamma + \delta_1 * NetLiquidityProvision_{AT} + \delta_2 * NetLiquidityProvision_{HFT} \\ + \delta_3 * NetLiquidityProvision_{Human} + \delta_4 * Activity + \sum_{n=5}^{43} \delta_n * Controls_n + \theta\end{aligned} \tag{4}$$

Where ϵ represents the abnormal order book recovery quality, $NetLiquidityProvision$ the submission to deletion ratio as introduced in equation 1 for each trader faction, i.e. AT, HFT, and human traders (the distribution of each $NetLiquidityProvision$ measure is presented in the appendix). Again $Activity$ represents the control variable for the overall activity level measured by the sum of all submissions and deletions within the five and ten seconds after the liquidity shock. In addition, we include dummy variables for all stocks and all trading days ($\sum_{n=5}^{43} \delta_n * Controls_n$). The regression is performed on the relative bid-ask spread for the five and ten seconds period. Subsequently, the depth measure is analyzed. We estimate the regression for each $NetLiquidityProvision$, i.e. AT, HFT, and Human separately (AT, HFT and $Human$) as well as combined with all three explanatory variables. The regression is performed on the five as well as on the ten seconds period.

Table 7: Results of the bid-ask spread resiliency regression performed on the five and ten seconds interval respectively. Variables AT, HFT, and $Human$ refer to the coefficient of the respective $NetLiquidityProvision$ of that faction within five and ten seconds after the liquidity shock. Heteroskedastic robust variance estimators are applied. Standardized beta coefficients; t statistics in parentheses;* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Bid-Ask Spread - 5 seconds				Bid-Ask Spread - 10 seconds			
	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AT_5	-0.045			-0.031				
	(-1.01)			(-0.69)				
HFT_5		-0.107*		-0.112*				
		(-2.16)		(-2.21)				
$Human_5$			-0.078	-0.086				
			(-1.63)	(-1.76)				
AT_{10}					-0.119**			-0.107*
					(-2.62)			(-2.39)
HFT_{10}						-0.137**		-0.125*
						(-2.81)		(-2.57)
$Human_{10}$							-0.004	-0.005
							(-0.08)	(-0.09)
$Activity_5$	-0.265***	-0.277***	-0.273***	-0.290***				
	(-3.85)	(-4.01)	(-4.04)	(-4.25)				
$Activity_{10}$					-0.226***	-0.244***	-0.211**	-0.255***
					(-3.48)	(-3.69)	(-3.14)	(-3.86)
Observations	267	267	267	267	267	267	267	267
Adjusted R^2	0.483	0.490	0.485	0.492	0.496	0.498	0.482	0.505

Table 8: Results of the Depth(10) resiliency regression performed on the five and ten seconds interval respectively. Variables AT, HFT, and $Human$ refer to the coefficient of the respective $NetLiquidityProvision$ of that faction within five and ten seconds after the liquidity shock. Heteroskedastic robust variance estimators are applied. Standardized beta coefficients; t statistics in parentheses;* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Depth(10) - 5 seconds				Depth(10) - 10 seconds			
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
AT_5	0.053			0.033				
	(1.04)			(0.66)				
HFT_5		0.003		0.019				
		(0.05)		(0.38)				
$Human_5$			0.214**	0.212**				
			(3.12)	(3.11)				
AT_{10}					0.090*			0.087
					(2.02)			(1.88)
HFT_{10}						0.053		0.043
						(1.17)		(0.96)
$Human_{10}$							0.143	0.144*
							(1.94)	(1.96)
$Activity_5$	0.205*	0.203*	0.230**	0.234**				
	(2.34)	(2.32)	(2.65)	(2.68)				
$Activity_{10}$					0.164*	0.166*	0.169*	0.191*
					(1.99)	(1.99)	(2.03)	(2.25)
Observations	267	267	267	267	267	267	267	267
Adjusted R^2	0.255	0.252	0.284	0.279	0.266	0.260	0.271	0.275

Results

The results give different insights on the specific quality of liquidity provision. Keeping in mind that human traders are among the faction with the highest net liquidity provision ratio, especially in the post-shock phase, their contribution to the recovery of the bid-ask spread is highly questionable. Within the five as well as the ten seconds observation period, no abnormal positive recovery effect is measurable when human traders provide more liquidity. Although coefficients are negative, they are not significantly different form zero on the five percent significance level. The same result can be observed in the ten seconds interval. Focusing on AT participants, we likewise observe no significant relation within the five seconds after the event. Within the ten second window however, a higher net liquidity provision ratio is associated with a significant positive abnormal recovery rate in the relative bid-ask spread. Thus, AT traders that provide net liquidity to the order book following a market order shock target for the top of the order book and therefore improve the relative bid-ask spread. However, based on our results, AT traders need several seconds before this effect becomes significant, which is indicated by the differences between the five and ten seconds observation window. In contrast, HFT traders, that rely on co-located infrastructure, show a significant and robust relation between their net liquidity provision ratio and the abnormal spread recovery rate. Hence, HFT traders instantaneously affect and recover the widened bid-ask spread after the liquidity shock when providing additional liquidity to the limit order book. This effect remains significant in the five as well as in the ten seconds observation period indicating that the effect size is considerably strong.

Concerning the recovery of the limit order book depth measured via the Depth(10) measure of Degryse et al. (2011), results again give a different impression. Both, AT as well as HFT traders do not significantly participate in the recovery of the order book depth, even during events where their submissions heavily outweigh their deletions. The specific net liquidity provision ratios remain insignificant within the short-term as well as in the long-term observation period. Thus, even if submissions heavily affect the relative bid-ask spread, the actual order sizes are too low in order to achieve a significant increase in the order book depth. Only regression model (15) shows a positive effect for AT participants, which vanishes with the inclusion of the remaining net liquidity provision ratios. In contrast, human traders show the opposite characteristic. Even within five seconds after the liquidity shock, submissions coming from human traders are significantly recovering the lost order volume. In contrast to AT and HFT traders, their submission volumes are of relevant sizes in order to impact the order book depth. These results are in line with the descriptive aggregation of the submitted order sizes of each faction in the previous section. In the ten seconds before and after the market order shock, human traders submit on average orders sizes two times larger than the size of HFT traders' orders and three times larger than the size of AT traders' orders. Besides the relative low activity levels of human traders as shown in Table 2, their high net liquidity provision ratios combined with the larger order sizes depicted in 1 are the key components in depth recovery. On the other side, AT and HFT participants do not contribute to the recovery of the order book depth due to their transient liquidity commitment and relative small order sizes.

Conclusion

We study the submission and deletion behavior and the respective contribution to order book resiliency of high-frequency traders (HFTs) using co-located servers, algorithmic traders (ATs) without co-location connection, and human traders around liquidity shocks caused by large market orders. Our analysis is based on a unique data set provided by Deutsche Boerse that enables the identification of each trader faction's messages sent to the exchange system and order book snapshots from Thomson Reuters Tick History (TRTH). We find that speed does in fact leverage one characteristic of order book resiliency namely the recovery of the relative bid-ask spread. In particular, the results suggest that spread levels revert abnormally fast respectively abnormally strong if HFT traders contribute liquidity to the limit order book. However, our results show that order book depth, the second important characteristic of order book resiliency, only recovers due to human trader's submission of relatively large orders. Therefore, the analysis aimed at answering the question whether algorithmic trading and trading speed matter for open limit order book resiliency leads to controversial results for the role of HFT for order book resiliency. The results provided by this study are in line with the observations made by Haferkorn and Zimmermann (2015) although they analyze general trading activity whereas our study focuses on non-standard market conditions due to liquidity shocks initiated by large market orders.

In particular, we find bid-ask spread recovery to be critically determined by HFTs and ATs, i.e. participants that rely on automated order submission. Especially, automated traders using co-located machines (i.e. HFT) are found to be the driving force in reestablishing tight spreads. In terms of the effect's magnitude, we refer to the proposed short- and long-term observation window as well as the aggregated second-wise visualization in Figure 2. The largest part of spread recovery happens within the first five seconds and is therefore attributable to the HFT activity that subsequently follows the market order liquidity shock. However, our study reveals a major drawback. HFT and AT participants refrain from restoring the order book depth level. This is only achieved by human traders contributing to order book depth with high net liquidity provision combined with large order sizes. As indicated in Figure 2, this process consumes additional time compared to the spread recovery, giving further indications that HFTs as well as ATs do not participate in the resiliency of order book depth. Therefore, our conclusions are twofold. Firstly, transient liquidity commitment of HFT and AT participants targets only a very distinct dimension of market liquidity, i.e. order book bid-ask spread. The speed of trading therefore indeed significantly leverages the recovery of spread levels. Secondly, bid-ask spread recovery is only one dimension of order book resiliency. Bid-ask spread recovery needs at best only the submission of one precise order. In order to absorb further liquidity shocks, order book depth levels have to be refitted by manifold orders. As shown in our analysis, this is only achieved with the help of various human traders that persistently stay in the order book and offer a vast amount of liquidity.

Some caveats are present in our analysis, however. On the one hand, our data sample covers a rather short period of time with only ten trading days. Therefore, one might argue that not enough remarkable market impact events are included in the analysis. Nevertheless, our price-based approach to identify market orders initiating large price impacts following Biais (1995) helps to detect the largest market impact events in our data set. Moreover, the mean price impact of 0.07 euro of the events included in this study as shown by Table 9 in the appendix appears to be quite substantial given that we analyze the most liquid German stocks. On the other hand, a second caveat relates to the precise attribution of the order submissions and deletions to the respective trader factions. Although market participants using algorithmic trading engines have a high incentive to participate in the Automated Trading Program (ATP) offered by Deutsche Boerse, they are not obliged to do so. Therefore, not all messages sent by algorithmic trading engines might be flagged as such. Nonetheless, the unique flag for algorithmic trading activity in the data set used in this study seems to be the best proxy available.

Finally, our results have important implications for academics, regulators and market operators alike. Although there exist several academic studies that highlight the importance of HFT for liquidity provision, our results show that liquidity provision of HFTs should not be overestimated. At least in non-standard market conditions as analyzed in this study, human traders provide meaningful amounts of liquidity. While HFTs are the ones who tighten the enlarged bid-ask spread after a liquidity shock within one second or even less, they do not significantly contribute to order book depth.

References

Biais, B. (1995). An empirical analysis of the limit order book and the order flow in the paris bourse. *The Journal of Finance*, *50*, 1665-1689.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *The Review of Financial Studies*, *27*(8).

Carrion, A. (2013). Very fast money: high-frequency trading on the NASDAQ. *Journal of Financial Markets*, *16*(4), 680 - 711.

Chlistalla, M. (2011). From minutes to seconds and beyond: Measuring order-book resiliency in fragmented electronic securities markets. *Proceedings of the 19*$^{\text{th}}$ *European Conference on Information Systems*.

Degryse, H., Jong, F. de, & Kervel, V. van. (2011). Equity market fragmentation and liquidity: the impact of mifid. *Working Paper*.

Deutsche Boerse. (2004). *Automated Trading Program (ATP) Initiative.* Retrieved April 14$^{\text{th}}$, 2015, from https://deutsche-boerse.com/INTERNET/XETRA/x4_member.nsf/0/BBDBE6D09D2EB149C1256F5E0054C7B5/$FILE/171_04e.pdf/171_04e.pdf?OpenElement.

Deutsche Boerse. (2009). *Deutsche boerse extends transaction cost advantages for xetra trading.* Retrieved April 14$^{\text{th}}$, 2015, from http://deutsche-boerse.com/dbg/dispatch/en/notescontent/dbg_nav/press/10_Latest_Press_Releases/10_All/INTEGRATE/mr_pressreleases?notesDoc=D823086DCF290D55C12575D70042D43F&newstitle=deutscheboerseextendstransacti&location=press.

Fidessa. (2015). *Fidessa fragmentation index.* Retrieved April 15, 2015, http://fragmentation.fidessa.com/fragulator/.

Gomber, P., Schweickert, U., & Theissen, E. (2015). Liquidity dynamics in an electronic open limit order book: an event study approach. *European Financial Management*, *21*(1), 52–78.

Haferkorn, M., & Zimmermann, K. (2015). The german high frequency trading act. *Proceedings of the Annual Conference of the Swiss Society for Financial Market Research*.

Hagstroemer, B., & Norden, L. (2013). The diversity of high-frequency traders. *Journal of Financial Markets*, *16*(4), 741 - 770.

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

Hendershott, T., & Riordan, R. (2011). Alhorithmic trading and information. *Working Paper*.

Jarnecic, E., & Snape, M. (2014). The provision of liquidity by high-frequency participants. *Financial Review*, *49*(2), 371–394.

Large, J. (2007, 1). Measuring the resiliency of an electronic limit order book. *Journal of Financial Markets*, *10*, 1-25.

Malinova, K., Park, A., & Riordan, R. (2013). Do retail traders suffer from high frequency traders? *Working Paper*.

Appendix

Table 9: Descriptive statistics of events per instrument (mean)

Instrument (RIC)	No. of Events	Market Impact (euro)	Ordersize (no. of shares)	Volume (euro)	Volume/Standard Market Size
ADSG.DE	7	0.06	5,010	160,626	10.71
ALVG.DE	10	0.18	5,269	418,815	16.75
BASF.DE	10	0.05	11,999	427,908.97	17.12
BAYG.DE	10	0.06	6,860	300,053	12.00
BEIG.DE	8	0.05	2,050	76,509	5.10
BMWG.DE	10	0.05	7,043	220,575	14.71
CBKG.DE	9	0.04	50,309	390,361	26.02
DAIGn.DE	9	0.05	7,744	256,504	10.26
DB1Gn.DE	8	0.12	2,923	158,068	6.32
DBKGn.DE	10	0.10	7,209	349,308	13.97
DPWGn.DE	10	0.02	12,183	142,387	9.49
DTEGn.DE	9	0.01	34,559	327,255	13.09
EONGn.DE	10	0.04	13,739	391,627	26.11
FMEG.DE	8	0.03	3,181	99,521	6.63
FREG_p.DE	8	0.06	3,370	125,694	8.38
HNKG_p.DE	8	0.04	3,238	86,904	11.59
HNRGn.DE	7	0.05	2,164	4,602	8.61
LHAG.DE	9	0.02	14,946	167,435	11.16
LING.DE	8	0.09	2,238	156,094	10.41
MANG.DE	9	0.10	3,981	220,546	14.70
MEOG.DE	9	0.04	2,066	77,119	5.14
MRCG.DE	10	0.08	2,350	152,761	10.18
MUVGn.DE	10	0.15	2,430	252,576	10.10
RWEG.DE	8	0.09	8,806	553,403	22.14
SAPG.DE	9	0.03	6,808	232,125	9.28
SDFG.DE	9	0.07	4,050	149,951	10.00
SIEGn.DE	10	0.07	5,502	343,813	13.75
SZGG.DE	9	0.17	2,628	171,100	11.41
TKAG.DE	9	0.04	8,698	202,841	13.52
VOWG.DE	7	0.22	882	108,616	3.10
Mean	9	0.07	8,141	226,170	12.06
Median	9	0.06	5,139	186,971	10.94
Min	7	0.01	882	64,603	3.10
Max	10	0.22	50,309	553,404	26.11

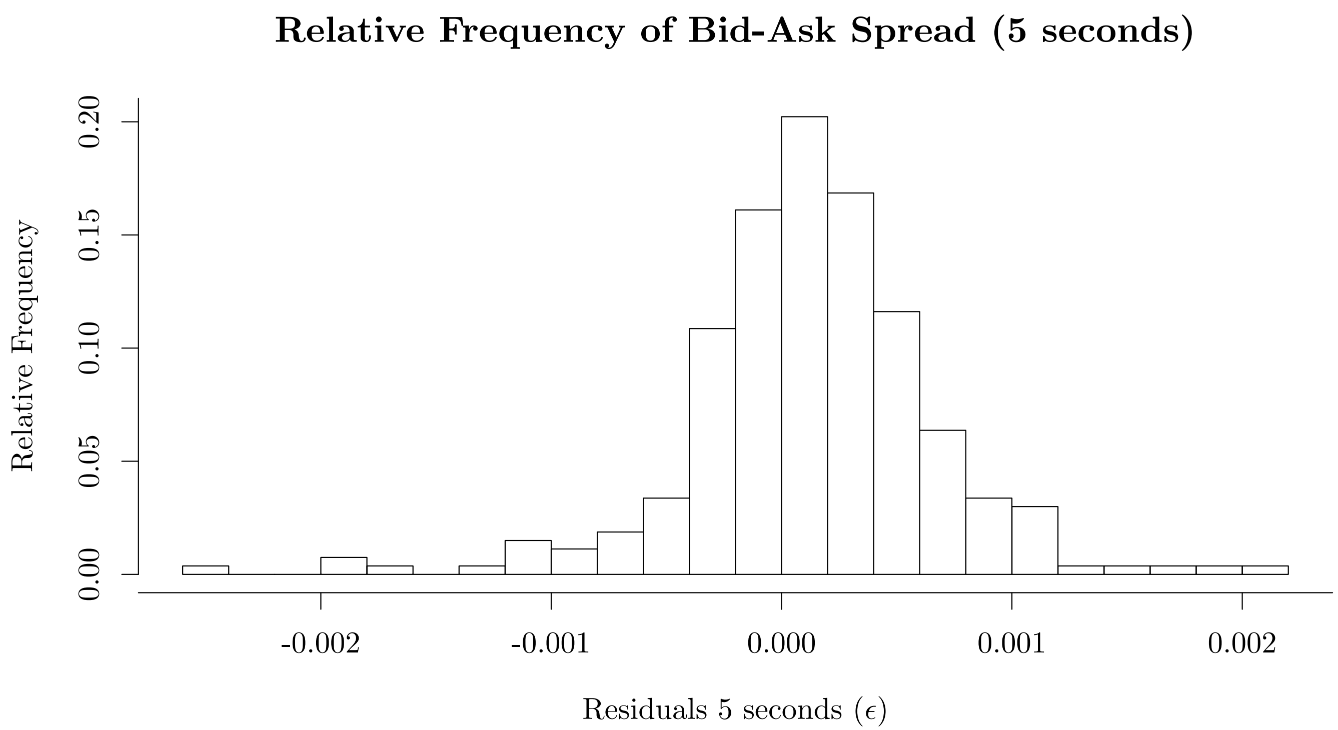

Figure 3. : This Figure captures the relative distribution of the estimated bid-ask spread liquidity measure residuals in equation 3 based on the five seconds observation period. The regression is based on the following equation:

$$Spread_{post,5} = \beta * Spread_{event,5} + \epsilon$$

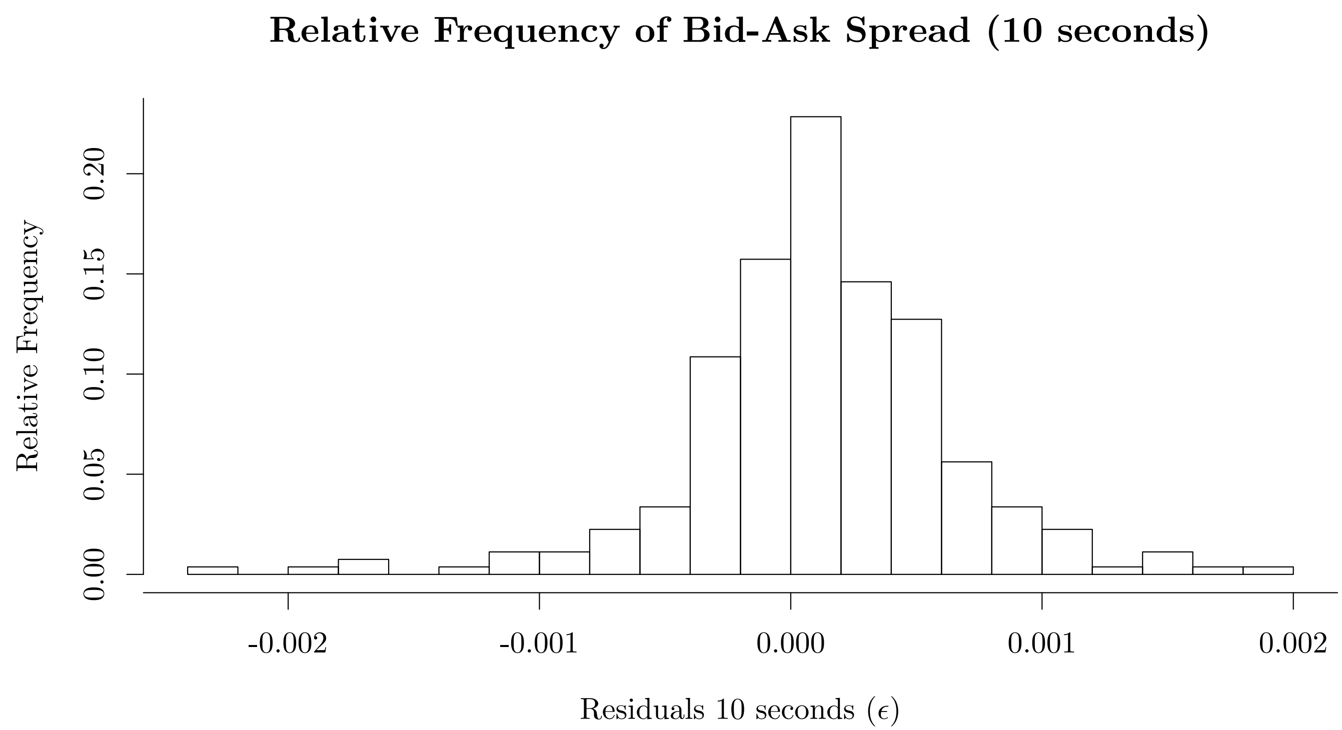

Figure 4. : This Figure captures the relative distribution of the estimated bid-ask spread liquidity measure residuals in equation 3 based on the ten seconds observation period. The regression is based on the following equation:

$$Spread_{post,10} = \beta * Spread_{event,10} + \epsilon$$

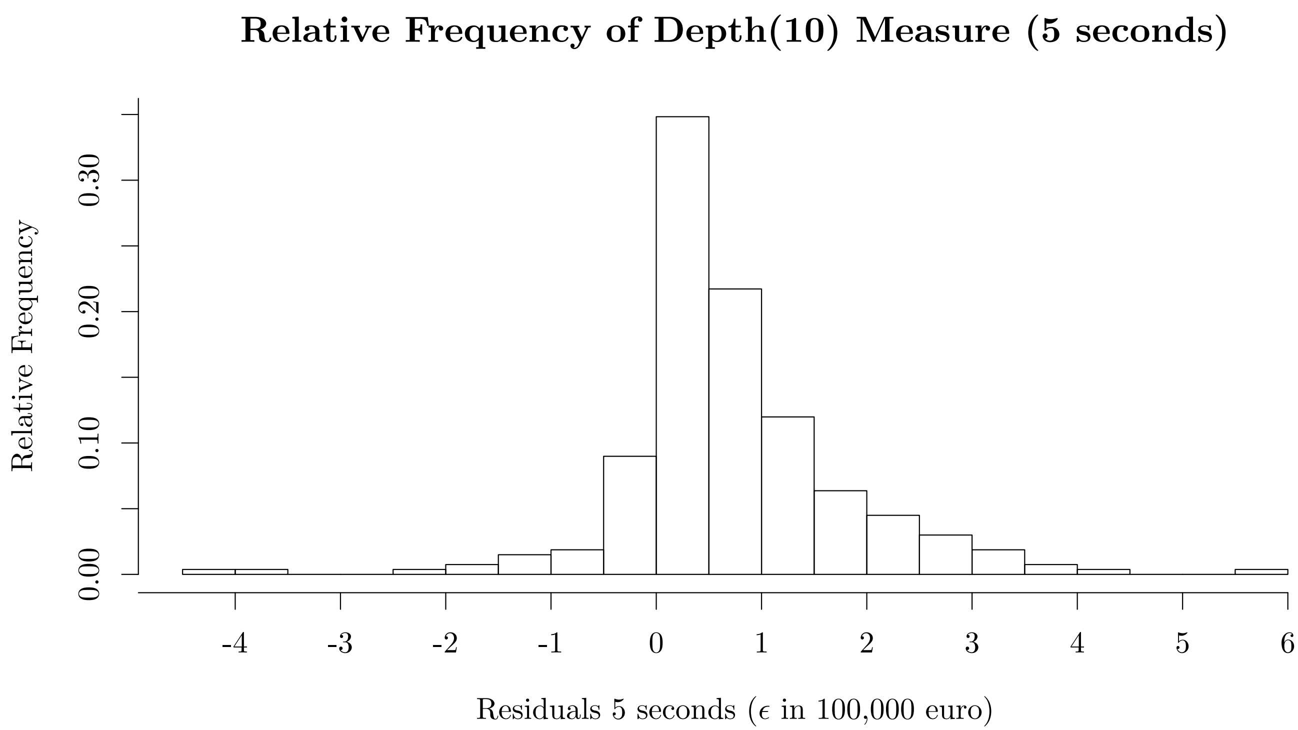

Figure 5. : This Figure captures the relative distribution of the estimated Depth(10) liquidity measure residuals in equation 3 based on the five seconds observation period. The regression is based on the following equation:

$$Depth(10)_{post,5} = \beta * Depth(10)_{event,5} + \epsilon$$

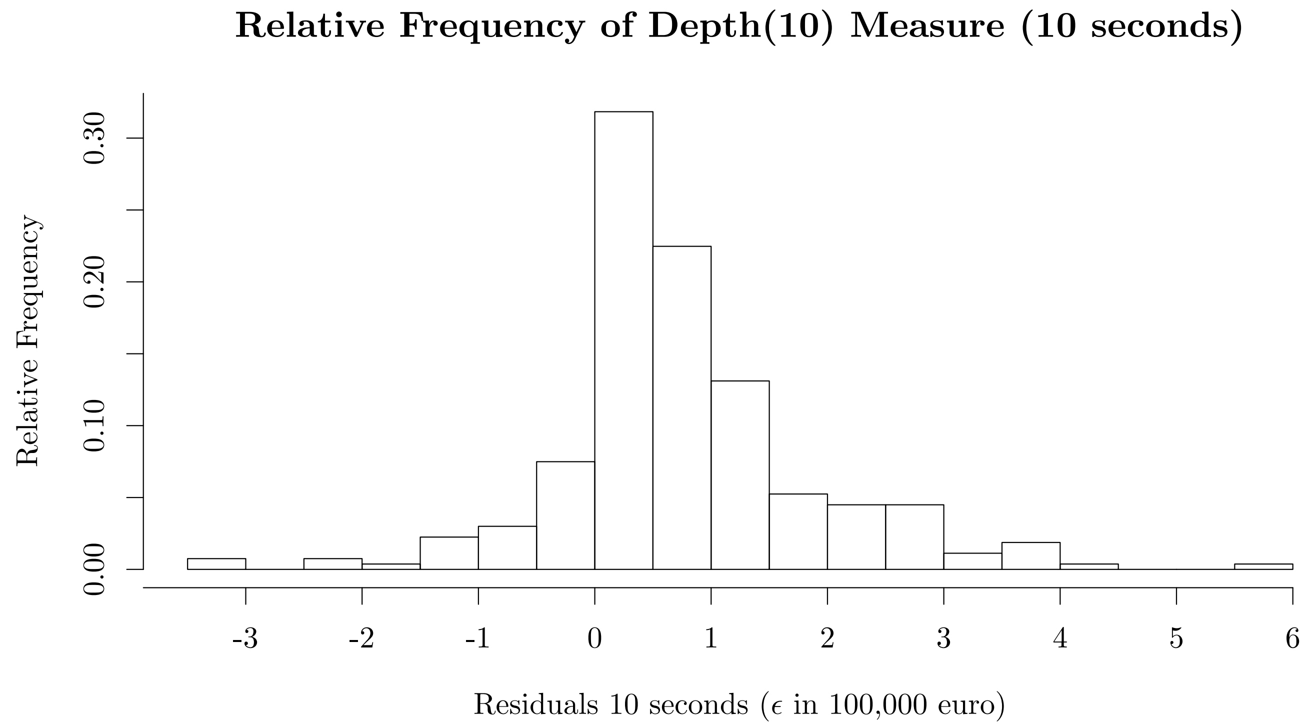

Figure 6. : This Figure captures the relative distribution of the estimated Depth(10) liquidity measure residuals in equation 3 based on the ten seconds observation period. The regression is based on the following equation:

$$Depth(10)_{post,10} = \beta * Depth(10)_{event,10} + \epsilon$$