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

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Abstract
This paper analyzes limit order book resiliency following liquidity shocks initiated by large market orders. Based on a unique data set, we investigate whether high-frequency traders are involved in the replenishment of the order book. Therefore, we relate the net liquidity provision of high-frequency traders, algorithmic traders, and human traders around liquidity shocks to order book resiliency. While all groups of traders react to the liquidity shock, our results show that only high-frequency traders reduce the spread within the first seconds after the shock. Order book depth replenishment, however, takes significantly longer and is accomplished by human traders’ liquidity provision.

Keywords: High-Frequency Trading, Liquidity, Resiliency, Market Quality
JEL Classification: G10, G14, G18

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1 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 issues is the impact of high-frequency traders (HFTs) on market quality in open limit order books (Haferkorn, 2017). In particular, proponents of high-frequency trading (HFT) argue that automated decision making and low-latency infrastructure favor liquidity provision because information evaluation and the corresponding trading reaction are conducted more efficiently. Therefore, liquidity increases which leads to a reduction of implicit transaction costs for all market participants. The positive effect of HFTs on liquidity particularly holds for HFTs acting as market makers, which represent the majority of HFTs in terms of trading volume and order messages (Hagströmer and Nordén, 2013). Various academic studies have shown the positive impact of HFT on spreads and order book depth, which account for the price and quantity dimension of liquidity. However, very little empirical evidence exists concerning the contribution of HFTs to the third dimension of liquidity - order book resiliency - which is the dynamic characteristic of liquidity representing the recovery of the order book after a liquidity shock\(^1\). Especially in case of liquidity shocks or market turmoil, HFTs are able to react quicker and more precisely to order book changes and accompanying new information than other groups of traders. Consequently, particularly HFTs might contribute to the recovery of market liquidity, thereby fostering order book resiliency which in turn increases price efficiency and decreases implicit transaction costs.

Based on the outlined debate about the role of HFT for liquidity provision, this paper determines the contribution of HFTs to order book resiliency following liquidity shocks in open limit order books in contrast to non-HFT participants. During and after such shocks, low-latency traders can maximize their speed advantages and benefit from the widened spread respectively the reduced depth. Given HFTs follow such strategies, other market participants may profit from the increased order book resiliency. Moreover, a fast recovery of liquidity in terms of spread and depth lowers implicit transaction costs for investors and ultimately the liquidity component of companies’ cost of capital. Therefore, we aim to investigate the contribution of

\[^1\]Order book resiliency as the third dimension of liquidity is already described by early papers on market microstructure. Black (1971), Kyle (1985), and also Harris (2003) describe resiliency as the quick recovery of prices after liquidity shocks. Building on this, Foucault et al. (2005) develop a model of order book resiliency which defines market resiliency as the spread reversion to its former level after a liquidity shock.
different groups of traders to order book resiliency by applying a data sample of
large market orders that hit the open limit order book and walk through several
order book levels leading to liquidity shocks. In particular, we focus on the net
liquidity provision of HFTs and non-HFTs around these liquidity shocks to add
further evidence on the dynamic aspect of liquidity. We rely on a proprietary data set
provided by Deutsche Boerse, which enables us to identify HFT as well as algorithmic
trading (AT) activity based on respective flags. Thus, we are able to provide detailed
insights into the order book resiliency dynamics in the presence of HFTs.

Our results show that HFTs contribute significantly to the replenishment of the
open limit order book. Specifically, we find HFTs to be the driving force behind
reestablishing tight spreads within short periods of time. In contrast, algorithmic
traders (ATs) without low-latency infrastructure do not significantly support spread
resiliency. The recovery of the spread is accomplished within the first few seconds
after the liquidity shock, while the largest fraction of the widened spread recovers
already within the first second. Human traders, although adapting their submission
behavior within the very first seconds after the shock, do not significantly affect
spread resiliency. However, considering the resiliency of order book depth, results
considerably change. HFTs and ATs do not sufficiently replenish order book depth
as they predominantly submit small volume orders mostly aiming at the top of the
order book. Depth resiliency, therefore, is only achieved by human traders showing
high net liquidity provisions after liquidity shocks. Therefore, fast liquidity provision
by HFTs, that is also prevailing after liquidity shocks, represents only a very specific
and limited contribution to overall order book resiliency. In order to mitigate the
impact of further liquidity shocks, order book depth has to be replenished by various
limit orders of relevant size. As shown in our analysis, this is only achieved with
the help of human traders that persistently stay in the order book and offer a vast
amount of non-transient liquidity. Therefore, this paper shows that different groups
of traders, in particular HFTs and human traders pursuing different strategies are
needed to accomplish order book resiliency on all dimensions (i.e., spread and depth)
in an efficient and fast manner.

The remainder of the paper is structured as follows: Within Section 2, related litera-
ture on HFT and liquidity as well as order book resiliency as a specific dimension of
liquidity is presented. In Section 3, we describe our data set and provide a descrip-
tive analysis. Section 4 and Section 5 outline the methodological approach as well
as the results of our empirical analysis. Finally, we discuss our results in Section 6
and Section 7 concludes.
2 Related Literature

2.1 Liquidity Provision by High-Frequency Traders

One of the most discussed and analyzed questions regarding HFT is whether and how HFTs provide liquidity to market participants in different trading situations (Kirilenko et al., 2017). Liquidity is defined by the three dimensions spread, order book depth and resiliency (Black, 1971; Harris, 2003; Kyle, 1985). The first part of literature review in this subsection focuses on the impact of HFT on liquidity in terms of spread and order book depth. Thereafter, the following subsection outlines current research on HFT and the third dimension of liquidity, i.e., order book resiliency.

Research concerning the relation between HFT and liquidity in terms of spread and depth is mostly conducted using time-series regression techniques. Regarding the spread, it has been shown that HFTs provide liquidity when spreads are wide and consume liquidity when spreads are tight (Carrion, 2013; Zhang and Riordan, 2011). In line with these results, Brogaard et al. (2014) observe that HFTs 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. Thus, HFTs contribute to decreasing spreads, which is further observed by Hasbrouck and Saar (2013). These results, which are obtained using a sample from NASDAQ, suggest that HFTs resolve temporal imbalances in the order flow by providing liquidity if the public supply is insufficient. Therefore, HFTs provide a valuable service during periods of high uncertainty. Similar observations are made for European markets, e.g., by Hagströmér and Nordén (2013) who find that HFTs mostly use market-making strategies at the Stockholm based NASDAQ OMX market. A deeper investigation into market-making activities of HFTs is provided by Menkveld (2013) who observes that 80% of a large high-frequency trader’s orders in the Dutch market are passive, i.e., liquidity providing. Jarnecic and Snape (2014) examine the liquidity supply of HFTs in the limit order book at the LSE in 2009. Similar to Menkveld (2013), the authors observe that HFTs use small aggressively placed limit orders. Even though the orders are rapidly cancelled, they reduce order book imbalances because they are submitted to both sides of the order book. Regarding algorithmic trading, Hendershott et al. (2011) find that ATs reduce the bid-ask spread on the New York Stock Exchange. Using a similar data set to our paper, Hendershott and Riordan (2013) report that ATs consume liquidity when bid-ask spreads are narrow and provide liquidity when they are wide. Contrary to these results, Lee (2015) finds that HFT has no effect on liquidity as spread and depth remain unaffected.
Considering regulatory initiatives where HFT was either directly or indirectly regulated, these constraints of HFT activity caused an increase of relative spreads in Canada (Malinova et al., 2013) as well as in Germany (Haferkorn and Zimmermann, 2014). However, regulatory acts concerning HFT do not always lead to changes in liquidity. For example, Friederich and Payne (2015) could not observe an effect on spreads in Italy where HFTs faced comparable regulation. Similar observations are also reported by Jørgensen et al. (2018) for the Norwegian market.

2.2 Order Book Resiliency and High-Frequency Trading

Electronic open limit order books are the core of today’s securities markets in terms of providing continuous liquidity as well as price discovery. However, they depend on public limit orders and quotes providing such liquidity which also have to be replenished quickly by traders after liquidity shocks. Order book resiliency represents this dynamic aspect of liquidity, i.e., the speed at which the static liquidity dimensions relative spread and order book depth revert to “normal” levels after a liquidity shock. The importance of resiliency is also emphasized by the findings of Obizhaeva and Wang (2013), who show that optimal trading strategies do not depend on static liquidity properties such as relative spread and depth but on the speed at which supply of and demand for a security recover after a trade.

Foucault et al. (2005) develop a theoretical model of spread resiliency in a limit order book with traders differing in their degree of impatience. Specifically, traders face a trade-off between the spread as a cost of immediacy and the cost of delayed execution as first described by Demsetz (1968). In the model of Foucault et al. (2005), the proportion of patient traders as well as the order arrival rate are the essential drivers of market resiliency. This is due to the fact that traders are more likely to submit aggressive limit orders on a voluntary basis to the open limit order book when the competition among patient traders is high (i.e., when the proportion of patient traders is high) or when the arrival rate of new orders is low.

Turning to depth resiliency, Coppejans et al. (2004) are the first to analyze the variation of order book depth over time, however, with a focus on the interaction between volatility and liquidity. Based on impulse response functions, they derive that electronic order books exhibit high degrees of resiliency as liquidity shocks are resolved quickly. Nevertheless, this variation affects trading strategies. These findings are consistent with the observations by Gomber et al. (2015), who study the impact of large orders on their exchange liquidity measure XLM, which calculates the transaction costs of a round trip trade of a given size. They show that this
alternative measure for order book depth reverts quickly to a “normal” level and that large orders are timed, meaning they appear when liquidity is unusually high.

This mean reversion of spread and depth around a “normal” level is also shown by Degryse et al. (2005) and regarding the spread already observed by Biais (1995) when studying the order flow at the Paris Bourse. Degryse et al. (2005) investigate aggressive orders that demand more liquidity than is available at the best bid respectively ask. They empirically show that spread and depth revert to their initial level within 20 best limit updates after the liquidity shock indicating market resiliency.

Kempf et al. (2015) draw on the observation of mean reversion and develop a mean reversion model of liquidity providing strong support for the Foucault et al. (2005) model. They measure resiliency as the rate of mean reversion in both spread and depth in FTSE 100 stocks over a two-year time period. Different to previous studies, the authors do not revert to certain market events to determine liquidity shocks but use their model to measure the rate of resiliency over the whole observation period. By extending their model with a variable capturing algorithmic trading activity, Kempf et al. (2015) find that algorithmic trading has a positive impact on spread and order book depth resiliency. However, they do not directly infer their conclusions based on the trading behavior of algorithmic traders but rely on the intensity of order cancellations. Moreover, the results are based on five-minute intervals which are too long to infer the behavior of HFTs representing a sub-group of algorithmic traders that react within a fraction of a second.

Therefore, our study adds insights into the research gap regarding the role of HFT for order book resiliency. As our proprietary data set includes all order messages by HFTs and non-HFTs time-stamped to a hundredth of a second, we are able to precisely study the contribution of HFTs to order book resiliency. There is only one but not empirical paper that provides first evidence regarding HFT and market resiliency (Leal and Napoletano, 2019). The authors investigate HFT regulation based on an agent-based model concerning flash crashes caused by the interaction of HFTs and non-HFTs. Their results show that HFTs are fundamentally involved both in the cause of a flash crash but also in the liquidity recovery after a shock leading to a trade-off for HFT-targeted policies. Thus, HFTs have a positive impact on market resiliency according to their model.
3 Data and Descriptive Statistics

3.1 Data Set
Our study focuses on the German blue chip index DAX 30 which includes the 30 largest and most actively traded German companies. The data set provided by Deutsche Boerse contains all order book messages concerning its electronic open limit order book Xetra for the DAX 30 stocks within the two-week time period from August 31st to September 11th, 2009, thereby covering ten trading days. In this time interval, 74.4% of the lit trading volume of those 30 securities was executed on Xetra (Fidessa, 2017). For comparison, in September 2017, 70.6% of total DAX 30 trading volume in lit order books was executed on Xetra. For every order book message, the data set contains a timestamp, the International Securities Identification Number (ISIN) of the respective stock, an order number which allows to identify all other messages related to a certain message (e.g., an order submission can be linked to the corresponding (partial) execution(s) or cancellation), the information whether the respective order was a buy or a sell order as well as information about price limit and order size. Moreover, the data set contains several flags such as order and message type, which provide further information about each message.

What makes the data set at hand especially useful for the purpose of this study is the 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). We will refer to non-algorithmic orders as human traders’ or human-generated orders hereafter. The identification of algorithmic traders is possible because Deutsche Boerse implemented a special pricing model for computer generated trades called Automated Trading Program in 2005 to promote 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 a limit), timing (time of order entry), and quantity (number of securities) (Deutsche Boerse, 2004). Moreover, an electronic system must submit or cancel 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 algorithm. 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 (2013) show that the savings associated with the Automated Trading Program are significant for algorithmic and in particular high-frequency trading firms, whose turnover is higher than the amount of capital invested. Therefore, the Algo-flag appears to be highly reliable and a suitable proxy for algorithmic trading activity. 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.

Due to a second flag, which 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), we can further differentiate orders submitted by algorithms. Specifically, fast algorithmic traders using co-location services, i.e., high-frequency traders (HFTs) can be differentiated from relatively slower ones, i.e., non-HFT algorithmic traders (ATs). Consequently, the data set allows us to analyze the trading behavior and the respective role for order book resiliency of three different groups of traders: HFTs, ATs, and human traders.

Table 1 reports descriptive statistics for the DAX 30 constituents between August 31st, 2009 and September 11th, 2009. Stock price and volume related data as well as market capitalization of the stocks are gathered from Deutsche Boerse\(^2\). Market capitalization is reported as of December 31st, 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 ten trading days). While the data set contains the largest and most actively traded German blue chips, it still shows some variation regarding market capitalization, price level, and trading volume of the 30 stocks. Nevertheless, the constituents of the DAX 30 are highly liquid securities with a mean daily trading volume of 92.73 million euro.

Table 1: Descriptive statistics of the DAX 30 constituents.

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

\(^2\)See [http://en.boerse-frankfurt.de/stock/adidas-share/ETR](http://en.boerse-frankfurt.de/stock/adidas-share/ETR) as an example for the stock of Adidas AG.
In order to study the role of HFTs, ATs, and human traders for order book resiliency, we only focus on data generated during continuous trading phases since market impacts caused by liquidity shocks are less prevalent in highly liquid call auctions. The data set contains 1,243,083 messages created during continuous trading, thereof 49.1% submissions, 40.9% cancellations, 5.2% executions, 2.7% partial executions, and 2.0% modifications. The number of modifications is rather low compared to the number of submissions and cancellations because only an adjustment of the order’s volume leads to a modification while all other changes which affect price-time priority lead to the cancellation of the order and the insertion of a “new” order with a new timestamp and order number. The remaining 3.2% of all messages represent technical messages generated by the exchange system which are not relevant for the following analysis. Therefore, all messages other than submissions, modifications, cancellations, executions and partial executions are dropped from the data set. Moreover, submissions that resulted in a cancellation within the same hundredth of a second are excluded together with their cancellations 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 HFTs. As depicted in Table 2, 64.9% of all messages in the data set at hand are generated by HFTs, 15.4% by ATs, and 19.7% by human traders.

Table 2: Proportion of messages triggered by each of the three groups of traders.

| Group of Traders | Number of Messages | Proportion of All Messages |
|------------------|--------------------|---------------------------|
| HFTs             | 680,865            | 64.9%                     |
| ATs              | 161,559            | 15.4%                     |
| Human Traders    | 206,788            | 19.7%                     |

3.2 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 determine market impact events (e.g., Large (2007), Chlistalla (2011)). However, a relatively large order does not necessarily lead to a notable price change and thus market impact. Gomber et al. (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 best bid and ask. Specifically, we identify market impact events
based on the number of order book levels that have been affected by an aggressive order leading to significant price impact. Since every partial execution in our data set 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. Consequently, we count the partial executions that follow a specific market order to identify market impact events. We choose market orders instead of limit orders since market orders in general are even more aggressive and are executed for any price available while limit orders are only executed as long as the price is above/below a certain limit. Following this approach, we determine market impact events based on an order’s relative impact on liquidity resting in the order book and thus circumvent the timing issues of abnormal large orders that do not necessarily lead to significant price impact.

For our analysis, we take the ten market orders with the highest market impact (i.e., those with the highest number of cleared order book levels) for every stock listed in the German blue chip index DAX 30 during our observation period. Thereby, we are able to identify 300 liquidity shocks in our data set. If there are several market orders for a given stock leading to the same number of affected order book levels and not all of them can be considered in the sample of ten events per stock, market orders with higher volume are given preference. Additionally, we do 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 liquidity shocks directly follow each other in order to avoid a bias from these special trading situations. By selecting the top ten orders, we are able to ensure that we only look at the most severe market impacts events. Since the data set only covers a two-week period, these ten events represent a good compromise between data set size and event singularity.

In order to analyze order book resiliency for the identified market impact events, we match order book snapshots retrieved from Thomson Reuters Tick History (TRTH) to the message data provided by Deutsche Borse. Thereby, 33 events were lost during the matching process because the timestamps of both data sources are not synchronized and the market impact was not visible in the TRTH data. The other events could properly be identified and were double-checked manually. Additionally, we exclude two observations where the market order leading to the liquidity shock is smaller than the respective stock’s Standard Market Size (SMS) reported by the European Securities and Markets Authority (ESMA). Since the stocks in our sample are highly liquid, an order size smaller than SMS leading to a market impact

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3ESMA reports Standard Market Sizes for listed securities in the ESMA Registers, accessible via https://registers.esma.europa.eu/publication/searchRegister?core=esma_registers_fitrss_equities.
event indicates an unusually illiquid order book which could bias our results. The distribution of the remaining 265 events over the observation period and over the trading day is provided in Figures A1 and A2 in the appendix. Market orders causing liquidity shocks are almost evenly split between buyer- (133) and seller-initiated (132) orders. However, 91.4% of these orders are submitted by human traders while 6.4% are inserted by ATs and only 2.2% by HFTs (see Table 3).

Table 3: Initiators of market orders leading to market impact events.

| Initiated by | Number of Events | Ratio  |
|--------------|------------------|--------|
| Buyer        | 133              | 50.2%  |
| Seller       | 132              | 49.8%  |
| HFTs         | 6                | 2.2%   |
| ATs          | 17               | 6.4%   |
| Human Traders| 210              | 91.4%  |

This finding seems reasonable since ATs 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, HFTs predominantly operate on the top levels of the order book submitting and cancelling limit orders within short time frames as shown by Jarnecic and Snape (2014). The following Table 4 depicts the descriptive statistics of the 265 events included in the sample. The descriptive statistics per stock are provided in Table A1 in the appendix.

Table 4: Descriptive statistics of events.

| Market Impact | No. of Affected Price Levels | Order Volume (euro) | Volume/Standard Market Size |
|---------------|------------------------------|----------------------|------------------------------|
| Mean          | 17.10                        | 6.62                 | 234,337                      | 12.39                        |
| Median        | 13.87                        | 6.00                 | 173,254                      | 9.92                         |
| Min           | 5.57                         | 3.00                 | 18,623                       | 1.24                         |
| Max           | 77.05                        | 18.00                | 1,590,104                    | 63.60                        |

Although we have not explicitly searched for the largest orders to identify order book situations with large market impact, the volume of the market orders that initiated the liquidity shocks covered in this study are on average 12.39 (median 9.92) times larger than the SMS of the respective stock for the analyzed time period. Moreover, the average market impact\(^4\) of 17.10 bps (median 13.87 bps) is quite significant.

\(^4\)Market impact is defined as the absolute difference between the first and the last price level affected by an aggressive, i.e., liquidity-consuming, order. To ensure comparability across stocks...
given that we study the most liquid German stocks. Also, more than six price levels are on average affected by the market orders in our sample showing that these orders significantly walk up the book and consume liquidity. These findings also highlight the economic relevance of our research on order book resiliency. Due to the consumed liquidity and the related market impact, implicit transaction costs for orders executed at the top of the order book increase by 171% compared to a mean spread of 9.99 bps averaged across all stocks and over the ten trading days in our data set. If the order book was not resilient and liquidity would not return to the pre-market impact event level, all market participants and orders demanding immediacy would have to bear these additional costs. Therefore, order book resiliency is a key component of liquidity ensuring consistently low implicit transaction costs and trading possibilities at appropriate prices, i.e., close to the midpoint which many traders assess to reflect the benchmark price of a stock (Harris, 2003).

Having identified the market impact events, we drop all partial and full execution messages (95,990 messages in total) because they do not represent traders’ 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. However, as already discussed, there are only few modifications since a modification that changes the price-time priority of an order leads to the insertion of a new order. For the resiliency analysis after the order book is hit by a large market order that walks through several order book levels, we focus on each group of traders’ activity and related net liquidity provision before and after the event by investigating their submission (liquidity providing) and cancellation (liquidity withdrawing) behavior.

In a first step, we analyze the submission and cancellation behavior during the five (ten) seconds before and after the 265 market impact events. This time frame is appropriate given that we analyze HFTs, ATs, and human traders’ activity. Moreover, the time frame is also supported by the findings depicted in Figures 2 and 3 in the following subsection.

Tables 5 and 6 report the mean number of submissions and cancellations for each group of traders within five (ten) seconds before and after a liquidity shock. These with different price levels, we divide the absolute market impact in euro by the volume-weighted average price of the trades resulting from the aggressive market order.
figures give a first impression of how the different groups of traders react to liquidity shocks caused by a large market order. Relative activity is calculated by aggregating the number of submissions and cancellations for each group of traders divided by all submissions and cancellations in the respective time interval. Both tables clearly indicate that HFTs, ATs, and human traders react to the liquidity shock by changing their submission and cancellation behavior. All three groups of traders increase their submissions by at least 310% compared to the pre-event number. Since the number of cancellations rises to a lesser degree, the intensified limit order submissions imply an increase in net liquidity provision. In both observation periods, especially human traders increase their limit order submissions relative to the pre-event number. In absolute terms, HFTs show the highest number of limit order submissions, however, they also exhibit the highest number of limit order cancellations.

**Table 5:** Mean number of submissions and cancellations for each group of traders within five seconds before and after a liquidity shock. Relative activity is calculated based on each group’s number of submissions and cancellations relative to all submissions and cancellations in the respective time period.

| Message Activity | HFTs | ATs | Human Traders |
|-----------------|------|-----|---------------|
| Submissions     | -5   | +5  | -5            | +5           |
| 10.0            | 46.6 | 2.4 | 12.2          | 3.0          | 14.8         |
| \( \Delta \) (in %) | 465.9 | 501.7 | 499.4 |
| Cancellations   | 8.9  | 38.1| 2.3           | 10.0         | 1.9          | 8.1          |
| \( \Delta \) (in %) | 427.5 | 433.2 | 433.1 |
| Relative Activity (in %) | 66.4 | 65.3 | 16.6 | 17.1 | 17.0 | 17.7 |

**Table 6:** Mean number of submissions and cancellations for each group of traders within ten seconds before and after a liquidity shock. Relative activity is calculated based on each group’s number of submissions and cancellations relative to all submissions and cancellations in the respective time period.

| Message Activity | HFTs | ATs | Human Traders |
|-----------------|------|-----|---------------|
| Submissions     | -10  | +10 | -10           | +10          |
| 20.7            | 64.2 | 5.0 | 15.6          | 5.6          | 19.1         |
| \( \Delta \) (in %) | 310.1 | 313.5 | 341.3 |
| Cancellations   | 18.3 | 53.6| 4.7           | 13.0         | 3.4          | 10.4         |
| \( \Delta \) (in %) | 293.2 | 276.4 | 306.8 |
| Relative Activity (in %) | 67.6 | 67.0 | 16.8 | 16.2 | 15.6 | 16.8 |

Similar to the complete sample analysis presented in Table 2, HFTs are the most active group of traders in terms of submissions and cancellations contributing between 65% and 68% of all messages around liquidity shocks. ATs and especially human traders generate significantly fewer submissions and cancellations ranging from 16%
to 17% and 16% to 18% respectively. Moreover, the number of human traders’ submissions is almost twice as high as the number of cancellations while HFTs and ATs cancel a large proportion of their submissions. This, in turn, means that HFTs and ATs frequently cancel their orders before they are being executed. Most notably, human traders increase their relative activity levels in both observation periods after the shock indicating a considerable rise in trading activity relative to HFTs and ATs, although ATs also show a weak increase in relative activity within the five seconds interval.

![Bar chart showing order volume](image)

**Figure 1:** Order volume of each group of traders before and after our event.

The increasing commitment of liquidity by all groups of traders as suggested by the numbers in Tables 5 and 6 is also supported by the observations reported in Figure 1 which depicts the mean euro order volume of all groups of traders five (ten) seconds before and after the liquidity shock. All traders increase the mean euro order size after the market impact event thereby providing additional liquidity. This finding is true for both time windows analyzed in this study. Additionally, the chart shows that human traders submit orders with on average significantly larger order sizes than ATs and HFTs. Their mean order size across all 265 events amounts to 29,012 euro (33,239 euro) in the five (ten) seconds interval before the order book is hit by a large market order and 44,185 euro (43,982 euro) in the five (ten) seconds interval after the market impact event. ATs submit the smallest mean order sizes of all groups of traders with 7,084 euro (10,432 euro) before and 11,032 euro (11,717 euro)

---

5Two uncancelled limit orders for Deutsche Bank and Allianz with exceptionally large volumes of 484,101 euro and 406,193 euro respectively were removed (also for the subsequent analysis) in order to avoid a potential bias of the results. Both orders were submitted by human traders in two of the ten-second post-event intervals.
after the liquidity shock. This finding seems reasonable since 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 groups of traders with on average 16,440 euro
(17,528 euro) before and 19,956 euro (19,665 euro) after the liquidity shock.

3.3 Liquidity around Market Impact Events
Before investigating the contributions of ATs, HFTs, and human traders to order
book resiliency, we provide descriptive statistics regarding the liquidity development
around the market impact events analyzed in this study. As discussed in the previous
subsection, we rely on two different observation periods in order to obtain robust
insights. We make use of a short-term window of five seconds before and after the
execution of the market order as well as a ten-second time window in order to account
for delayed effects. The time periods chosen seem to be relevant time intervals that
account for the differences in speed and reaction time between the groups of traders
in our sample. Moreover, both time windows are highly relevant for our sample as
indicated by the average second-wise aggregation of relative spread and order book
depth around the liquidity shocks provided in Figures 2 and 3. We measure order
book depth ten basis points around the midpoint (i.e., Depth(10)) as proposed by
Degryse et al. (2015).

\begin{figure}[h]
\centering
\includegraphics[width=0.7\textwidth]{figure2.png}
\caption{Relative spread five seconds before the liquidity shock, directly after the
shock (time 0), and its recovery ten seconds after the market impact event.}
\end{figure}
The Role of HFT for Order Book Resiliency

Figure 3: Depth(10) five seconds before the liquidity shock, directly after the shock (time 0), and its recovery ten seconds after the market impact event.

In the figures, the bars depict the one-second average relative spread (depth) five seconds before until ten seconds after the liquidity shock as well as the relative spread (depth) just after the execution of the market order (time interval 0). The line represents the average relative spread (depth) for the 30 DAX constituents included in our sample over the ten trading days under investigation in this study.

Several observations can be made in this high-level aggregation. First, a significant liquidity shock is visible after the market order has hit the order book. Regarding the relative spread depicted in Figure 2, there is an extreme increase of the mean relative spread to 24.29 bps directly after the liquidity shock which is also significantly larger than the ten days average across all DAX 30 constituents of 9.99 bps. Second, the relative spread seems to recover quite fast. While the strongest recovery occurs within the first second after the event, it takes further four seconds until the relative spread is not significantly different from the ten days average. After five seconds following the initial impact, no significant changes in the average relative spreads are observable. The differences between the average relative spread in each second and the ten days average as well as the test statistics for significance are provided in Table 7. Third, the relative spreads in the seconds prior to the liquidity shock are significantly lower than their average over the whole investigation period meaning that liquidity is provided considerably cheaper at the top of the order book. As the market orders leading to liquidity shocks are considerably larger than the SMS
of the respective stock, lower relative spreads prior to the liquidity shock support previous findings that large orders are timed when liquidity is unusually high.

Turning now to the second liquidity measure, i.e., order book depth, depicted in Figure 3, the picture looks slightly different. First, there is also a significant dry up of liquidity in terms of order book depth which is reduced to as low as 77,357 euro after the shock compared to an average depth of 254,520 euro in our investigation period. However, order book depth needs additional time to reach a similar constant level as the relative spread. Even though the largest recovery contribution is within the first second, it takes up to eight more seconds to establish a constant level. Different to the relative spread, the recovery of the order book depth takes longer and does not reach the “normal” average depth over the whole period after ten seconds as indicated by the significant differences in Table 7. Nevertheless, the differences to the average order book depth remain stable from the eighth second after the shock onwards. Therefore, our proposed observation periods of five and ten seconds after the liquidity shock are supported by this high-level analysis. Finally and contrary to relative spreads, there is no evidence for the timing of large orders by looking at order book depth.

Table 7: Difference between relative spread (Depth(10)) in each one-second interval around market impact events and the mean relative spread (mean Depth(10)) over the whole ten trading days covered by the data set. T-statistics are shown in parentheses; * \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \).

| Time Interval | Delta Mean Relative Spread in bps | Delta Mean Depth(10) in 1,000 euro |
|---------------|----------------------------------|-----------------------------------|
| [-5;-4]       | -2.038 (-5.203) ***              | -2.460 (-0.131)                   |
| [-4;-3]       | -2.263 (-7.187) ***              | -2.882 (-0.175)                   |
| [-3;-2]       | -2.429 (-8.443) ***              | -9.196 (-0.606)                   |
| [-2;-1]       | -2.334 (-8.307) ***              | -8.687 (-0.592)                   |
| [-1:0]        | -2.056 (-6.696) ***              | -22.075 (-1.632)                  |
| Event         | 14.301 (19.458) ***              | -177.163 (-19.599) ***            |
| [0;1]         | 3.559 (9.717) ***                | -118.489 (-13.385) ***            |
| [1;2]         | 1.657 (4.656) ***                | -92.574 (-8.587) ***              |
| [2;3]         | 0.949 (2.811) **                 | -81.438 (-7.315) ***              |
| [3;4]         | 0.656 (2.051) *                 | -74.030 (-6.464) ***              |
| [4;5]         | 0.156 (0.499)                    | -72.689 (-6.446) ***              |
| [5;6]         | 0.104 (0.345)                    | -65.246 (-5.502) ***              |
| [6;7]         | -0.049 (-0.163)                  | -62.110 (-5.114) ***              |
| [7;8]         | 0.010 (0.030)                    | -59.142 (-4.641) ***              |
| [8;9]         | 0.023 (0.071)                    | -55.313 (-4.317) ***              |
| [9;10]        | -0.180 (-0.570)                  | -55.313 (-4.317) ***              |
So far, our observations only descriptively show that all groups of traders react to the liquidity shock and argue in favor of the proposed observation periods. One might ask whether five and ten seconds are reasonable time periods to analyze trading activity, especially if HFT is the subject of interest since previous studies confirm that HFT activity takes place within fractions of seconds (Brogaard et al., 2014; Jarnecic and Snape, 2014). However, the methodology we propose does not aim at a millisecond-wise liquidity provision leader and follower perspective. HFTs react much faster than ATs or human traders based on their superior infrastructure. In contrast, our approach aims at identifying each group of traders’ overall contribution to the entire resiliency 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.

We also have examined price changes after the liquidity shock and could not find any persistent price impact ten seconds after the large market order hit the order book. Moreover, we have checked for news or other information related to the shock. However, there were no ad hoc messages regarding the companies in our sample on the event dates included in the sample except for one ad hoc message released by Lufthansa about the successful conclusion of a merger on September 3rd, 2009. Yet, this message was published four hours before the market impact event under investigation and our results remain robust if we exclude this event. Therefore, the market impact events included in our analysis seem to be purely liquidity driven.

4 Reactions to Market Order Liquidity Shocks

4.1 Research Approach

The overall objective of this paper is to evaluate the role of different groups of traders, i.e., ATs, HFTs, and human traders, for order book resiliency. Based on the endogenous liquidity shock caused by a large market order, we analyze the reaction and contribution of each group of traders separately in order to derive distinct patterns that characterize the behavior and commitment of these market participants. In this section, we focus on the reaction of ATs, HFTs, and human traders to liquidity shocks while we further evaluate each groups’ trading activity based on its contribution to the quality of the subsequent order book resiliency dynamic within Section 5. In order to study the respective reaction to the liquidity shock, we analyze whether the traders change their liquidity provision behavior in response to the market impact event. Specifically, we relate each group of traders’ net liquidity provision following a market impact event to the respective five- and
ten-second interval before the large market order hits the order book. Measuring the net liquidity provision of each group of traders is important since especially ATs and HFTs cancel a large proportion of their orders thereby taking their own liquidity provision away from the market. We define net liquidity provision as the difference between submitted limit order volume and cancelled limit order volume (both denoted in euro). Equation (1) shows the formal definition of the net liquidity provision measure \((NLP)\). We calculate each group of traders’ \((g)\) net liquidity provision for each pre- and post-event observation interval \(i\) based on all submitted limit orders \(l\).

\[
NLP_{i,g} = \sum_{l=1}^{L} \text{Submitted Volume}_{i,g} - \sum_{l=1}^{L} \text{Cancelled Volume}_{i,g}
\]

Consequently, a positive net liquidity provision of group \(g\) indicates that the group of traders submitted more limit order volume to the book than it cancelled within the five- or ten-second interval \(i\). On the other hand, a negative net liquidity provision means that the respective group of traders removed a larger limit order volume from the order book than it provided during the same period. If a group of traders neither submitted nor cancelled orders within the five or ten seconds window, the measure is set to zero. For the following analysis, the net liquidity provision behavior of each group of traders within five and ten seconds before and after the liquidity shock is obtained and evaluated in a cross-sectional regression setup. The estimated regression model is based on the following Equation (2):

\[
NLP_i = \alpha + \beta_1 \cdot HFT + \beta_2 \cdot AT + \beta_3 \cdot PrePost \cdot HFT
+ \beta_4 \cdot PrePost \cdot AT + \beta_5 \cdot PrePost \cdot Human
+ \beta_6 \cdot Activity_i + \sum_{n=7}^{44} \beta_n \cdot Controls_n + \epsilon_i
\]

Within the regression model, all five-second (ten-second) net liquidity provisions \((NLP)\) 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 1,590 since each of our 265 events has a pre- and a post-event observation and is calculated for HFTs, ATs, and human traders. \(HFT\) (\(AT\)) is a dummy variable indicating that the liquidity provision contains only submissions and cancellations of HFTs (ATs). Consequently, \(PrePost\) is a dummy variable that
equals zero if the net liquidity provision is measured based on five (ten) seconds before the shock. $PrePost$ switches to one, if the respective net liquidity provision is measured after the shock. The interaction terms $PrePost \cdot HFT$, $PrePost \cdot AT$ and $PrePost \cdot Human$ subsequently indicate the changes in the respective HFTs’, ATs’, and human traders’ net liquidity provision before and after the shock. Additionally, we apply control variables capturing further idiosyncratic differences in net liquidity provision. Foremost important is the overall activity level (Activity) which is computed by summing up each group’s number of submissions and cancellations in the specific five (ten) seconds observation window. Intuitively, the net liquidity provision 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. For the purpose of this study, we are most interested in the estimated coefficients of $PrePost \cdot HFT$, $PrePost \cdot AT$, and $PrePost \cdot Human$ that provide indications about a systematic change of each group’s behavior after market impact events.

Besides traders’ net liquidity provision and to provide further robustness of our results, we also consider each group of traders’ net limit order submissions ($\text{NLOS}$) reflecting traders’ liquidity provision activity. As shown in Equation (3), the number of net limit order submissions for each group of traders is computed by the number of limit order submissions minus the number of limit order cancellations by the respective group $g$ in a given time interval $i$ independent of the order volume connected to an order.

$$\text{NLOS}_{i,g} = \text{Submissions}_{i,g} - \text{Cancellations}_{i,g}$$

### 4.2 Results

The results of the regression model described in the previous subsection are provided in Table 8, which includes the estimates based on both net liquidity provision $\text{NLP}$ and net limit order submissions $\text{NLOS}$ for the five- as well as the ten-second aggregation period. In contrast to the descriptive statistics, the regressions provide a deeper insight into how the different groups of traders react to the liquidity shock. From a general perspective, HFTs and ATs exhibit significantly lower net liquidity provisions and net limit order submissions compared to human traders as shown by the negative coefficients $HFT$ and $AT$ in the pre-event phase. Most important for our research on order book resiliency, however, is the change in liquidity provision after the liquidity shock which is depicted by the coefficients of the $PrePost$ interaction terms. Regarding the mere submission and cancellation activity captured
by net limit order submissions (\textit{NLOS}), all groups of traders react to the liquidity shock by submitting significantly more limit orders relative to limit order cancellations compared to the pre-event period. In particular, HFTs and human traders increase their net limit order submissions the most by submitting 3.72 (4.31) respectively 4.59 (5.53) more limit orders minus potential cancellations in the five (ten) seconds after the market impact event. The net limit order submissions of ATs, in contrast, increase by only 1.08 respectively 1.42 orders in the same observation windows.

\textbf{Table 8:} Results of the liquidity provision regression based on Equation (2) for the five- and ten-second interval respectively. Controls for stock and date are included. Heteroskedastic robust variance estimators are applied, \textit{t}-statistics are shown in parentheses; \(^* p < 0.05\), \(^{**} p < 0.01\), \(^{***} p < 0.001\).

|                | (1)  | (2)  | (3)  | (4)  |
|----------------|------|------|------|------|
|                | NLP  | NLP  | NLOS | NLOS |
| 5 seconds      |      |      |      |      |
| \textit{HFT}   | -14.376 | -26.011* | -0.805*** | -1.289*** |
|                | (-1.83) | (-2.09) | (-3.57) | (-3.87) |
| \textit{AT}    | -19.443*** | -47.026*** | -0.999*** | -2.010*** |
|                | (-3.16) | (-4.38) | (-6.36) | (-8.51) |
| \textit{PrePost} \cdot \textit{HFT} | 59.188*** | 75.573*** | 3.724*** | 4.312*** |
|                | (4.40) | (4.90) | (7.64) | (7.58) |
| \textit{PrePost} \cdot \textit{AT} | 4.116 | 9.308 | 1.080*** | 1.421*** |
|                | (0.79) | (1.58) | (5.42) | (5.72) |
| \textit{PrePost} \cdot \textit{Human} | 136.389*** | 157.992*** | 4.593*** | 5.528*** |
|                | (10.49) | (8.87) | (12.95) | (11.66) |
| \textit{Activity}\_5  | 1.039*** | 0.056*** |      |      |
|                | (5.21) | (8.30) |      |      |
| \textit{Activity}\_10 |      | 0.802*** | 0.049*** |      |
|                |      | (6.32) | (8.22) |      |
| \textit{Constant} | -29.766 | -11.782 | 0.180 | 0.837 |
|                | (-1.66) | (-0.54) | (0.30) | (1.12) |
| Observations   | 1,590 | 1,590 | 1,590 | 1,590 |
| Adjusted \textit{R}^2 | 0.374 | 0.360 | 0.543 | 0.525 |
| Mean VIF       | 2.34 | 2.33 | 2.34 | 2.33 |
| Max VIF        | 2.96 | 2.96 | 2.96 | 2.96 |

Considering the net liquidity provision (\textit{NLP}) of the three groups of traders, the interaction term for all groups is again positive indicating an increase in liquidity.
provision after the market impact event. However, only the increase in HFTs’ and human traders’ net liquidity provision is significant indicating that in particular these two groups provide additional liquidity to the order book after the shock compared to the pre-event period. While we observe a small but significant change in ATs’ net limit order submissions, the net aggregate limit order volume provided by ATs after a market impact event is not significantly larger than in the pre-event window.

For HFTs, the coefficient of the \textit{PrePost} interaction term indicates a significant increase in net liquidity provision of 59,188 euro (75,573 euro) in the five (ten) seconds after the event. Human traders show an even stronger reaction and increase their net liquidity provision by 136,389 euro (157,992 euro) compared to the pre-event level. Consequently, the changes in the three groups of traders’ liquidity provision indicate that in particular HFTs and human traders react strongly to the market impact event and might thus play a crucial role for order book resiliency. Yet, this analysis only covers the quantitative change in net 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-second intervals. This way, we are able to extend the previous analysis to the specific utility of the change in traders’ net liquidity provision for order book resiliency.

5 Order Book Resiliency

5.1 Research Approach

Although different in the specific magnitude, each group of traders’ reaction to the market impact event is considered positive for the resiliency of the order book since they significantly increase their net liquidity provision or at least their net limit order submissions. How this increase actually contributes to order book resiliency is the focus of this section. Therefore, we aim to evaluate whether and how the different groups of traders affect order book 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. Thereafter, the quality measure is related to the specific net liquidity provision of each group of traders within the five- and ten-second periods following the liquidity shock. Thus, we are able to identify which group systematically contributes to different dimensions of liquidity recovery.

In order to measure order book resiliency for each of our 265 events, we assume that resiliency is conducted in a more efficient way, the stronger and faster liquidity is restored after the liquidity shock. The most common liquidity dimensions are the relative spread as well as the order book depth. Both dimensions account for different
order book characteristics and are affected by the liquidity shock as indicated in Figures 2 and 3. Hence, the stronger and the faster 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 stronger order book resiliency from weaker resiliency. We therefore estimate the specific abnormal order book recovery level of each event based on the following regression model described in Equation (4):

\[
Liquidity_{i}^{\text{post}} = \beta \cdot Liquidity_{i}^{\text{event}} + \epsilon_i
\]  

\(Liquidity_{i}^{\text{post}}\) denotes the average liquidity (relative spread or depth) within five and ten seconds after each liquidity shock \(i\) excluding the order book snapshot right after the execution of the large market order. Within the five and ten seconds, the average relative spread (depth) incorporates the respective level of liquidity resiliency. A strong or a very fast liquidity recovery will result in a lower (higher) average relative spread (depth) in the post-shock observation period. Likewise, \(Liquidity_{i}^{\text{event}}\) denotes the single liquidity snapshot (relative spread or depth) following the liquidity shock, i.e., the first order book situation after the execution of the large market order. Thus, \(\beta\) estimates the average rate of liquidity recovery based on all 265 observations. As shown in Table 9, the coefficient is smaller (larger) than one in the spread (depth) regression indicating that the average liquidity level following the shock has significantly improved compared to the liquidity situation right after the shock. \(\beta\) therefore represents the expected liquidity recovery after the liquidity shock.

**Table 9:** Expected liquidity recovery based on Equation (4). Heteroskedastic robust variance estimators are applied, \(t\)-statistics are shown in parentheses; \(^* p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001\).

|                | (1) Spread\(^{\text{post}}\) 5 seconds | (2) Spread\(^{\text{post}}\) 10 seconds | (3) Depth\(^{\text{(10)post}}\) 5 seconds | (4) Depth\(^{\text{(10)post}}\) 10 seconds |
|----------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| \(Spread^{\text{event}}\) | 0.456***                        | 0.431***                        | 1.063***                        | 1.136***                        |
|                | (23.27)                          | (22.68)                          | (14.59)                          | (15.32)                          |
| \(Depth^{(10)\text{event}}\) |                                  |                                  |                                  |                                  |
| Observations   | 265                              | 265                              | 265                              | 265                              |
| Adjusted \(R^2\) | 0.825                            | 0.833                            | 0.653                            | 0.654                            |
Furthermore, this simple linear relation covers the abnormal order book recovery quality specific for each observation indicated by the error term $\epsilon_i$. In case $\epsilon_i$ is negative, $\beta \cdot \text{Liquidity}_{i}^{\text{event}}$ is further reduced, i.e., we observe a positive (negative) deviation from the expected spread (depth) recovery as the $\text{Liquidity}_{i}^{\text{post}}$ is smaller than anticipated in this situation. In contrast, a positive $\epsilon_i$ indicates that $\text{Liquidity}_{i}^{\text{post}}$ is larger than the expected overall liquidity recovery, i.e., the relative spread (depth) recovery took longer (shorter) or was less (more) effective within the observed observation window. The distributions of the abnormal order book resiliency $\epsilon_i$ for five as well as ten seconds are depicted in Figures A3 to A6 in the appendix.

Within the next step, we relate the abnormal order book recovery quality $\epsilon_i$ to the respective $NLP_i$ measure of ATs, HFTs, and human traders 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 net liquidity contribution of one specific group of traders, then a regression setup can estimate such a significant relation. Otherwise, if a specific group of traders regularly exhibits a high net liquidity provision but abnormal order book recovery quality remains negative, the contribution of this group of traders to order book resiliency must be doubted. Equation (5) shows the regression model relating abnormal order book resiliency to the net liquidity provision of the different groups of traders.

$$
\epsilon_i = \gamma + \delta_1 \cdot NLP_{i}^{\text{AT,post}} + \delta_2 \cdot NLP_{i}^{\text{HFT,post}} + \delta_3 \cdot NLP_{i}^{\text{Human,post}} + \delta_4 \cdot \text{Activity}_{i}^{\text{post}} + \sum_{n=5}^{42} \delta_n \cdot \text{Controls}_n + \theta_i
$$

Where $\epsilon$ represents the abnormal order book resiliency for each market impact event $i$, and $NLP$ the net liquidity provision as introduced in Equation (1) for each group of traders, i.e., HFTs, ATs, and human traders. Again, $\text{Activity}$ represents the control variable for the overall activity level measured by the sum of all submissions and cancellations within the five and ten seconds after the liquidity shock. In addition, we include dummy variables for all stocks and trading days as further controls. The regression on the relative spread is performed for the five- and ten-second periods. Subsequently, order book depth is analyzed. We estimate the regression for each group of traders’ NLP separately (i.e., AT, HFT, and Human) as well as combined with all three explanatory variables. To provide further robustness of our results, we repeat the regression considering only one group of traders’ net liquidity provision at a time.
5.2 Results

The results give different insights into the specific quality of the increased net liquidity provision after market impact events. Although human traders exhibit the strongest increase in net liquidity provision, their contribution to the recovery of the relative spread is highly questionable. Within the five- as well as the ten-second observation period, no abnormal positive recovery effect is measurable when human traders provide more liquidity. Although the respective coefficients are negative indicating decreasing spreads across all models of the spread resiliency regression except for model (8) as depicted in Table 10, they are not significantly different from zero. Focusing on ATs, we likewise observe no significant negative relation to the relative spread within the five and ten seconds after the event.

In contrast, HFTs show a significant and robust relationship between their net liquidity provision and the abnormal relative spread recovery. Across all models (1), (4), (5), and (8), we observe a negative and significant effect of HFTs’ net liquidity provision on spread resiliency. Hence, HFTs instantaneously recover the widened relative spread after the liquidity shock when providing additional liquidity to the order book.

The positive effect of HFTs for spread recovery remains robust and significant in the five- as well as in the ten-second observation period indicating that HFTs already contribute to spread resiliency in the short observation period of five seconds. The effect size is also considerably strong already in the five-second period although it increases from -0.16 to -0.20 in the ten-second period as shown in the full models (4) and (8). In conclusion, HFTs are the group of traders being responsible for spread resiliency and do so within the very first seconds after the liquidity shock as depicted in Figure 2.

Since the relative spread is independent of the volume connected to submitted and cancelled limit orders, we repeat the spread resiliency regression using net limit order submissions $NLOS$ instead of the net liquidity provision to provide further robustness of our results. Based on the net limit order submissions of the three groups of traders as dependent variables, we obtain similar results, which are reported in Table A2 in the appendix. Again, HFTs’ net limit order submissions contribute the most to abnormal spread recovery while human traders’ order submissions do not have a significant effect. Yet, based on the pure number of net limit order submissions, also ATs seem to contribute to spread resiliency. However, their effect on spread resiliency is smaller in magnitude compared to the effect of HFTs’ net limit order submissions.
Table 10: Results of the relative spread resiliency regression (Equation (5)) conducted for the five- and ten-second interval respectively. Variables HFT, AT, and Human refer to the coefficient of the respective net liquidity provision (NLP) of that group within five and ten seconds after the liquidity shock. Controls for stock and date are included. Heteroskedastic robust variance estimators are applied. Standardized beta coefficients; t-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

| Variable | Relative Spread - 5 seconds | Relative Spread - 10 seconds |
|----------|-----------------------------|------------------------------|
|          | (1)                         | (2)                          | (3)                         | (4)                         | (5)                         | (6)                         | (7)                         | (8)                         |
| $HFT_5$  | -0.176**                    | -0.156**                     | -0.199**                    | -0.202***                   |
|          | (-3.11)                     | (-2.74)                      | (-3.26)                     | (-3.34)                     |
| $AT_5$   | -0.078                      | -0.038                       | -0.061                      | -0.004                      |
|          | (-1.53)                     | (-0.76)                      | (-0.95)                     | (-0.06)                     |
| $Human_5$| -0.096                      | -0.060                       | -0.035                      | 0.020                       |
|          | (-1.67)                     | (-1.08)                      | (-0.48)                     | (0.27)                      |
| $HFT_{10}$| -0.199**                   | -0.202***                    | -0.119                      | -0.125                      |
|          | (-3.26)                     | (-3.34)                      | (-1.86)                     | (-1.82)                     |
| $AT_{10}$| -0.061                      | -0.004                       | -0.035                      | 0.020                       |
|          | (-0.95)                     | (-0.06)                      | (-0.48)                     | (0.27)                      |
| $Human_{10}$| -0.035                   | 0.020                        | -0.119                      | -0.125                      |
|          | (-0.95)                     | (0.27)                       | (-1.86)                     | (-1.82)                     |
| $Activity_5$| -0.163*                | -0.218**                     | -0.223**                    | -0.130                      |
|          | (-2.30)                     | (-3.09)                      | (-3.098)                    | (-1.71)                     |
| $Activity_{10}$| -0.125                  | -0.192**                     | -0.109                      | -0.125                      |
|          | (-2.83)                     | (-1.82)                      | (-2.59)                     | (-1.82)                     |
| Observations | 265                      | 265                          | 265                         | 265                         |
| Adjusted $R^2$ | 0.487                   | 0.474                        | 0.476                       | 0.486                       |
| Mean VIF | 2.14                       | 2.39                         | 2.39                        | 2.42                        |
| Max VIF  | 2.98                       | 2.97                         | 2.98                        | 3.00                        |
Table 11: Results of the Depth(10) resiliency regression (Equation (5)) conducted for the five- and ten-second interval respectively. Variables \( HFT \), \( AT \), and \( Human \) refer to the coefficient of the respective net liquidity provision (\( NLP \)) of that group within five and ten seconds after the liquidity shock. Controls for stock and date are included. Heteroskedastic robust variance estimators are applied. Standardized beta coefficients; \( t \)-statistics in parentheses; \( * p < 0.05 \), \( ** p < 0.01 \), \( *** p < 0.001 \).

| Variables | Depth(10) - 5 seconds | Depth(10) - 10 seconds |
|-----------|-----------------------|------------------------|
| HFT\(_5\) | 0.203 (1.80)          | 0.146 (1.30)           |
| AT\(_5\)  | 0.158 (1.87)          | 0.100 (1.10)           |
| Human\(_5\)| 0.218** (3.48)        | 0.172** (2.64)         |
| HFT\(_{10}\)| 0.206* (2.04)        | 0.150 (1.48)           |
| AT\(_{10}\)| 0.128 (1.30)          | 0.047 (0.42)           |
| Human\(_{10}\)| 0.215* (2.45)      | 0.162* (2.00)          |
| Activity\(_5\)| 0.080 (0.87)         | 0.012 (-0.14)          |
| Activity\(_{10}\)| 0.053 (0.62)        | 0.087 (1.16)           |
| Observations | 265                   | 265                    |
| Adjusted \( R^2 \)| 0.264                  | 0.257                  |
| Mean VIF | 2.41                 | 2.39                   |
| Max VIF | 2.98                 | 2.97                   |
Concerning the recovery of order book depth measured by Depth(10) as proposed by Degryse et al. (2015), the three groups of traders’ contributions to order book resiliency again give a different impression. As depicted in Table 11, HFTs do not significantly contribute to the recovery of order book depth despite their increased net liquidity provision in the post-event period. This also holds for ATs. The respective coefficients are positive but remain insignificant in the full models (4) and (8) within the short-term as well as in the long-term observation period. Thus, even if HFTs’ net liquidity provision (and to a lesser extent ATs’ net limit order submissions) affect the relative spread, the actual order sizes are too low in order to achieve a significant increase in order book depth. Only regression model (5) of the Depth(10) resiliency regression shows a positive effect for HFTs, which vanishes with the inclusion of the remaining net liquidity provision of the other groups of traders. In contrast, human traders show the opposite characteristic. Even within five seconds after the liquidity shock, their net liquidity provision significantly recovers order book depth as indicated by the positive and significant coefficient in model (4). The positive effect of human traders’ net liquidity provision behavior on depth recovery is also significant in the full model (8) of the ten-second observation window. Human traders increase their net liquidity provision particularly strong as already shown in Table 8. Consequently, human traders’ submitted liquidity in terms of euro volume is of relevant size in order to restore order book depth. These results are in line with the descriptive aggregation of the submitted order sizes of each group of traders in Figure 1 within the descriptive analysis. 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 HFTs’ orders and three times larger than the size of ATs’ orders. Besides the relative low activity levels of human traders as shown in Table 2, their high net liquidity provision combined with the larger order sizes depicted in Figure 1 are the key components for depth recovery. On the other hand, HFTs and ATs contribute less to the recovery of order book depth due to their transient liquidity commitment and relatively small order sizes.

6 Discussion

The analysis of order book resiliency is an area of interest for researchers and market participants alike since our data highlights the economic relevance of liquidity shocks and the necessary replenishment of the order book. After the liquidity shocks included in our sample, implicit transaction costs for orders executed at the top of the order book increase by 171% compared to the mean relative spread. Further, they would stay at this high level if there was no resiliency or if the order book was only resilient at a very slow pace. Consequently, order book resiliency is a key compo-
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The component of liquidity ensuring consistently low implicit transaction costs. In this study, we focus on the contribution of different groups of traders to order book resiliency, which differs from the general analysis of a market’s resiliency as in Foucault et al. (2005).

Our results show that speed does in fact leverage one characteristic of order book resiliency, which is the recovery of relative spreads. In particular, we find that speed resiliency is critically determined by HFTs, i.e., participants relying on trading algorithms and co-location services. Relative spreads revert abnormally fast and abnormally strong if HFTs contribute liquidity to the open limit order book and the largest part of relative spread recovery happens within the first five seconds after the liquidity shock. However, our results reveal that HFTs and also ATs do not restore order book depth, which is the second important characteristic of order book resiliency. The recovery of order book depth is only achieved by human traders contributing with a high net liquidity provision combined with large order sizes. This process consumes additional time compared to the relative spread recovery, providing further indications that HFTs as well as ATs do not participate in the resiliency of order book depth. Therefore, our conclusions are twofold. First, liquidity provision of HFTs contributes only to a very distinct dimension of order book resiliency, i.e., the recovery of relative spreads. Consequently, the speed of trading indeed matters for spread resiliency since the recovery of a tight bid-ask spread needs only the submission of one precise order at best. Second, in order to absorb further liquidity shocks, order book depth has to be replenished by various orders of relevant size. As shown in our analysis, this is only achieved with the help of various human traders that persistently stay in the order book and provide a vast amount of liquidity.

In contrast to Kempf et al. (2015), who use five-minute aggregation intervals and find that algorithmic trading in general is responsible for order book resiliency, we show that rather HFTs as a subgroup of ATs are responsible for spread resiliency since speed matters regarding this dimension of liquidity. Moreover, we find that human traders and not ATs significantly contribute to order book depth resiliency. Furthermore, our results are in line with the observations made by Haferkorn and Zimmermann (2014), who show that HFTs only impact bid-ask spreads and not order book depth. However, they analyze general trading activity and static liquidity dimensions whereas our study focuses on order book resiliency, i.e., the dynamic aspect of liquidity, in non-standard market conditions due to liquidity shocks initiated by large market orders.
Some limitations are present in our analysis. On the one hand, our data set, which includes ten trading days, covers a rather short period of time. 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 market impact of 17.10 bps for the liquidity shocks included in this study as shown in Table 4 appears to be quite substantial given that we analyze the most liquid German stocks. This is further supported by more than six price levels that are on average affected by the liquidity demanding market orders in our sample. On the other hand, a second limitation relates to the precise attribution of the order submissions and cancellations to the respective groups of traders. Although market participants conducting algorithmic trading have a high incentive to participate in the Automated Trading Program offered by Deutsche Boerse, they are not obliged to do so. Therefore, not all messages sent by trading algorithms 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. Moreover, our analysis is based on blue chips stocks that are characterized by high levels of liquidity and heterogeneity of trading participants. Therefore, our results may not be generalizable to small cap or other illiquid stocks where less algorithmic and high-frequency trading takes place.

Our results have important implications for academics, regulators, and investors alike. From an academic perspective, our findings contribute to the research on HFT and its impact on liquidity in financial markets. While there exist several academic studies that provide evidence for a positive effect of HFT on liquidity in terms of spread and depth at the top of the book, the contribution of HFT to order book resiliency is still an open question. We add to this research gap by showing that HFTs indeed recover one dimension of liquidity, i.e. the bid-ask spread. However, liquidity provision by HFTs should not be overestimated with respect to resiliency of order book depth. At least in non-standard market conditions as analyzed in this study, human traders provide meaningful amounts of liquidity thereby contributing to order book depth resiliency. While HFTs are the ones who tighten the enlarged relative spread after a liquidity shock within one second or even less, they do not significantly contribute to order book depth.

From a regulatory point of view, the results reveal that HFTs play a crucial role for at least one dimension of order book resiliency by ensuring that enlarged spreads almost instantaneously revert to previous levels. With respect to ongoing discussions regarding the regulation of HFT, these results should be taken into consideration
to ensure resilient financial markets. Putting our findings in the perspective of investors, this study shows that neither HFTs nor ATs replenish large quantities of liquidity deeper in the order book. Thus, especially institutional investors should be aware that they cannot rely on these groups of traders to fulfill their liquidity demands after market impact events.

7 Conclusion

We study the liquidity provision and the respective contribution to order book resiliency of high-frequency traders (HFTs), algorithmic traders (ATs), and human traders around liquidity shocks caused by large market orders. Order book resiliency as the dynamic dimension of liquidity is a key determinant of market quality that ensures consistently low implicit transaction costs in securities markets. Our results show that spread resiliency is accomplished by HFTs, who replenish the top of the order book within five seconds after the liquidity shock. Liquidity recovery in terms of order book depth, however, takes considerably longer and is only accomplished by liquidity providing orders of human traders. In contrast, HFTs and ATs do not significantly contribute to order book depth resiliency. Consequently, our results show that the speed of trading only matters for one dimension of order book resiliency. HFTs and their low-latency infrastructure are responsible for spread resiliency since the recovery of a tight bid-ask spread needs only the submission of one precise order at best. Resiliency in terms of order book depth, however, that is necessary for a market to absorb further liquidity demands of larger orders, is only achieved by human traders, who persistently stay in the order book with sufficient order volumes.
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### 8 Appendix

#### Table A1: Descriptive statistics of events per instrument (mean).

| Instrument (RIC) | No. of Events | Market Impact (in bps) | No. of Affected Price Levels | Order Volume (in euro) | Volume/Standard Market Size |
|------------------|---------------|------------------------|-----------------------------|------------------------|-----------------------------|
| ADSG.DE          | 7             | 20.18                  | 6.29                        | 160,626                | 10.71                       |
| ALVG.DE          | 10            | 22.02                  | 10.50                       | 418,816                | 16.75                       |
| BASF.DE          | 10            | 15.14                  | 5.90                        | 427,909                | 17.12                       |
| BAYG.DE          | 10            | 14.32                  | 6.40                        | 300,054                | 12.00                       |
| BEIG.DE          | 8             | 13.43                  | 5.13                        | 76,510                 | 5.10                        |
| BMWG.DE          | 10            | 15.05                  | 7.40                        | 220,575                | 14.71                       |
| CBBG.DE          | 9             | 51.68                  | 8.44                        | 390,362                | 26.02                       |
| DAIGn.DE         | 9             | 14.33                  | 8.78                        | 256,505                | 10.26                       |
| DB1Gn.DE         | 8             | 21.97                  | 7.38                        | 158,069                | 6.32                        |
| DBKGn.DE         | 10            | 21.53                  | 10.60                       | 349,309                | 13.97                       |
| DPWGN.DE         | 10            | 14.96                  | 4.20                        | 142,387                | 9.49                        |
| DTEGn.DE         | 8             | 11.90                  | 3.25                        | 365,743                | 14.63                       |
| EONGn.DE         | 10            | 13.65                  | 4.60                        | 391,627                | 26.11                       |
| FMEG.DE          | 8             | 10.41                  | 4.13                        | 99,521                 | 6.63                        |
| FREG_p.DE        | 8             | 17.06                  | 6.13                        | 125,695                | 8.38                        |
| HNKG_p.DE        | 8             | 15.85                  | 5.13                        | 86,904                 | 11.59                       |
| HNRgn.DE         | 7             | 16.72                  | 5.14                        | 64,603                 | 8.61                        |
| LHAG.DE          | 9             | 18.29                  | 5.00                        | 167,456                | 11.16                       |
| LING.DE          | 8             | 13.07                  | 6.50                        | 156,094                | 10.41                       |
| MANG.DE          | 9             | 18.88                  | 7.89                        | 220,547                | 14.70                       |
| MELOG.DE         | 9             | 11.59                  | 4.11                        | 77,120                 | 5.14                        |
| MRSG.De          | 10            | 12.56                  | 6.40                        | 152,761                | 10.18                       |
| MUVGn.DE         | 10            | 13.95                  | 8.90                        | 252,576                | 10.10                       |
| RWEG.DE          | 8             | 13.70                  | 7.75                        | 553,404                | 22.14                       |
| SAPG.DE          | 9             | 9.90                   | 6.22                        | 232,125                | 9.28                        |
| SDFG.DE          | 9             | 19.60                  | 7.22                        | 149,952                | 10.00                       |
| SIEGn.DE         | 10            | 10.43                  | 6.70                        | 343,813                | 13.75                       |
| SZGG.DE          | 9             | 25.44                  | 8.33                        | 171,101                | 11.41                       |
| TKAG.DE          | 9             | 18.01                  | 4.89                        | 292,841                | 13.52                       |
| VOWG.DE\(^5\)    | 6             | 18.15                  | 7.67                        | 122,828                | 3.51                        |

| Mean             | 9             | 17.13                  | 6.57                        | 227,927                | 12.12                       |
| Median           | 9             | 15.10                  | 6.40                        | 186,971                | 10.94                       |
| Min              | 6             | 9.90                   | 3.25                        | 64,603                 | 3.51                        |
| Max              | 10            | 51.68                  | 10.60                       | 553,404                | 26.11                       |

\(^5\)As our data set includes the DAX 30 constituents as of August/September 2009, Volkswagen common stock is included in our sample and not Volkswagen preference shares that are part of the German stock index DAX 30 since December 2009.
Figure A1: Distribution of market impact events over the observation period.

Figure A2: Occurrence of market impact events during the trading day.
Figure A3: This Figure shows the relative distribution of the estimated bid-ask spread residuals in Equation (4) based on the five seconds observation period. The regression is based on the following equation: \( \text{Spread}_{i}^{\text{post5}} = \beta \ast \text{Spread}_{i}^{\text{event}} + \epsilon_{i}. \)

Figure A4: This Figure shows the relative distribution of the estimated bid-ask spread residuals in Equation (4) based on the ten seconds observation period. The regression is based on the following equation: \( \text{Spread}_{i}^{\text{post10}} = \beta \ast \text{Spread}_{i}^{\text{event}} + \epsilon_{i}. \)
Figure A5: This Figure shows the relative distribution of the estimated Depth(10) residuals in Equation (4) based on the five seconds observation period. The regression is based on the following equation: $\text{Depth}(10)_{i}^{post5} = \beta \times \text{Depth}(10)_{i}^{event} + \epsilon_i$.

Distribution of Estimated Depth(10) Residuals (10 seconds)

Figure A6: This Figure shows the relative distribution of the estimated Depth(10) residuals in Equation (4) based on the ten seconds observation period. The regression is based on the following equation: $\text{Depth}(10)_{i}^{post10} = \beta \times \text{Depth}(10)_{i}^{event} + \epsilon_i$. 
Table A2: Results of the relative spread resiliency regression (Equation (5)) conducted for the five- and ten-second interval respectively. Variables HFT, AT, and Human refer to the coefficient of the respective number of net limit order submissions (NLOS) of that group within five and ten seconds after the liquidity shock. Controls for stock and date are included. Heteroskedastic robust variance estimators are applied. Standardized beta coefficients; t-statistics in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

|            | Relative Spread - 5 seconds | Relative Spread - 10 seconds |
|------------|-----------------------------|-------------------------------|
|            | (1) (2) (3) (4)             | (5) (6) (7) (8)               |
| HFT5       | -0.244*** (-3.81)           | -0.208*** (-3.29)             |
| AT5        | -0.182*** (-2.92)           | -0.125*** (-2.10)             |
| Human5     | -0.086 (-1.28)              | -0.036 (-0.57)                |
| HFT10      |                            | -0.243*** (-3.90)             |
| AT10       |                            | -0.147* (-1.96)               |
| Human10    |                            | -0.007                        |
| Activity5  | -0.104 (-1.35)              | -0.146** (-2.02)              |
| Activity10 | -0.034 (-0.43)              | -0.077 (-1.13)                |
| Observations | 265 265 265 265         | 265 265 265 265               |
| Adjusted R^2 | 0.502 0.489 0.474 0.507  | 0.508 0.487 0.473 0.508      |
| Mean VIF  | 2.41 2.40 2.41 2.46  | 2.39 2.38 2.41 2.43          |
| Max VIF  | 2.97 2.97 2.97 3.27  | 2.97 2.96 3.01 3.02          |