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DOES SPEED MATTER? THE ROLE OF HIGH-FREQUENCY TRADING FOR ORDER BOOK RESILIENCY

Benjamin Clapham

Goethe University Frankfurt

Martin Haferkorn

European Securities and Markets Authority

Kai Zimmermann

Goethe University Frankfurt

Abstract

We analyze 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 replenishing the order book. Therefore, we relate the net liquidity provision of high-frequency traders, algorithmic traders, and human traders around these market impact events to order book resiliency. Although all groups of traders react, our results show that only high-frequency traders reduce the spread within the first seconds after the market impact event. Order book depth replenishment, however, takes significantly longer and is mainly accomplished by human traders' liquidity provision.

JEL Classification: G10, G14, G18

I. Introduction

Since the emergence of highly automated trading desks and fully electronic securities markets, 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

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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 in implicit transaction costs for all market participants. The positive effect of HFTs on liquidity holds particularly for HFTs acting as market makers, which represent the majority of HFTs in terms of trading volume and order messages (Hagströmer and Nordén 2013). Several studies report the positive impact of HFT on spreads and order book depth (e.g., Hasbrouck and Saar 2013), which account for the price and quantity dimension of liquidity. However, little empirical evidence exists concerning the contribution of HFTs to the third dimension of liquidity: order book resiliency (e.g., Hasbrouck and Saar 2013), which is the dynamic characteristic of liquidity representing the recovery of the order book after a liquidity shock.[1] Especially for sudden drops in liquidity, HFTs can react quicker and more precisely to such order book changes than other groups of traders. Consequently, HFTs in particular might contribute to the recovery of liquidity and thus foster order book resiliency, which leads to increased price efficiency and lower implicit transaction costs after liquidity shocks.

Based on the debate surrounding the role of HFT for liquidity provision, we study how different types of traders (i.e., HFTs, algorithmic traders [ATs], and human traders) replenish liquidity in the order book following a large aggressive order leading to market impact and a sudden drop in liquidity. Thereby, we aim to reveal the contribution of HFTs to order book resiliency relative to non-HFT participants. During and after such events, low-latency traders can maximize their speed advantage and benefit from widened spreads and reduced order book depth. Given that HFTs follow such strategies, other market participants may profit from increased order book resiliency due to HFT. Moreover, fast liquidity recovery in terms of spread and depth lowers implicit transaction costs for investors and ultimately the liquidity component of companies' cost of capital. Therefore, we investigate the contribution of different types of traders to order book resiliency by using a sample of large market orders that hit the open limit order book and walk through several order book levels leading to market impact. In particular, we focus on the net liquidity provision of HFTs and non-HFTs around these market impact events 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 corresponding flags. Thus, we can provide detailed insights on order book resiliency in the presence of HFTs.

Our results show that HFTs contribute significantly to open limit order book replenishment. Specifically, we find HFTs to be the driving force behind reestablishing tight spreads within short periods. In contrast, ATs without low-latency infrastructure and human traders do not significantly support spread resiliency. The recovery of bid–ask spreads is accomplished within the first few seconds after a market impact event, and the largest fraction of widened spread recovers within the first second.

[1]Order book resiliency as the third dimension of liquidity is described in early papers on market microstructure. Black (1971), Kyle (1985), and Harris (2003) describe resiliency as the quick recovery of prices after market impact events. Building on this, Foucault, Kadan, and Kandel (2005) develop a model of order book resiliency that defines market resiliency as the spread reversion to its former level after a liquidity shock.

Human traders, although adapting their submission behavior within the first seconds after the event, do not significantly affect spread resiliency. When considering the resiliency of order book depth, however, the results change considerably. HFTs do not sufficiently replenish order book depth as they predominantly submit small-volume orders, focusing on the top of the order book. This also holds for ATs. Depth resiliency, therefore, is mainly achieved by human traders showing high net liquidity provisions after market impact events. Therefore, fast liquidity provision by HFTs, which also prevails after a significant market impact, represents only a specific and limited contribution to overall order book resiliency. To mitigate the price impact of further large orders, order book depth must be replenished by various limit orders of relevant size. As shown in our analysis, this is mainly achieved with the help of human traders that persistently stay in the order book and offer vast amounts of nontransient liquidity. Therefore, we show that different types of traders, namely HFTs and human traders, pursuing different strategies are needed to accomplish order book resiliency in all dimensions (i.e., spread and depth) in an efficient and fast manner.

II. Related Literature

Liquidity Provision by HFTs

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 three dimensions: spread, order book depth, and order book resiliency (Black 1971; Kyle 1985; Harris 2003). The first part of our literature review focuses on the impact of HFT on liquidity in terms of spread and order book depth, followed by a summary of the research on order book resiliency.

Research concerning the relation of HFT and liquidity in terms of spread and depth is mostly conducted using time-series regression techniques. Regarding bid–ask spreads, studies show that HFTs provide liquidity when spreads are wide and consume liquidity when spreads are tight (Zhang and Riordan 2011; Carrion 2013). In line with these results, Brogaard, Hendershott, and Riordan (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 order book depth is low. Thus, HFTs contribute to decreasing spreads, which is further observed by Hasbrouck and Saar (2013). These results are supported by the observation that HFTs mostly follow market-making strategies and submit passive (i.e., liquidity-providing) orders (Hagströmer and Nordén 2013; Menkveld 2013). Regarding AT in general, Hendershott, Jones, and Menkveld (2011) find that ATs reduce the bid–ask spread on the New York Stock Exchange (NYSE). Using a similar data set to ours, Hendershott and Riordan (2013) confirm this finding.

In contrast to these positive results concerning the impact of HFT on liquidity, Lee (2015) finds that HFT has no effect on liquidity as spread and depth remain unaffected. Goldstein, Kwan, and Philip (2018) likewise analyze the contribution of HFTs to overall liquidity and conclude that liquidity provision by HFTs should not be overestimated as they provide liquidity in the opposite direction of order imbalance.

Different from our study, the authors focus on regular trading conditions showing how the trading decisions of HFTs depend on and influence order book imbalance. Instead, we analyze the contribution of HFTs to order book resiliency after market impact events especially in light of HFTs' speed advantage in comparison to other traders. Thus, our article contributes to financial market research by revealing how different types of traders react after a market impact event leading to decreased liquidity and, more interesting, how these traders contribute to the replenishment of different dimensions of liquidity, that is, spread and order book depth resiliency. In contrast to Goldstein, Kwan, and Philip, we find evidence that HFTs do not act opportunistically during market impact events but initiate the resiliency process that other non-HFT traders join. Hautsch, Noé, and Zhang (2017) find that HFTs tend to consume rather than provide liquidity around scheduled macroeconomic announcements. In contrast, we analyze market impact events due to sudden, non-news-related excess liquidity demand. We provide evidence on how order book resiliency is accomplished by HFTs and human traders in the absence of macroeconomic buy or sell pressure, which affects market participants differently.

Order Book Resiliency and HFT

The viability and efficiency of open limit order books depends on public limit orders and quotes standing in the order book, which have to be replenished quickly by traders after market impact events leading to a sharp decrease in liquidity. Order book resiliency represents this dynamic aspect of liquidity, that is, the recovery of static liquidity dimensions relative spread and order book depth to their "normal" levels after a liquidity shock. The importance of resiliency is 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 order book depth but on the speed at which supply of and demand for a security recover after a trade.

Foucault, Kadan, and Kandel (2005) develop a theoretical model of spread resiliency in a limit order book where traders face a trade-off between the spread as a cost of immediacy and the cost of delayed execution. Concerning depth resiliency, Coppejans, Domowitz, and Madhavan (2004) analyze the variation of order book depth over time. They find that electronic order books exhibit high degrees of resiliency as liquidity shocks are resolved quickly. Nevertheless, the variation in order book depth affects trading strategies. These findings are consistent with the observations by Gomber, Schweickert, and Theissen (2015), who find that implicit transaction costs of a round-trip trade of given size quickly revert to a "normal" level after a liquidity shock 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 for the spread observed by Biais (1995). Kempf et al. (2015) develop a mean reversion model of liquidity measuring resiliency as the rate of mean reversion in both spread and depth in the Financial Times Stock Exchange 100 Index (FTSE 100) stocks over a two-year period. By extending their model with a variable capturing AT activity, Kempf et al. find that AT has a positive impact on spread and order book depth resiliency. However, they do not observe trading behavior of ATs but instead approximate AT activity based on the intensity of order cancellations. Moreover, their results are based on five-minute intervals, which are too long to infer the behavior of HFTs representing a subgroup of ATs that react within a fraction of a second.

Therefore, we help fill the research gap regarding the role of HFT for order book resiliency by investigating what types of traders replenish liquidity in the order book following a large aggressive order and the associated sudden drop in liquidity. As our proprietary data set includes all order messages by HFTs and non-HFTs time-stamped to a hundredth of a second, we can precisely study the contribution of HFTs, ATs, and human traders to order book resiliency. There is only one theoretical paper that provides first evidence regarding HFT and order book resiliency (Leal and Napoletano 2019). Based on an agent-based model concerning flash crashes, Leal and Napoletano (2019) show that HFTs are fundamentally involved in both the cause of a flash crash and the liquidity recovery after a shock.

III. Data and Descriptive Statistics

Data Set

Our article focuses on the most actively traded and largest German stocks, that is, the constituents of the German blue chip index DAX 30. The data set provided by Deutsche Boerse contains all order book messages of its electronic open limit order book Xetra for the DAX 30 stocks within the two weeks from August 31 to September 11, 2009 (10 trading days). For every order book message, the data set contains a time stamp, the International Securities Identification Number (ISIN), an order number that allows identification of all other messages related to a certain message (e.g., submissions can be linked to the corresponding [partial] executions or cancellations), whether the respective order was a buy or sell order, and the 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.

The first flag that makes our data set especially useful is the additional AT flag (Algo-flag). It indicates whether a certain message has been generated by an algorithm (Algo-flag = 1) or not (Algo-flag = 0). We refer to nonalgorithmic orders as human traders' orders. The identification of ATs is possible because Deutsche Boerse implemented a special pricing model for computer-generated trades called the Automated Trading Program in 2005 to promote AT on its electronic trading platform Xetra (Deutsche Boerse 2004). Traders participating in the Automated Trading Program can take advantage of fee rebates for transactions that have been submitted by an algorithm if they agree to exclusively use their Automated Trading User-ID whenever they trade using computer algorithms. 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), time (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/human intervention. Because the rebates increase with a customer's number of algorithmic trades per month, it is economically

TABLE 1. Descriptive Statistics for the DAX 30 Constituents: August 31, 2009 to September 11, 2009

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

Note: Market capitalization is reported as of December 31, 2009 and the standard deviation of daily returns is determined for each stock during the observation period. All other variables are calculated based on 300 observations (30 stocks and 10 trading days).

rational for banks and brokers to use their Automated Trading User-ID for every order generated by an algorithm. This is also confirmed by Hendershott and Riordan (2013). Consequently, the Algo-flag appears to be highly reliable and a suitable proxy for AT activity. Since Deutsche Boerse extended the fee reduction program to all Xetra orders in November 2009, it effectively ended the possibility of differentiating between ATs and non-ATs (Deutsche Boerse 2009). Therefore, a more recent data set is not available.

The second important flag is the Colo-flag, which indicates whether the submitter of an order is colocated at Deutsche Boerse (Colo-flag = 1) or not (Colo-flag = 0). Hence, we can further differentiate orders submitted by algorithms into the following two groups: fast ATs using colocation services, that is, HFTs and relatively slower traders, that is, non-HFT ATs. Based on these flags, the data set allows us to distinctively analyze the trading behavior and respective role of order book resiliency of three types of traders: HFTs, ATs, and human traders.

Table 1 reports descriptive statistics for the DAX 30 constituents between August 31, 2009 and September 11, 2009. Market capitalization is reported as of December 31, 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). Although 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 for the 30 stocks.

To study the role of HFTs, ATs, and human traders for order book resiliency, we focus on the continuous trading phase, as market impacts caused by significant liquidity demands are less prevalent in highly liquid call auctions. The data set contains 1,243,083 messages logged during continuous trading, 49.1% of which are submissions,[2] 40.9% are cancellations, 5.2% are executions, 2.7% are partial executions, and 2.0% are modifications. The number of modifications is low compared to the number of submissions and cancellations because only an adjustment of the order's volume leads to a modification. All other changes that affect price-time priority lead to the cancellation of the order and the insertion of the same order as a "new"

[2]Order submissions in our sample either relate to limit orders (98.8%), market orders (0.4%), or iceberg orders (0.8%). There are no hidden orders on Xetra.

TABLE 2. Proportion of Messages Triggered by Each of the Three Groups of Traders

Group of Traders	No. of Messages	Proportion of All Messages
High-frequency traders	680,865	64.9%
Algorithmic traders	161,559	15.4%
Human traders	206,788	19.7%

order with a new time stamp and order number. The remaining 3.2% of all messages represent technical messages generated by the exchange system, which are not relevant for our analysis. Therefore, all messages other than submissions, modifications, cancellations, executions, and partial executions are removed. 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, most of which are triggered by HFTs. As depicted in Table 2, 64.9% of all messages in the data set are generated by HFTs, 15.4% by ATs, and 19.7% by human traders.

Market Impact Events

To analyze order book resiliency, we must 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 market impact. Gomber, Schweickert, and Theissen (2015), for example, show that large orders are timed, which implies that large orders are 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). Specifically, we identify market impact events based on the number of order book levels affected by an aggressive order. Because 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 or affected by an order. Consequently, we count the partial executions that follow each market order to identify market impact events. We choose market orders instead of limit orders because market orders in general are more aggressive and are executed for any price available, whereas limit orders are executed only as long as the price is above/below the specified limit. Following this approach, we determine market impact events based on an order's relative impact on liquidity in the order book and thus circumvent the timing issue of large orders.

For our analysis, we take the 10 market orders with the highest market impact (i.e., those with the highest number of affected order book levels[3]) for every stock

[3]If this procedure results in more than 10 potential events for a specific stock because there are several market orders with the same number of affected order book levels, market orders with higher volume are given preference.

TABLE 3. Initiators of Market Orders Leading to Market Impact Events

Initiated by:	No. of Events	Proportion
Buyer	133	50.2%
Seller	132	49.8%
High-frequency traders	6	2.3%
Algorithmic traders	17	6.4%
Human traders	242	91.3%

listed in the German blue chip index DAX 30 during our observation period. Thereby, we can identify 300 market impact events. We do not consider any market impact event in our sample that happened 15 minutes before or after an auction as well as circumstances in which two market impact events directly follow each other, to avoid potential biases from these special trading situations. With this selection process, we ensure that we are analyzing the most severe market impact events. Because the data set covers only a two-week period, these 10 events per stock represent a good compromise between data set size and strength of market impact. We explicitly search for non-news-related market impact events that are purely order book driven to avoid potential biases due to new information or other exogenous events that might influence traders' decisions. Therefore, every event is checked for companies' ad-hoc disclosures that might have caused the market impact event, to rule out that our events are information driven. Moreover, no single earnings announcement date is included in our sample. Concerning other potential information causing these events, we find that 15 company presentations at (industry) conferences often hosted by large investment banks and investor roadshows happened on one of the observation days.[4] Our results remain robust when we exclude these observations. Thus, our selection of market impact events ensures that our results on order book resiliency are purely liquidity driven and not biased by exogenous events.

To analyze order book resiliency for our market impact events, we match order book snapshots retrieved from Thomson Reuters Tick History (TRTH) to the message data provided by Deutsche Boerse. Thereby, 33 events were lost during the matching process because the time stamps of both data sources are not synchronized and the corresponding market impact is 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 market impact event is smaller than the respective stock's standard market size (SMS) as reported by the European Securities and Markets Authority (ESMA).[5] Because the stocks in our sample are highly liquid, an order size smaller than SMS leading to a market impact 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

[4]Information on earnings announcement dates and company presentations are obtained from Datastream.

[5]ESMA reports SMSs for listed securities in the ESMA Registers (see https://registers.esma.europa.eu/publication/searchRegister?core=esma_registers_fitrs_equities).

TABLE 4. Descriptive Statistics of Events

	Market Impact (bps)	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

Note: This table provides descriptive statistics for the 265 market impact events caused by large market orders. Market impact describes the mean absolute difference between the first and last price levels affected by the aggressive order relative to the current stock price. Number of affected price levels shows how many order book levels were on average cleared by the incoming market order. Order volume provides the average euro volume of the market orders leading to market impact events, and volume/standard market size reports this value relative to the standard market size.

trading day is provided in Figures AI and AII in the Appendix. Market orders causing market impact events are almost evenly split between buyer- (133) and seller-initiated (132) orders. However, 91.3% of these orders are submitted by human traders, 6.4% are generated by ATs, and only 2.3% by HFTs (see Table 3).

This finding seems reasonable because ATs regularly slice large orders into smaller parts using limit orders to avoid market impact, and human traders might also trade large quantities with market orders, for example, if they need to fulfill contracts or close positions within a short time. Moreover, HFTs predominantly operate on the top of the order book, submitting and canceling limit orders within short time frames as shown by Jarnecic and Snape (2014). Table 4 provides descriptive statistics for the 265 events included in our sample. The descriptive statistics per stock are provided in Table A1 in the Appendix.

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 market impact events in this study are on average 12.39 (median 9.92) times larger than the SMS of the respective stock. Moreover, the average market impact[6] of 17.10 basis points (bps) (median 13.87 bps) is significant given that we study the most liquid German stocks. Also, more than six price levels are on average affected by the market orders leading to market impact events. This shows that these orders significantly walk through the book and consume liquidity, which needs to be replenished.[7]

[6]Market impact is defined as the absolute difference between the first and last price levels affected by an aggressive, that is, liquidity-consuming, order. To ensure comparability across stocks 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.

[7]These descriptive results also show the economic relevance of our research on order book resiliency. Because of 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 10 trading days in our data set. If the order book is not resilient and liquidity does not revert to the pre-market impact event level, all market participants and orders demanding immediacy have to bear these additional costs. Therefore, order book resiliency can be seen as a key component of liquidity ensuring consistently low implicit transaction costs and trading possibilities at appropriate spreads.

TABLE 5. Mean Number of Submissions and Cancellations for Each Group of Traders within 5 and 10 Seconds before and after a Market Impact Event

Panel A. Submissions and Cancellations 5 Seconds before and after a Market Impact Event

	High-Frequency Traders		Algorithmic Traders		Human Traders	
Message Activity	−5	+5	−5	+5	−5	+5
Submissions	10.0	46.6	2.4	12.2	3.0	14.8
Δ (in %)		465.9		501.7		499.4
Cancellations	8.9	38.1	2.3	10.0	1.9	8.1
Δ (in %)		427.5		433.2		433.1
Relative activity (in %)	66.4	65.3	16.6	17.1	17.0	17.7

Panel B. Submissions and Cancellations 10 Seconds before and after a Market Impact Event

	High-Frequency Traders		Algorithmic Traders		Human Traders	
Message Activity	−10	+10	−10	+10	−10	+10
Submissions	20.7	64.2	5.0	15.6	5.6	19.1
Δ (in %)		310.1		313.5		341.3
Cancellations	18.3	53.6	4.7	13.0	3.4	10.4
Δ (in %)		293.2		276.4		306.8
Relative activity (in %)	67.6	67.0	16.8	16.2	15.6	16.8

Note: Relative activity is calculated based on each group's number of submissions and cancellations relative to all submissions and cancellations in the respective period.

For the resiliency analyses based on the identified market impact events, 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 5 and 10 seconds before and after the 265 market impact events. These intervals appear to be appropriate given that we simultaneously analyze HFTs', ATs', and human traders' activity, which differs in speed and reaction time. Table 5 reports the mean number of submissions and cancellations for each group of traders within 5 (10) seconds before and after a market impact event. These numbers give a first impression of how the groups of traders react to market impact events. 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 interval. Both panels in Table 5 clearly indicate that HFTs, ATs, and human traders react to the market impact event 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. Because 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 period. In absolute terms, HFTs show the

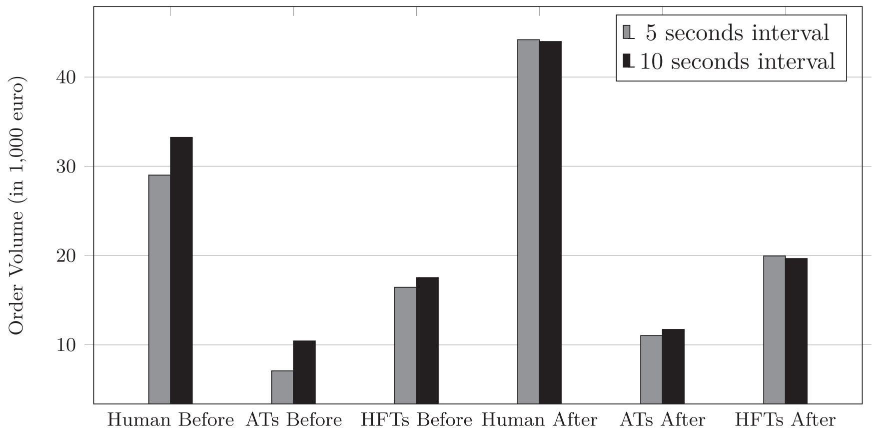

Figure I. Order Volume of Each Group of Traders before and after the Market Impact Event.

highest number of limit order submissions; however, they also exhibit the highest number of limit order cancellations.

The increasing commitment of liquidity by all trader types is also supported by the observations shown in Figure I, which depicts the mean euro order volume of HFTs, ATs, and human traders 5 and 10 seconds before and after the market impact event. All traders increase their average order size after the market impact event, thereby providing additional liquidity. Moreover, the figure shows that human traders submit significantly larger order sizes than do ATs and HFTs. Their mean order size across all 265 events amounts to 29,012 euro (33,239 euro) in the 5- (10-) second interval before the market impact event and 44,185 euro (43,982 euro) in the 5- (10-) second interval after the market impact event. ATs submit the smallest mean order sizes of all traders with 7,084 euro (10,432 euro) before and 11,032 euro (11,717 euro) after the market impact event. The mean order sizes of HFTs are in between, with on average 16,440 euro (17,528 euro) before and 19,956 euro (19,665 euro) after the market impact event.

Liquidity around Market Impact Events

Before investigating the contributions of ATs, HFTs, and human traders to order book resiliency, we provide descriptive statistics regarding liquidity development around the market impact events in this study. Figures II and III show changes in relative spreads and order book depth before and after the market impact event. The bars depict the 1-second average relative spread (order book depth) 5 seconds before until 10 seconds after the market impact event as well as the relative spread (order book depth) right after the execution of the market order (time 0). The line represents the average relative spread (order book depth) for the 30 DAX constituents included in our sample over the 10 trading days in our sample period. We do not use the pre-event window as a benchmark because research shows that large orders are timed and tend to be submitted when the liquidity level is abnormally high (Gomber, Schweickert, and Theissen 2015). Therefore, the pre-event window is not the best benchmark to study and visualize the

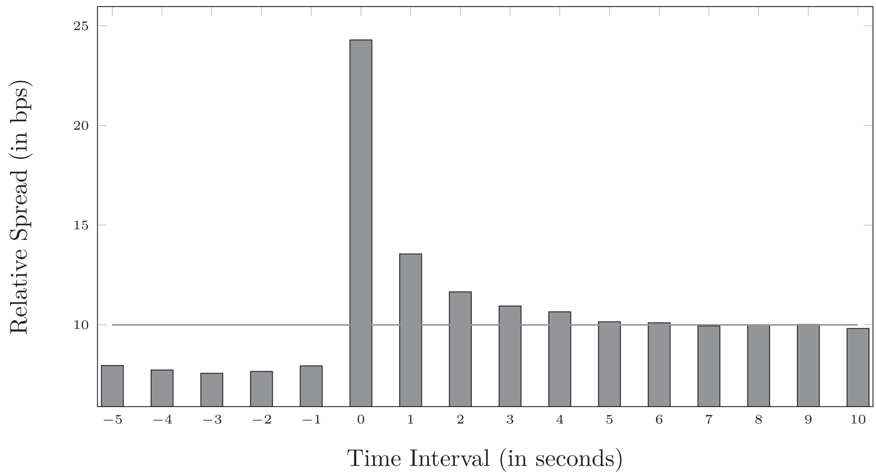

Figure II. Relative Spread 5 Seconds before the Market Impact Event, Directly after the Event (Time 0), and Its Recovery 10 Seconds after the Market Impact Event.

resiliency process. Moreover, research shows that liquidity follows a mean-reversion process (Kempf et al. 2015). Consequently, the 10-day average of spread and depth appears to be the appropriate benchmark to visualize the resiliency process. We measure order book depth using the *Depth*(10) measure proposed by Degryse, De Jong, and Van Kervel (2015), which sums up the quoted euro-volume available 10 bps around the midpoint.

Several observations can be made in this high-level aggregation. First, a significant drop in liquidity is visible after the market order hits the order book. The relative spread depicted in Figure II drastically increases to on average 24.29 bps directly after the market impact event, which is also significantly larger than the 10-day

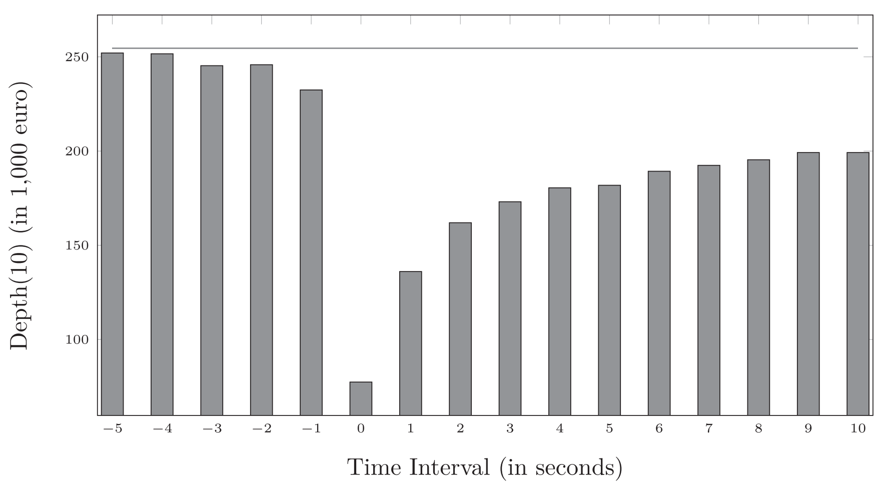

Figure III. *Depth* (10) 5 Seconds before the Market Impact Event, Directly after the Event (Time 0), and Its Recovery 10 Seconds after the Market Impact Event.

average of 9.99 bps across all DAX 30 constituents. Second, the relative spread seems to recover quickly. Although the strongest recovery occurs within the first second after the event, it takes a further four seconds until the relative spread is not significantly different from the 10-day average. After five seconds following the initial impact, no significant changes in average relative spreads are observable. The differences between the average relative spread in each second and the 10-day average as well as the test statistics for significance are provided in Table 6. Third, the relative spreads in the seconds before the market impact event are significantly lower than their average over the whole investigation period, meaning that liquidity is provided cheaper at the top of the order book. As the market orders leading to market impact events are considerably larger than the SMS of the respective stock, lower relative spreads before the market impact event support previous findings that large orders are timed when liquidity is unusually high.

Turning now to the second liquidity measure, that is, order book depth measured by *Depth*(10), depicted in Figure III, the picture looks slightly different. First, there continues to be a significant dry-up of liquidity in terms of depth, which is reduced to as low as 77,357 euro after the market impact event compared to an average depth of 254,520 euro in our observation 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 8 more seconds to establish a constant level. Different from the relative spread, the recovery of order book

TABLE 6. Difference between *Relative Spread*, *Depth*(5), and *Depth*(10) in each 1-Second Interval around Market Impact Events and Their Respective Means over the Whole 10 Trading Days Covered by the Data Set

Interval (in seconds)	Delta Mean *Relative Spread* (in bps)	Delta Mean *Depth*(5) (in 1,000 euro)	Delta Mean *Depth*(10) (in 1,000 euro)
[−5;−4[	−2.038 (−5.203)***	7.322 (0.804)	−2.460 (−0.131)
[−4;−3[	−2.263 (−7.187)***	10.615 (1.307)	−2.882 (−0.175)
[−3;−2[	−2.429 (−8.443)***	10.820 (1.532)	−9.196 (−0.606)
[−2;−1[	−2.334 (−8.307)***	8.800 (1.247)	−8.687 (−0.592)
[−1; 0[	−2.056 (−6.696)***	4.675 (0.755)	−22.075 (−1.632)
Event	14.301 (19.458)***	−74.150 (−70.606)***	−177.163 (−19.599)***
]0;1]	3.559 (9.717)***	−54.759 (−26.921)***	−118.489 (−13.385)***
]1;2]	1.657 (4.656)***	−43.391 (−12.635)***	−92.574 (−8.587)***
]2;3]	0.949 (2.811)**	−38.605 (−10.047)***	−81.438 (−7.315)***
]3;4]	0.656 (2.051)*	−36.174 (−8.678)***	−74.030 (−6.464)***
]4;5]	0.156 (0.499)	−32.294 (−7.489)***	−72.689 (−6.446)***
]5;6]	0.104 (0.345)	−31.914 (−7.379)***	−65.246 (−5.502)***
]6;7]	−0.049 (−0.163)	−31.589 (−7.404)***	−62.110 (−5.114)***
]7;8]	0.010 (0.030)	−29.489 (−6.374)***	−59.142 (−4.641)***
]8;9]	0.023 (0.071)	−25.819 (−5.293)***	−55.313 (−4.317)***
]9;10]	−0.180 (−0.570)	−22.241 (−4.141)***	−55.313 (−4.317)***

Note: The mean relative spread over the whole observation period amounts to 9.99 basis points (bps) and average *Depth*(5) (*Depth*(10)) equals 76,503 euro (254,520 euro). The *t*-statistics are reported in parentheses.

*Significant at the 5% level.

**Significant at the 1% level.

***Significant at the 0.1% level.

depth takes longer and does not reach the "normal" level within 10 seconds after the event, as indicated by the significant differences compared to the 10-day average provided in Table 6. Nevertheless, the differences to the average depth remain stable from the 8th second after the market impact event onward. Therefore, our proposed observation periods of 5 and 10 seconds after the market impact event are supported by this high-level analysis. Moreover, and contrary to relative spreads, there is no evidence for the timing of large orders by looking at order book depth.

To provide further robustness of our results, we repeat our analysis using *Depth*(5) as a measure for order book depth, which considers only quoted volumes closer to the midpoint, that is, 5 bps around the midpoint.[8] The descriptive results are qualitatively similar for order book depth measured by *Depth*(5) as shown in Table 6 and Figure AIII in the Appendix.

IV. Reactions to Market Impact Events

Research Approach

Based on the descriptive analyses of the market impact events in our sample and the corresponding resiliency process, we now turn to the statistical evaluation of the role HFTs, ATs, and human traders for order book resiliency. In this section, we first focus on the reaction of HFTs, ATs, and human traders to non-news-related market impact events. Next, we evaluate each trader types' contribution to order book resiliency in Section V. To study the reaction to the sudden drop in liquidity, 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 5- and 10-second interval before the large market order hits the order book. Measuring the net liquidity provision of each type of traders is important especially because HFTs and ATs cancel a large proportion of their orders, thereby withdrawing liquidity provision from the market. We define net liquidity provision as the difference between submitted limit order volume and canceled 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:

$$NLP_{i,g} = \sum_{l=1}^{L} Submitted\ Volume_{i,g} - \sum_{l=1}^{L} Canceled\ Volume_{i,g}. \tag{1}$$

Consequently, a positive net liquidity provision of group g indicates that this group of traders submitted more limit order volume to the book than it canceled within

[8]To provide a deeper understanding of the *Depth*(x) measure, Table A2 in the Appendix provides an overview of how many order book levels are regularly considered for the calculation of both depth measures based on our sample and observation period. Whereas *Depth*(5) in almost 80% of the cases only captures the euro volume quoted on the first order book level, *Depth*(10) more often also considers the volume on deeper order book levels.

the 5- or 10-second interval i. 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 canceled orders within the 5- or 10-second window, the measure is set to 0. For the following analysis, the net liquidity provision behavior of each group of traders within 5 and 10 seconds before and after the market impact event is obtained and evaluated in a cross-sectional regression setup. The estimated regression model is based on the following equation:

$$NLP_i = \alpha + \beta_1 \times HFT + \beta_2 \times AT + \beta_3 \times PrePost \times HFT + \beta_4 \times PrePost \times AT + \beta_5 \times PrePost \times Human + \sum_{n=6}^{35} \beta_n \times Controls_n + \varepsilon_i. \quad (2)$$

In the regression model, all 5-second (10-second) net liquidity provisions (*NLP*) before and after the market impact event are explained and compared according to their characteristics. Consequently, the number of observations is increased by the factor 6 to 1,590 because each of our 265 events has a pre- and post-event observation and is calculated for HFTs, ATs, and human traders. *HFT*, *AT*, and *Human* are dummy variables indicating whether the respective *NLP* reflects HFTs', ATs', or human traders' liquidity provision. The dummy variable *PrePost* equals 0 if the net liquidity provision is measured based on 5 (10) seconds before the market impact event and switches to 1 if *NLP* is measured after the event. The interaction terms *PrePost* × *HFT, PrePost* × *AT*, and *PrePost* × *Human* indicate the changes in the HFTs', ATs', and human traders' net liquidity provision before and after the market impact event. Additionally, we apply control variables capturing further idiosyncratic differences in net liquidity provision. Most important is the overall activity level, which is computed by counting all submissions and cancellations in the specific 5- (10-) second observation window. Moreover, the net liquidity provision may systematically be different for each stock in our sample. Therefore, we apply stock-specific controls by including a dummy variable for each of the analyzed stocks. For the purpose of this study, we are most interested in the estimated coefficients of *PrePost* × *HFT, PrePost* × *AT*, and *PrePost* × *Human* that provide indications about a systematic change of each group's behavior after market impact events.

In addition to traders' net liquidity provision and to provide further robustness of our results, we consider each group of traders' net limit order submissions (*NLOS*) reflecting traders' activity in terms of liquidity provision. 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 group g in a given interval i independent of the order volume connected to an order:

$$NLOS_{i,g} = Submissions_{i,g} - Cancellations_{i,g}. \quad (3)$$

Results

The results of the regression model described in the previous subsection are provided in Table 7, which includes the estimates based on both net liquidity provision (*NLP*)

TABLE 7. Results of the Liquidity Provision Regression Based on Equation (2) for 5- and 10-Second Intervals

	NLP		*NLOS*	
Variable	5 Seconds (1)	10 Seconds (2)	5 Seconds (3)	10 Seconds (4)
HFT	−14.79	−26.44*	−0.814***	−1.303***
	(−1.89)	(−2.13)	(−3.68)	(−3.96)
AT	−19.44**	−47.03***	−0.998***	−2.010***
	(−3.25)	(−4.44)	(−6.59)	(−8.71)
PrePost × *HFT*	57.25***	74.44***	3.680***	4.277***
	(4.19)	(4.73)	(7.56)	(7.58)
PrePost × *AT*	3.600	9.037	1.068***	1.412***
	(0.70)	(1.60)	(5.57)	(5.97)
PrePost × *Human*	135.9***	157.7***	4.581***	5.518***
	(10.39)	(8.77)	(12.48)	(11.24)
Activity	1.069***	0.816***	0.057***	0.050***
	(5.31)	(6.32)	(8.41)	(8.49)
Constant	−4.954	14.05	0.83	1.604**
	(−0.36)	(0.85)	(1.61)	(2.62)
Obs.	1,590	1,590	1,590	1,590
Adj. R^2	0.367	0.335	0.529	0.513
Mean VIF	2.18	2.17	2.18	2.17
Max VIF	2.70	2.73	2.70	2.73

Note: *NLP* (*NLOS*) refers to a group of traders' net liquidity provision (net limit order submissions) in the 5- or 10-second interval before or after a market impact event. *HFT, AT*, and *Human* are dummy variables indicating whether *NLP* (*NLOS*) is calculated based on HFTs', ATs' or human traders' trading activity. *PrePost* is a dummy variable that equals 0 if *NLP* (*NLOS*) is measured before the market impact event, and 1 afterward. *Activity* accounts for the overall trading activity measured by the sum of submissions and cancellations in each 5- or 10-second observation window. VIF stands for variance inflation factor. Stock-specific controls are included. Heteroskedastic-robust variance estimators are applied, and *t*-statistics are reported in parentheses.
*Significant at the 5% level.
**Significant at the 1% level.
***Significant at the 0.1% level.

and net limit order submissions (*NLOS*) for the 5- and 10-second aggregation period. 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 of *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 market impact event, which is depicted by the coefficients of the *PrePost* interaction terms. Regarding the mere submission and cancellation activity captured by net limit order submissions, all groups of traders react to the market impact event 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 3.68 (4.28) and 4.58 (5.52), respectively, more limit orders minus potential cancellations in the 5 (10) seconds after the market impact event. The net limit order submissions of ATs, in contrast, increase by only 1.07 and 1.41 orders, respectively, in the same observation windows.

Considering the net liquidity provision (*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 market impact event compared to before the event. For HFTs, the coefficient of the *PrePost* interaction term indicates a significant increase in net liquidity provision by 57,246 euro (74,443 euro) in the 5 (10) seconds after the event. Human traders show an even stronger reaction and increase their net liquidity provision by 135,857 euro (157,698 euro) compared to the pre-event level. Consequently, the changes in the three groups of traders' liquidity provision indicate that HFTs and human traders react strongly to the market impact event and thus might play a crucial role for order book resiliency. Yet this analysis covers only the quantitative change in net liquidity provision. To provide an indication of the qualitative effect of these changes, we must analyze the resiliency dynamics using order book characteristics within the 5- and 10-second intervals. This way, we can extend the previous analysis to the specific utility of the change in traders' net liquidity provision for order book resiliency.

V. Order Book Resiliency

Research Approach

Although different in magnitude, each group of traders' reaction to the market impact event appears to be positive for order book resiliency because 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 evaluate whether and how different groups of traders affect order book resiliency in the post-event phase. Hence, we propose an intuitive regression approach, which relates the post-event change in spreads and order book depth to the specific net liquidity provision of each group of traders within the 5- and 10-second periods following the market impact event. Hence, the stronger both measures recover after the market impact event (i.e., spread reductions and depth improvements), the more efficient the resiliency dynamic is assumed.[9] We explicitly do not rely on any pre-event or average benchmark to analyze the resiliency process but instead investigate which groups of traders contribute to liquidity recovery compared to the decreased liquidity level directly after the market impact event. Thereby, we can identify which trader type systematically contributes to different dimensions of liquidity recovery. We estimate the following regression model:

[9]We do not restrict our analysis to require a full recovery of liquidity because our sample, which focuses on significant order book impact events only, already justifies at least a temporal price impact right after the event. Although we try to rule out any exogenous events that might lead to a permanent price impact, our analysis therefore is not biased if the price after some events does not fully recover after 10 seconds.

$$Liquidity_i^{post} - Liquidity_i^{event} = \gamma + \delta_1 \times NLP_i^{HFT,post} + \delta_2 \times NLP_i^{AT,post} + \delta_3 \times NLP_i^{Human,post} + \sum_{n=4}^{36} \delta_n \times Controls_n + \varepsilon_i. \quad (4)$$

$Liquidity_i^{post}$ denotes the average liquidity (relative spread or order book depth) within 5 and 10 seconds after each market impact event i excluding the order book snapshot right after the execution of the large market order. Likewise, $Liquidity_i^{event}$ denotes the single liquidity snapshot (relative spread or depth) following the market impact event, that is, the first order book situation after the execution of the large market order. Thus, the difference between $Liquidity_i^{post}$ and $Liquidity_i^{event}$ measures the strength of the spread (depth) resiliency. A strong or a very fast liquidity recovery results in a larger spread reduction (depth improvement) from the event to post-event period. To determine which group of traders is responsible for order book resiliency, we relate liquidity recovery to the respective NLP_i measure of HFTs, ATs, and human traders in the 5 and 10 seconds after the market impact event. If positive or negative expected overall liquidity recovery in terms of spread or depth can regularly be associated with the net liquidity contribution of one group of traders, a regression setup can estimate such a significant relation. In contrast, if a group of traders regularly exhibits high net liquidity provision but order book recovery is small, the contribution of this group of traders to order book resiliency must be doubted. Again, we control for the overall activity level measured by the sum of all submissions and cancellations within the 5 and 10 seconds after the market impact event. In addition, we control for differences in the pre-event liquidity level by including the pre-event spread, order book depth (*Depth*(10)), and order book imbalance,[10] all based on the 1-second pre-event average. Also, we apply stock-specific controls. The resiliency regression is run separately for liquidity recovery in terms of relative spreads and order book depth (*Depth*(10) and *Depth*(5)) and for both the 5- and 10-second periods. To provide further robustness of our results, we repeat the regression considering only one group of traders' (i.e., *HFT*, *AT*, and *Human*) net liquidity provision at a time and perform the regression based on *NLOS* for spread resiliency because order volumes are not important for spread determination.

Results

The results in Table 8 reveal that HFTs show a significant and robust relation between net liquidity provision and relative spread recovery. Across models (1), (2), (5), and (6), we observe a negative and significant effect of HFTs' net liquidity provision on spread changes from the event to post-event interval, indicating spread improvements. Therefore, HFTs recover the widened relative spread after a market impact event when

[10]Similar to Chordia, Roll, and Subrahmanyam (2002), we compute order book imbalance as $\frac{|Depth(10)_{Ask} - Depth(10)_{Bid}|}{Depth(10)}$ for each order book snapshot. In particular, Goldstein, Kwan, and Philip (2018) show that order book imbalance influences the trading decisions of HFTs.

TABLE 8. Results of the Relative Spread Resiliency Regression Based on Equation (4) for 5- and 10-Second Intervals

	Relative Spread: 5 Seconds				*Relative Spread*: 10 Seconds			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HFT	−0.200***	−0.198***			−0.215***	−0.192**		
	(−3.52)	(−3.47)			(−3.54)	(−2.87)		
AT	0.065		0.029		0.090		0.032	
	(1.37)		(0.58)		(1.28)		(0.47)	
Human	−0.041			−0.065	−0.014			−0.047
	(−0.70)			(−1.01)	(−0.21)			(−0.61)
Activity	−0.191*	−0.171*	−0.298***	−0.254**	−0.212**	−0.186**	−0.289***	−0.251***
	(−2.48)	(−2.31)	(−4.25)	(−3.27)	(−3.03)	(−2.98)	(−4.52)	(−3.66)
$Spread_{pre}$	−0.098	−0.096	−0.096	−0.097	−0.082	−0.084	−0.066	−0.069
	(−1.27)	(−1.24)	(−1.24)	(−1.25)	(−0.99)	(−1.02)	(−0.81)	(−0.84)
$Depth_{pre}$	−0.028	−0.030	−0.074	−0.056	−0.037	−0.036	−0.089	−0.077
	(−0.56)	(−0.61)	(−1.22)	(−0.98)	(−0.71)	(−0.71)	(−1.41)	(−1.31)
OIB_{pre}	−0.019	−0.024	−0.012	−0.016	−0.015	−0.020	−0.012	−0.016
	(−0.45)	(−0.58)	(−0.28)	(−0.38)	(−0.35)	(−0.46)	(−0.27)	(−0.37)
Obs.	265	265	265	265	265	265	265	265
Adj. R^2	0.561	0.561	0.540	0.542	0.548	0.546	0.525	0.525
Mean VIF	2.34	2.33	2.31	2.33	2.33	2.32	2.31	2.32
Max VIF	2.90	2.90	2.90	2.90	2.90	2.90	2.89	2.89

Note: *HFT, AT*, and *Human* refer to the coefficient of the respective net liquidity provision (*NLP*) of that group within 5 and 10 seconds after the market impact event. *Activity* accounts for the overall activity level measured by the sum of submissions and cancellations in the considered post-event period. Pre-event spread ($Spread_{pre}$), order book depth ($Depth_{pre}$), and order book imbalance (OIB_{pre}) are included to control for differences in the liquidity level right before the market impact event. Stock-specific controls and heteroskedastic-robust variance estimators are applied. VIF stands for variance inflation factor. Standardized beta coefficients are provided and *t*-statistics reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

providing additional liquidity to the order book. In contrast, ATs' and human traders' liquidity provision after market impact events does not lead to spread improvements. Although human traders exhibit the strongest increase in net liquidity provision after market impact events (see Table 7), they do not contribute to the recovery of the relative spread. The positive effect of HFTs for spread resiliency is robust for both the 5- and 10-second observation intervals. Yet the effect size is almost identical, indicating that HFTs accomplish spread resiliency within the very first seconds after a market impact event, which is further supported by Figure II.

Because the relative spread is independent of the volume connected to submitted and canceled limit orders, we repeat the spread resiliency regression using net limit order submissions (*NLOS*) instead of net liquidity provision (*NLP*) 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 A3 in the Appendix. Again, HFTs' net limit order submissions contribute most to the spread improvements after a market impact event, whereas human traders' and ATs' order submissions do not have a significant effect. We also perform an *F*-test for the full models of the spread resiliency regressions to investigate whether the spread improvement coefficient of HFTs is significantly different from the coefficients of the two other groups of traders. For both liquidity provision measures *NLP* and *NLOS* and both analyzed intervals, the results of the *F*-test confirm that the contribution of HFTs to spread resiliency is significantly higher than that of human traders and ATs. Consequently, the analysis reveals that order book resiliency in terms of bid–ask spreads is accomplished by HFTs only within the first few seconds after a market impact event.

Concerning the recovery of order book depth measured by *Depth*(10) and *Depth*(5) as proposed by Degryse, De Jong, and Van Kervel (2015), the three groups of traders' contributions to order book resiliency give a different impression. As depicted in Table 9, HFTs do not significantly contribute to the recovery of order book depth measured by *Depth*(10) despite their increased net liquidity provision in the post-event period. This also holds for ATs, although we find a significant effect on depth replenishment when only considering their net liquidity provision. Yet, the effect

TABLE 9. Results of the *Depth*(10) Resiliency Regression Based on Equation (4) for 5- and 10-Second Intervals

	Depth(10): 5 Seconds				*Depth*(10): 10 Seconds			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HFT	0.107	0.169			0.071	0.157		
	(0.99)	(1.56)			(0.76)	(1.67)		
AT	0.130		0.181*		0.133		0.187**	
	(1.58)		(2.27)		(1.71)		(2.71)	
Human	0.193**			0.238***	0.176**			0.225**
	(3.07)			(3.83)	(2.66)			(3.11)
Activity	−0.025	0.098	0.086	0.091	−0.028	0.079	0.060	0.046
	(−0.32)	(1.21)	(1.10)	(1.23)	(−0.40)	(1.07)	(0.95)	(0.68)
$Spread_{pre}$	0.005	0.002	−0.002	0.008	0.025	0.021	0.017	0.013
	(0.11)	(0.04)	(−0.03)	(0.17)	(0.55)	(0.47)	(0.38)	(0.29)
$Depth_{pre}$	0.115	0.164	0.176	0.144	0.279	0.302*	0.323*	0.302*
	(0.80)	(1.16)	(1.26)	(1.02)	(1.81)	(1.99)	(2.23)	(2.01)
OIB_{pre}	−0.016	−0.028	−0.019	−0.032	−0.024	−0.036	−0.028	−0.033
	(−0.26)	(−0.42)	(−0.31)	(−0.53)	(−0.43)	(−0.60)	(−0.50)	(−0.59)
Obs.	265	265	265	265	265	265	265	265
Adj. R^2	0.346	0.313	0.318	0.333	0.423	0.393	0.404	0.411
Mean VIF	2.34	2.33	2.31	2.31	2.33	2.32	2.31	2.32
Max VIF	2.90	2.90	2.90	2.90	2.90	2.90	2.89	2.89

Note: *HFT, AT*, and *Human* refer to the coefficient of the respective net liquidity provision (*NLP*) of that group within 5 and 10 seconds after the market impact event. *Activity* accounts for the overall activity level measured by the sum of submissions and cancellations in the considered post-event period. Pre-event spread ($Spread_{pre}$), order book depth ($Depth_{pre}$), and order book imbalance (OIB_{pre}) are included to control differences in the liquidity level right before the market impact event. Stock-specific controls and heteroskedastic-robust variance estimators are applied. VIF stands for variance inflation factor. Standardized beta coefficients are provided and *t*-statistics reported in parentheses.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

TABLE 10. Results of the *Depth*(5) Resiliency Regression Based on Equation (4) for 5- and 10-Second Intervals

	Depth(5): 5 Seconds				*Depth*(5): 10 Seconds			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HFT	0.180	0.214			0.142	0.220*		
	(1.46)	(1.78)			(1.36)	(1.98)		
AT	0.049		0.095		0.091		0.170	
	(0.69)		(1.28)		(1.19)		(1.85)	
Human	0.159*			0.196*	0.203**			0.261**
	(2.13)			(2.58)	(2.70)			(2.78)
Activity	−0.135*	−0.054	0.017	−0.012	−0.154**	−0.052	−0.030	−0.067
	(−2.15)	(−0.81)	(0.22)	(−0.22)	(−2.70)	(−1.03)	(−0.56)	(−1.48)
$Spread_{pre}$	−0.094*	−0.099*	−0.100*	−0.093*	−0.068	−0.073	−0.088*	−0.087*
	(−2.13)	(−2.20)	(−2.32)	(−2.19)	(−1.65)	(−1.71)	(−2.18)	(−2.11)
$Depth_{pre}$	0.078	0.115	0.151	0.114	0.165*	0.191*	0.233**	0.201*
	(0.83)	(1.27)	(1.47)	(1.15)	(2.18)	(2.55)	(2.78)	(2.53)
OIB_{pre}	0.009	0.006	0.009	0.004	0.001	−0.011	−0.002	−0.002
	(0.19)	(0.14)	(0.19)	(0.08)	(0.02)	(−0.27)	(−0.05)	(−0.04)
Obs.	203	203	203	203	220	220	220	220
Adj. R^2	0.419	0.407	0.386	0.405	0.521	0.490	0.480	0.504
Mean VIF	3.09	3.13	3.11	3.11	3.32	3.28	3.26	3.26
Max VIF	4.71	4.70	4.68	4.67	4.62	4.59	4.60	4.59

Note: *HFT, AT*, and *Human* refer to the coefficient of the respective net liquidity provision (*NLP*) of that group within 5 and 10 seconds after the market impact event. *Activity* accounts for the overall activity level measured by the sum of submissions and cancellations in the considered post-event period. Pre-event spread ($Spread_{pre}$), order book depth ($Depth_{pre}$), and order book imbalance (OIB_{pre}) are included to control differences in the liquidity level right before the market impact event. Stock-specific controls and heteroskedastic-robust variance estimators are applied. VIF stands for variance inflation factor. Observations with 0 *Depth*(5) before and after the event are not considered in the analysis. Standardized beta coefficients are provided and *t*-statistics reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.

vanishes in the full models with all traders' net liquidity provision measures being considered as explanatory variables. Thus, even if HFTs' net liquidity provision recovers the relative spread within the first seconds after a market impact event, their actual order sizes are too low to achieve a significant increase in order book depth.

In contrast, we find that human traders and their net liquidity provision recover *Depth*(10) as indicated by the positive and significant coefficient in models (1), (4), (5), and (8). Consequently, even within 5 seconds after the market impact event, human traders' net liquidity provision leads to order book resiliency in terms of order book depth. With respect to order book depth closer around the midpoint as measured by *Depth*(5), we find qualitatively similar effects (see Table 10). Yet, as *Depth*(5) is mostly based on the first order book level in our sample, the contribution of HFTs to *Depth*(5) recovery is higher than for *Depth*(10) recovery and is significant in model (6).

The results concerning order book depth resiliency remain robust if we additionally control for the size of the market order that caused the market impact event, thereby consuming varying amounts of quoted volumes.[11] Yet, we cannot confirm that the human traders' depth improvement coefficient is significantly different from that of HFTs based on an *F*-test (for both *Depth*(10) and *Depth*(5)). Consequently, although HFTs' contribution to order book depth is smaller, mostly insignificant, and noisier than that of human traders, the results for order book depth resiliency less clearly reveal one single group of traders as being responsible for depth resiliency, as the results for spread resiliency do. Nevertheless, the analysis provides strong support that human traders and not HFTs are the main contributors to depth resiliency.

Human traders' positive impact on order book depth resiliency can be explained by their submission (and noncancellation) of relatively large order sizes (see Figure I in the descriptive analysis). In the 10 seconds before and after a market impact event, human traders submit on average order sizes two times larger than HFTs' orders and three times larger than ATs' orders. The strong increase in net liquidity provision of human traders as revealed by the first regression analysis (see Table 7) combined with the large order sizes are the key components for depth recovery. HFTs and ATs, in contrast, contribute less to the recovery of order book depth because of their transient liquidity commitment and relatively small order sizes.

In summary, our results show that HFTs are mainly responsible for liquidity recovery in terms of bid–ask spreads, and human traders are the main contributors to order book depth resiliency. From an overall liquidity resiliency perspective, the spread is often seen as the most important liquidity dimension because it influences the implicit transaction costs for both large and small orders. Order book depth, however, is highly relevant for larger orders to minimize market impact. To shed further light on the relative importance of these two liquidity measures for order book resiliency, we repeat our analysis using the exchange liquidity measure (XLM) proposed by Gomber, Schweickert, and Theissen (2015), which measures the cost of a roundtrip trade of given size. Consequently, this measure accounts for both the implicit transaction costs associated with the bid–ask spread and the implicit costs due to market impact by walking through deeper levels of the order book.

The analysis provided in Table A4 in the Appendix shows that HFTs are mainly responsible for the recovery of XLM10k after a market impact event, that is, the reduction of implicit transaction costs associated with an order size of 10,000 euro as shown by the negative and significant coefficients for the net liquidity provision of HFTs. Because the spread is the main factor determining implicit transaction costs for such smaller order sizes, this result is in line with HFTs being responsible for the recovery of bid–ask spreads. Yet, human traders' contribution becomes increasingly important for larger order sizes (XLM20k and XLM50k), which also consume liquidity from deeper order book levels so that this liquidity dimension gains importance for implicit transaction costs.

[11]Because the results are highly comparable, we do not report them in separate tables. However, the results are available from the authors upon request.

VI. Discussion

The analysis of order book resiliency is of interest for researchers, market participants, and regulators alike as our data highlight the economic relevance of market impact events and the necessary replenishment of the order book. After the market impact events 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. Furthermore, they stay at this high level if there is no resiliency or if the order book is resilient only at a very slow pace. Consequently, order book resiliency is a key component of liquidity ensuring consistently low implicit transaction costs. In this article, we focus on the contribution of different types of traders to order book resiliency, which differs from the general analysis of a market's resiliency as in Foucault, Kadan, and Kandel (2005).

This article contributes to the discussion on HFTs' liquidity provision by revealing which types of traders are most relevant for the recovery of different dimensions of liquidity based on non-news-related and sudden market impact events that are triggered by large incoming market orders. Thereby, and different from, for example, Hautsch, Noé, and Zhang (2017), our results provide a clear picture of order book resiliency that is not biased by any changes in trading strategies due to exogenous events.

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 spread resiliency is determined by HFTs, that is, participants relying on trading algorithms and colocation services. Relative spread recovery is particularly strong when HFTs contribute liquidity to the open limit order book and happens within the first 5 seconds after a market impact event. However, our results reveal that HFTs and ATs do not substantially restore order book depth, which is the second important characteristic of order book resiliency. The recovery of order book depth is mainly achieved by human traders contributing high net liquidity combined with large order sizes. This process consumes additional time compared to the relative spread recovery, providing further indication that HFTs and ATs do not predominantly participate in the resiliency of order book depth.

Therefore, our conclusions are twofold. First, liquidity provision of HFTs contributes mainly to a distinct dimension of order book resiliency: the recovery of relative spreads. Consequently, the speed of trading does indeed matter for order book resiliency because the recovery of a tight bid–ask spread needs only the submission of one precise order at best. Second, to absorb further liquidity demands, order book depth must be replenished by various orders of relevant size. As shown in our analysis, this is mainly achieved by human traders that persistently stay in the order book and submit orders of relevant size. One potential explanation for our findings is that within the category of human traders (besides retail and other traders), there is also a variety of proprietary banks' and brokers' trading desks where a majority has larger risk limits and trading volumes than specialized HFT firms that focus on specific sectors or liquidity classes operating close to their risk limits.[12] Consequently, differences in

[12]This was confirmed in discussions with the exchange operator who provided us with the data.

higher risk limits and their lower use might explain why human traders rather than HFTs mainly recover liquidity in terms of order book depth.

In contrast to Kempf et al. (2015), who use 5-minute aggregation intervals and find that AT in general is responsible for order book resiliency, we show that HFTs as a subgroup of ATs are responsible for spread resiliency because speed matters regarding this dimension of liquidity. Moreover, we find that mainly human traders and not HFTs or 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 mainly affect bid–ask spreads and not order book depth. However, they analyze general trading activity and static liquidity dimensions whereas we focus on order book resiliency, that is, the dynamic aspect of liquidity, in nonstandard market conditions due to market impact events initiated by large market orders.

Our analysis has some limitations. The first limitation is our data set, which includes 10 trading days and thus covers a rather short period. Therefore, one might argue that not enough remarkable market impact events are included in the analysis. Nevertheless, the mean market impact of 17.10 bps for the market impact events in this study (see Table 4) appears to be 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 that lead to the analyzed events. The second limitation relates to the precise attribution of the order submissions and cancellations to the respective trader types. Although market participants conducting AT 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 are necessarily flagged as such. Nonetheless, the unique flag for AT activity in the data set used in this study seems to be the best proxy available. Third, our analysis is based on blue chip 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 AT and HFT takes place.

Our results have important implications for academics, regulators, and market participants. From an academic perspective, our findings contribute to research on HFT and its impact on liquidity in financial markets. Although several academic studies provide evidence for a positive effect of HFT on liquidity in terms of spread and depth at the top of the book (e.g., Hasbrouck and Saar 2013), the contribution of HFT to order book resiliency is still an open question. We fill this research gap by showing that HFTs do indeed recover one dimension of liquidity, that is, the bid–ask spread. However, liquidity provision by HFTs should not be overestimated with respect to resiliency of order book depth. After market impact events and the associated drops in liquidity, human traders provide meaningful amounts of liquidity, thereby contributing to order book depth resiliency. Although it is HFTs that tighten the enlarged relative spread within the first seconds after a market impact event, human traders are the main contributors to order book depth resiliency.

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 market participants, 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 types of traders to fulfill their liquidity demands after market impact events.

VII. Conclusion

We study the liquidity provision and the respective contribution to order book resiliency of HFTs, ATs, and human traders around market impact events 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 5 seconds after the market impact event. Liquidity recovery in terms of order book depth, however, takes considerably longer and is mainly accomplished by the 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 trading speed matters for only one dimension of order book resiliency. HFTs and their low-latency infrastructure are responsible for spread resiliency, as 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, which is necessary for a market to absorb further liquidity demands of larger orders, is mainly achieved by human traders, who persistently stay in the order book with relevant order volumes.

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Appendix

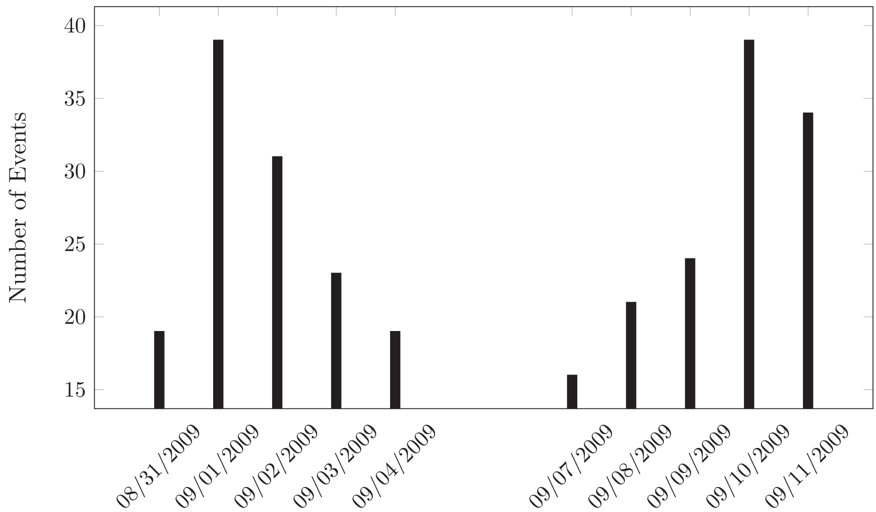

Figure AI. Distribution of Market Impact Events Over the Observation Period.

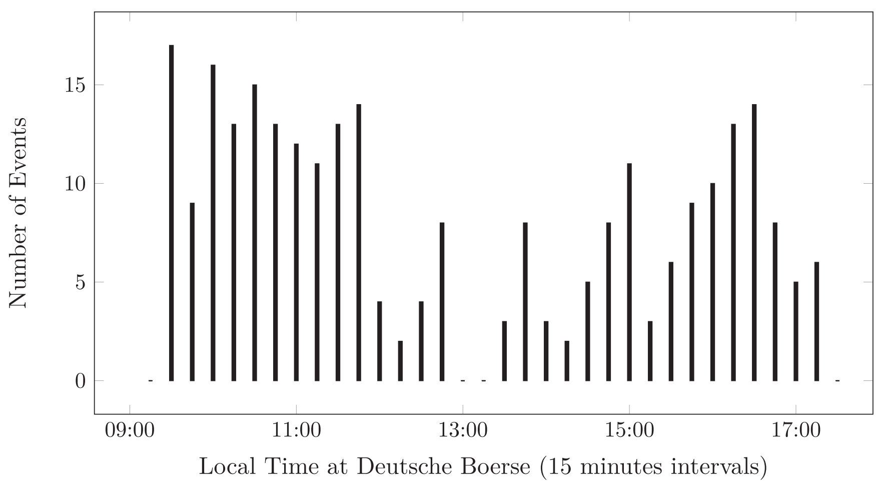

Figure AII. Occurrence of Market Impact Events during the Trading Day.

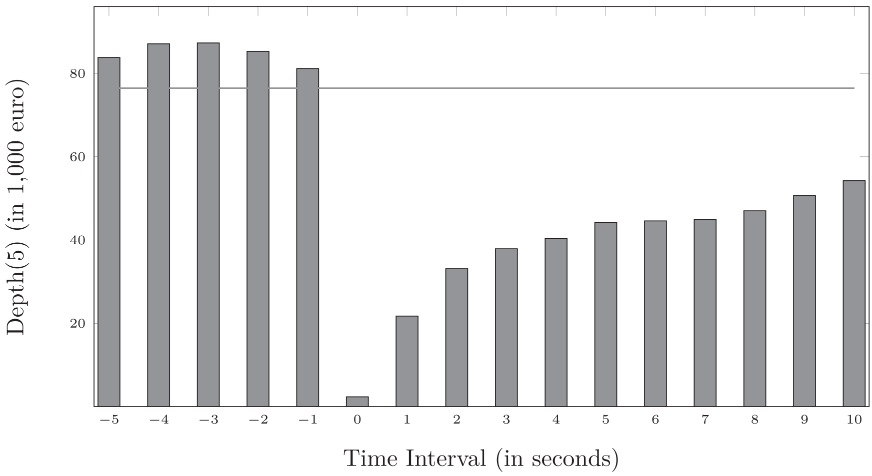

Figure AIII. ***Depth*** **(5) 5 Seconds before the Market Impact Event, Directly after the Event (Time 0), and Its Recovery 10 Seconds after the Market Impact Event.**

TABLE A1. Descriptive Statistics of Events per Stock

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
CBKG.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	11.9	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	167,436	11.16
LING.DE	8	13.07	6.50	156,094	10.41
MANG.DE	9	18.88	7.89	220,547	14.70
MEOG.DE	9	11.59	4.11	77,120	5.14
MRCG.DE	10	12.56	6.40	152,761	10.18
MUVGn.DE	10	13.95	8.90	252,576	10.10
RWEG.DE	8	13.7	7.75	553,404	22.14
SAPG.DE	9	9.9	6.22	232,125	9.28
SDFG.DE	9	19.6	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	202,841	13.52
VOWG.DEa	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

Note: Except for the number of events, all reported values are averaged over the market impact events for each stock in our sample. RIC stands for reuters instrument code.
[a]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.

TABLE A2. Order Book Levels Included in *Depth*(5) and *Depth*(10) for the Order Book Snapshots from 5 Seconds before to 10 Seconds after the 265 Analyzed Market Impact Events

	Depth(5)		*Depth*(10)	
Order Book Levels Included in *Depth*(x)	Obs.	Proportion	Obs.	Proportion
Up to level 1	38,616	78.87%	13,102	26.76%
Up to level 2	7,967	16.27%	12,214	24.95%
Up to level 3	2,144	4.38%	10,946	22.36%
Higher than level 3	232	0.47%	12,697	25.93%
Total	48,959	100.00%	48,959	100.00%

TABLE A3. Results of the Relative Spread Resiliency Regression Based on Equation (4) Using *NLOS* Conducted for the 5- and 10-Second Intervals

	Relative Spread: 5 Seconds				Relative Spread: 10 Seconds			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HFT	−0.245***	−0.255***			−0.215***	−0.223***		
	(−4.43)	(−4.55)			(−3.82)	(−3.95)		
AT	−0.073		−0.114		−0.034		−0.086	
	(−1.40)		(−1.88)		(−0.52)		(−1.24)	
Human	0.022			−0.022	0.026			0.009
	(0.37)			(−0.35)	(0.43)			(0.14)
Activity	−0.090	−0.123	−0.207**	−0.273***	−0.150*	−0.153*	−0.227***	−0.277***
	(−1.08)	(−1.64)	(−2.61)	(−3.45)	(−2.12)	(−2.37)	(−3.73)	(−3.96)
$Spread_{pre}$	−0.094	−0.100	−0.089	−0.097	−0.096	−0.099	−0.068	−0.067
	(−1.23)	(−1.30)	(−1.15)	(−1.25)	(−1.16)	(−1.19)	(−0.83)	(−0.83)
$Depth_{pre}$	−0.014	−0.025	−0.047	−0.068	−0.044	−0.046	−0.068	−0.087
	(−0.31)	(−0.50)	(−0.90)	(−1.16)	(−0.84)	(−0.88)	(−1.23)	(−1.40)
OIB_{pre}	−0.040	−0.038	−0.022	−0.016	−0.029	−0.029	−0.019	−0.014
	(−0.96)	(−0.91)	(−0.51)	(−0.37)	(−0.68)	(−0.67)	(−0.45)	(−0.32)
Obs.	265	265	265	265	265	265	265	265
Adj. R^2	0.574	0.575	0.547	0.540	0.550	0.552	0.529	0.524
Mean VIF	2.36	2.34	2.34	2.34	2.33	2.32	2.31	2.32
Max VIF	3.14	2.90	2.91	2.90	2.90	2.90	2.89	2.90

Note: *HFT*, *AT*, and *Human* refer to the coefficient of the number of net limit order submissions (*NLOS*) of each group within 5 and 10 seconds after the market impact event. *Activity* accounts for the overall activity level measured by the sum of submissions and cancellations in the considered post-event period. Pre-event spread ($Spread_{pre}$), order book depth ($Depth_{pre}$), and order book imbalance (OIB_{pre}) are included to control for differences in the liquidity level right before the market impact event. Stock-specific controls and heteroskedastic-robust variance estimators are applied. VIF stands for variance inflation factor. Standardized beta coefficients are provided and *t*-statistics reported in parentheses.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

TABLE A4. Results of Equation (4) Using the XLM for Order Sizes of 10,000, 20,000, and 50,000 Euro as the Liquidity Measure Based on the 5-Second Interval

	XLM10k				XLM20k				XLM50k			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HFT	−0.254***	−0.274***			−0.225***	−0.237***			−0.242***	−0.264***		
	(−3.79)	(−3.94)			(−3.60)	(−3.74)			(−3.87)	(−4.10)		
AT	0.024		−0.034		0.060		0.007		0.029		−0.031	
	(0.43)		(−0.57)		(1.19)		(0.13)		(0.49)		(−0.50)	
Human	−0.117			−0.159*	−0.110*			−0.139**	−0.133*			−0.172**
	(−1.77)			(−2.29)	(−2.23)			(−2.69)	(−2.37)			(−2.93)
Activity	−0.260**	−0.284***	−0.417***	−0.369***	−0.227***	−0.232**	−0.368***	−0.305***	−0.193**	−0.220**	−0.349***	−0.294***
	(−2.99)	(−3.40)	(−5.05)	(−4.08)	(−3.37)	(−3.22)	(−5.89)	(−4.46)	(−2.94)	(−3.19)	(−5.55)	(−4.34)
$Spread_{pre}$	−0.163*	−0.159*	−0.158*	−0.162*	−0.077	−0.073	−0.072	−0.076	−0.068	−0.064	−0.063	−0.068
	(−2.13)	(−2.09)	(−2.06)	(−2.11)	(−1.12)	(−1.06)	(−1.04)	(−1.08)	(−0.87)	(−0.83)	(−0.80)	(−0.86)
$Depth_{pre}$	−0.015	−0.035	−0.087	−0.055	−0.019	−0.034	−0.085	−0.051	0.002	−0.021	−0.072	−0.036
	(−0.28)	(−0.63)	(−1.21)	(−0.86)	(−0.45)	(−0.77)	(−1.42)	(−1.00)	(0.03)	(−0.47)	(−1.20)	(−0.69)
OIB_{pre}	0.006	0.005	0.014	0.015	−0.004	−0.008	0.004	0.001	0.012	0.010	0.020	0.020
	(0.12)	(0.09)	(0.29)	(0.31)	(−0.09)	(−0.20)	(0.09)	(0.02)	(0.28)	(0.25)	(0.45)	(0.48)
Obs.	265	265	265	265	265	265	265	265	265	265	265	265
Adj. R^2	0.408	0.405	0.363	0.378	0.580	0.575	0.544	0.556	0.546	0.539	0.500	0.518
Mean VIF	2.34	2.33	2.31	2.31	2.34	2.33	2.31	2.31	2.34	2.33	2.31	2.31
Max VIF	2.90	2.90	2.90	2.90	2.90	2.90	2.90	2.90	2.90	2.90	2.90	2.90

Note: This table reports the results of equation (4) using the exchange liquidity measure (XLM) for order sizes of 10,000, 20,000, and 50,000 euro as the liquidity measure based on the 5-second interval. Results for the 10-second interval are qualitatively similar. *HFT, AT*, and *Human* refer to the coefficient of the respective net liquidity provision *(NLP)* of that group within 5 seconds after the market impact event. *Activity* accounts for the overall activity level measured by the sum of submissions and cancellations in the post-event period. Pre-event spread ($Spread_{pre}$), order book depth ($Depth_{pre}$), and order book imbalance (OIB_{pre}) are included to control for differences in the liquidity level right before the market impact event. Stock-specific controls and heteroskedastic-robust variance estimators are applied. VIF stands for variance inflation factor. Standardized beta coefficients are provided and *t*-statistics reported in parentheses.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

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