Research Report

The Role of High-Frequency Trading for Order Book Resiliency

THE SPEED OF TRADING, AND IN PARTICULAR HIGH-FREQUENCY TRADING, IS ONE OF THE MOSTLY DEBATED ISSUES AMONG REGULATORS AND MARKET PARTICIPANTS. NEVERTHELESS, SEVERAL ACADEMIC STUDIES HAVE SHOWN THAT HIGH-FREQUENCY TRADERS USING LOW-LATENCY INFRASTRUCTURE PROVIDE ADDITIONAL LIQUIDITY THEREBY REDUCING TRANSACTION COSTS IN ORDINARY TIMES OF TRADING. WE STUDY WHETHER HIGH-FREQUENCY TRADERS ALSO CONTRIBUTE TO THE RECONSTRUCTION OF THE ORDER BOOK AFTER LIQUIDITY SHOCKS CAUSED BY LARGE ORDERS.

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Introduction

Not only since the Flash Crash of 2010, there is a controversial discussion on the speed of trading at which especially high-frequency trading (HFT) participants act and react within the open limit order book. Proponents argue that automated decision making and low-latency infrastructure favor liquidity provision leading to a reduction of implicit transaction costs. Opponents, on the other hand, emphasize the possibility of exaggerated price movements due to HFT.

While there exist several academic studies showing a positive contribution of HFT to liquidity provision (e.g., Haferkorn and Zimmermann, 2015; Brogaard et al., 2014; Hasbrouck and Saar, 2013), this paper examines the quality of order book resiliency after liquidity shocks in the presence of high-frequency traders. Based on a unique data set, we determine the contributions of HFTs in contrast to non-HFT participants following liquidity shocks to the open limit order book. During and after such shocks, low-latency traders can maximize their speed advantages and benefit from the widened bid-ask spread and the low order book depth, respectively. Given HFTs follow such strategies and support a fast replenishment of the order book, other market participants may profit from the increased order book resiliency due to lower implicit transaction cost.

We apply a data sample of large, aggressively placed market orders that hit the open order book and clear several order book levels thereby leading to significant price impact. We focus on the order submission behavior of HFTs and non-HFT participants around these market order shocks to add further evidence on the possible benefits of HFT for liquidity.

Data Set

Our data set contains all Xetra trading messages for the DAX30 securities within the two-weeks time period from August 31st to September 11th, 2009, thereby covering 10 trading days.

The uniqueness of the available data set is caused by an indicator of algorithmic trading showing whether a certain message has been triggered by an algorithm or not. Additionally, we can identify whether the submitter of an order is a subscriber of co-location services. Combining these two attributes, we are able to differentiate three different groups of traders: HFTs, non-HFT algorithmic traders, and human traders.

Based on the exogenous shock of a large market order, we analyze the reaction and the contribution of each trader group separately in order to derive distinct patterns that characterize the behavior and commitment of these market participants to liquidity provision.

Reactions to Market Order Liquidity Shocks

Drawing on a sample of 267 liquidity shocks, two distinct observations become obvious: On the one hand, relative bid-ask spreads recover very fast and it takes only a few seconds until they reach a standard width. On the other hand, order book depth needs additional time to reach a similar constant and persistent normal level (see Figure 1).

In order to answer whether and how the specific trader groups react to liquidity shocks, we determine each group's normal liquidity provision characteristics based on the respective net liquidity provision in the five- and ten-seconds interval before the shock. The net liquidity provision which we propose is based on the number of order submissions and cancellations each trader group sends to the exchange. Since HFT activity is associated with rapid order cancellations, our measure for liquidity provision takes the net effect of order submissions and cancellations into account.

Within the five and ten seconds before the shock, human traders show on average a positive net liquidity provision ratio, indicating that this group submits more limit orders to the order book than it actually deletes. Algorithmic trading (AT) as well as HFT participants show a lower commitment as both groups' net liquidity provision ratios within the pre-event phase is significantly lower. After the liquidity shock, human traders nearly double their engagement in terms of net liquidity provision. Likewise, AT as well as HFT participants increase their engagement significantly.

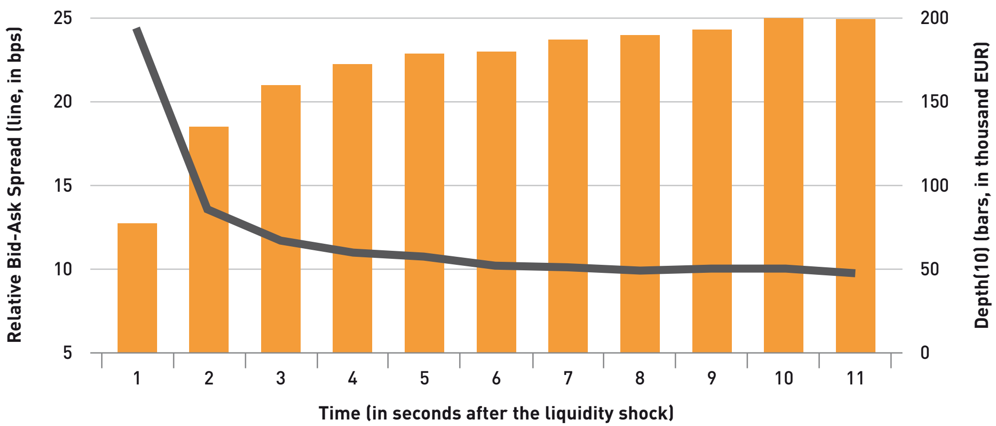

Figure 1: Liquidity Recovery in the Limit Order Book after a Liquidity Shock caused by a large Market Order

While all trading groups react to the liquidity gap due to the incoming market order, the commitment to liquidity provision of the human trader group remains the highest in both observation periods. Liquidity provision of AT as well as HFT participants, however, is more transient as order submissions are more regularly accompanied with subsequent order cancellations.

Contributions to Order Book Resiliency

In order to evaluate how the different groups' trading behavior affects order book liquidity resiliency in the post-shock phase, we determine the quality of the order book resiliency for each event. Therefore, we revert to the two characteristics of liquidity in the form of relative bid-ask spreads and order book depth as proposed by Degryse et al. (2015). The quality measures for liquidity are then related to the specific net liquidity provision ratios of each group within the period following the liquidity shock.

We find that even though human traders are among the group with the highest net liquidity provision ratio in the post-shock phase, their contribution to the recovery of the bid-ask spread is questionable. Within the five as well as the ten seconds observation period, no abnormal positive recovery effect is measurable when human traders provide more liquidity.

Focusing on AT participants, we observe a significant relation within the ten seconds after the event. Thus, algorithmic traders that provide net liquidity to the order book following a shock target for the top of the order book and therefore improve the relative bid-ask spread. However, AT participants need several seconds before this effect becomes significant.

In contrast, HFTs that rely on co-located infrastructure show a significant and robust relation between their net liquidity provision ratio and the abnormal spread recovery rate. Hence, HFTs instantaneously affect and recover the widened bid-ask spread after the liquidity shock when providing additional liquidity to the limit order book. This result is in line with the fast recovery of the bid-ask spread as depicted in Figure 1.

Concerning the recovery of the limit order book depth, results again give a different impression. Both AT as well as HFT traders do not significantly participate in the recovery of the order book depth, even during events when their submissions heavily outweigh their cancellations. The specific net liquidity provision ratios remain insignificant within the short-term as well as in the long-term observation period. Thus, even if submissions heavily affect the relative bid-ask spread, the actual order sizes are too low for achieving a significant increase in the order book depth. Human traders' net liquidity provision, however, shows the opposite characteristic. Even within five seconds after the liquidity shock, submissions coming from human traders are significantly recovering the lost order volume.

In contrast to AT and HFT traders, their submission volumes are of relevant sizes in order to impact the order book depth. Despite the relative low activity levels of human traders, their high net liquidity provision ratios combined with the larger order sizes are the key components in depth recovery.

Conclusion

Our results show, for the data set under investigation, that solely high-frequency traders reduce the bid-ask spread within the first seconds after a liquidity shock induced by a large market order thereby making use of their speed advantage. However, liquidity recovery in terms of order book depth, which is especially relevant for larger orders, takes significantly longer and is accomplished by human traders' submission activity only. This study has important implications for academics, regulators, and market operators alike as it unveils the distinct liquidity provision behavior of HFTs and human traders.

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