Algorithmic Trading & Market Liquidity

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1 Introduction

In this short paper, market liquidity will be defined and analysed by studying the impact of High Frequency (Algorithmic) Trading on market functioning, further denoted as "AT". AT is considered trading that relies to some extend on computer algorithms executing trades, making markets or hedge positions in the financial market. In order for them to produce reasonable profits with their trading algorithms, speed of execution is an important factor. The faster these HFT firms can execute an order on the market, the more likely they are to put the right price for the order in the market.

There has been a significant discussion since the arrival of AT, where academics often describe the advantages of AT and the practitioners that shine light on the opposite side. This short paper will shine more light on this discussion, focusing on AT affecting market liquidity. The paper is structured as follows; first the concept of market liquidity will be defined, continuing with the literature about market liquidity and its relationship with AT. Resulting in the discussion including a direct implementation of AT and a conclusion of the paper.

2 Market Liquidity

The all-encompassing definition of Market Liquidity is the ease and speed of with which an asset can be transformed into cash or the other way around, without incurring high cost for transforming. A liquid financial market would define a market in which a stock can be bought/sold fast and with minimal distance between the bid- and ask price. An illiquid financial market is often depicted as a market with few market participants, resulting in a flat order book where there are not a lot of orders a buyer/seller could choose from. This automatically results in a larger trade off for market investors between cost of the transaction on one side and speed of the execution on the other.
The market can be distinguished into two primary types: an order driven market and a quote driven market. In a quote driven market, the market maker is designated to provide liquidity in the market. In an order driven market the bid and ask orders from investors provide the liquidity in the market. This short paper focuses on the latter. Therefore, in order for the market to be liquid, enough orders and thus market participants must be actively trading. Whenever there are enough market participants placing orders in the market, it creates market competition in placing the best bid/ask possible to create the highest probability of execution. Evidently, resulting in an order book where the bid price is very close to the ask price, making the cost to purchase or sell a stock in the market, minimal.

2.1 Role of HFT's

In this paper AT will be subdivided into two AT strategies.

1. Market Marking Strategies. A Market Making strategy relates to the strategy of placing bid and ask prices in between the best bid- and ask price, simultaneously providing orders to the market. These Strategies are considered non-directional, as you are both buying and selling orders and are therefore not trading because of price movement expectations. The strategy profits are obtained with the spread in between the bid- and ask price you place in the market. Generally, market

making strategies provide more orders in the market, making the market therefore more liquid and decreasing the bid-ask spread for directional investors.

2. Liquidity Taking Strategies. A Liquidity Taking Strategy is considered to be a strategy that reduces the liquidity in the order book, making the spreads and thus the transaction costs larger. A liquidity Taking Strategy is considered directional as the market participants takes a one directional position in an asset, in order to profit from an increase/decrease in its price. In this strategy it is assumed that they buy or sell against the current orders, automatically removing these orders from market, thereby decreasing market liquidity.

Often AT are able to execute both strategies when trading in the market. Market making is a primary aspect but HFT firms have statistical arbitrage models running as well, in case price deviations are present from which they can benefit. The main discussion point of this paper is that these algorithms determine the course of action for a HFT. In doing so they affect the market with both liquidity- providing and taking strategies, but since these algorithms are essentially black boxes, kept secret at the HFT, it is not that easy to economically reason what the impact of AT is on the market liquidity.

3 literature

The literature has done extensive research on the impact of AT on market functioning. The interest in this topic increased significantly after the flash crash in 2010. Even though, AT might have not been solely responsible for this crash, questions regarding market efficiency became more prominent (Kirilenko et al., 2017). Madhavan (2012) has studied the relationship between fragmentation and flash crash and in doing so tried to find the relationship between market fragmentation and High Frequency Algorithmic Trading. Fragmented trading can thin out order books in any given venue, reducing the liquidity of the asset. Quote fragmentation captures the dynamic competition among traders for order flow, i.e. often market makers that are trying to place the right bid/ask price to create non-directional profits. The study finds diverging intraday AT activity during the event of the Flash Crash itself. Indicating that the algorithms directly adjusted their market making strategy when the prices showed abnormal behavior. The study also explains why the Flash Crash did not occur earlier, because the rapid growth of high-frequency trading and the use of sweep orders in a fragmented market has only recently been possible. The study concludes that the competition among Algorithmic Traders play an important role in the withdrawal of liquidity in times of market stress. Therefore, it is important to study the exact role of AT in the market.

3.1 Algorithmic Trading

Various articles have similar findings regarding market liquidity (Brogaard et al., 2014; Menkveld, 2013). Generally AT as a whole, increases market liquidity. Hasbrouck and Saar (2013) found that the low-latency activity, which they use as a proxy for high-frequency AT, causes the limit order book to be deeper, whilst narrowing the bid-ask spreads. They also find evidence that even in uncertain market situations AT maintains its positive impact on market quality, however they exclude severe market conditions from this statement as they are not sure whether this still held true during the aforementioned flash crash. In line with these findings are those of the study done by Hendershott et al. (2011). This study determines the causal relationship of AT and market liquidity in a 5 year window. Using an exogenous event that increases AT in a subset of the stocks on the NYSE. With this methodology they find that AT, does indeed increase liquidity. However, they are only able to find significant effects for large-cap stocks and not for small ones. Zooming in on the spreads, they find that AT decreases the effective spread, but seem to increase the realized spread of the asset. To elaborate, the effective spread compares the execution price to the mid-quote at the time. Indicating that market participants optimize their order entry to trade when spreads narrow. Hendershott et al. (2011) argue that this is the result of Adverse Selection among directional trading market participants. Realized spread on the other hand takes effective spreads (transaction cost at point of execution) and subtracts from it a price impact component. The less the price impact of any given trade, the greater the effective spread that is retained as profit by the liquidity provider. Therefore, this can be thought of as theoretical profits of a liquidity provider. Hendershott et al. (2011) argue similarly that the liquidity providers take a cut from the effective spread, due to the temporary market power of their algorithm. Zhang and Powell (2011) argues that the primary effect of AT is a positive one on market liquidity. This study also stresses the fact that this effect is observable under normal market circumstances and that this effect might be causing excessive price movement when the market is under severe circumstance, like the flash crash.

4 Discussion

It can be said that Algorithmic Trading has both advantages and disadvantages regarding the quality of the market. Even though, the arguments are not discussed in this paper, Algorithmic Trading affects additional factors besides market liquidity. Literature notes that AT often decreases volatility under normal market circumstances, increases price discovery in the short run and decreases market confidence of directional market participants (Zhang and Powell, 2011; Hendershott et al., 2011; Chaboud et al., 2014).

4.1 Application

The Algorithm composed for Question 2 in the Algorithmic Trading Exam combines both a market making and a cointegration based pairs strategy to maximize profits in this artificial market setup. In order to explain the dynamics of this strategy, both strategies will be discussed as two separate strategies.

4.1.1 Market Making Strategy

This is considered the liquidity providing strategy, where the algorithm places both bid and ask prices at the same time in order to create a more liquid order book. This non-directional trading strategy can be made profitable when both the bid and the ask orders are placed in between the current spread. Figure 1 provides a clear image of how this strategy contributes to a narrow spread. Due to the additional bid and ask order placed in the market, the limit order book has become more liquid. This market making strategy is performed on options of multiple underlying stocks (KPN, ADYEN, TWKY). Once an order has been placed and actually executed a position has been taking in this option. In order to hedge the position in the option, the underlying stock is bought. In order to hedge the position in the option, the algorithm takes some liquidity from the market when buying the stock with an IOC order. However, relative to its placement of option order it can still be considered liquidity providing.

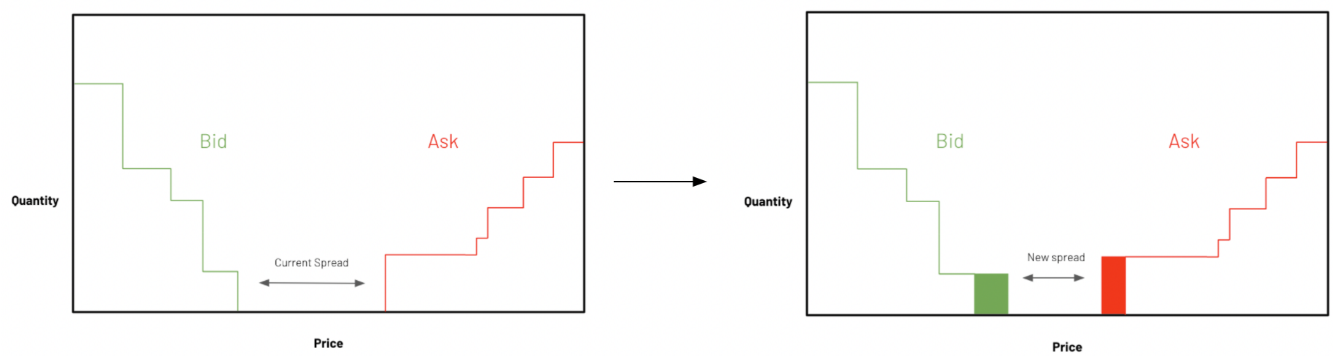

Figure 1: Visualisation of order placement by a Market Making algorithm

4.1.2 Cointegration Strategy

The second part of the algorithm uses a cointegration based pairs strategy to generate profits. In order to set up this cointegration based strategy, the stocks in the market are analysed in terms of cointegration. Whenever a pair of stock is significantly (α = 0.01) cointegrated, it means that they have a long-run equilibrium. To estimate the equilibrium and model parameters, a Vector Error Correction Model is used. In short, the VECM parameters can be used to estimate the long-run residuals and the strength of the mean reversion. This means that whenever a deviation in the long-run equilibrium is present, the prices of both stock will mean revert to their equilibrium.

$$\begin{bmatrix} \Delta Y_t \\ \Delta X_t \end{bmatrix} = \mu_0 + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \Big(Y_{t-1} - c - \gamma_1 X_{t-1} \Big) + \sum_{j=1}^{k-1} \Gamma_j \begin{bmatrix} \Delta Y_{t-j} \\ \Delta X_{t-j} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \tag{1}$$

Using parameters of the long-run equilibrium in equation 1, the residuals per second are estimated over a 200 second time window and transformed into Z-scores to provide trading signals. Figure 2 shows the Z-scores and the potential trading signals for entering a position. Whenever, the Z-score is above a threshold of 2.5, it means that according to the VECM the Y is overpriced. The algorithm will thus enter a short position in Y and a long position in X until the Z-score is equal or lower than 0, meaning that the long-run equilibrium is restored. This strategy has no market making properties whatsoever. It primarily focuses on the arbitrage opportunities in the market to achieve profitable results with a risk-less long/short strategy. Thereby, the algorithm is constantly placing IOC orders in the market, buying and selling at the best price available, essentially taking liquidity away from the market. When the position is closed, the algorithm again places IOC orders, selling against the best bid and buying against best ask, taking again liquidity from the market.

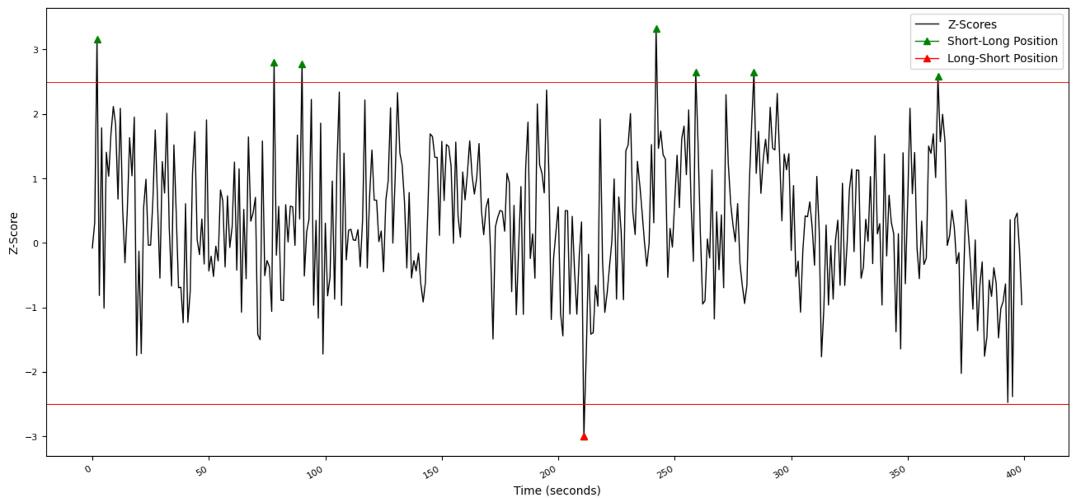

Figure 2: Visualisation of the z-scores estimated using the VECM in the Cointegration algorithm

5 Conclusion

- Overall, AT has significantly increased the liquidity in the market. Thereby, letting the directional trading participants benefit from the narrower spreads, lowering their indirect transaction cost.
- Determining the exact impact of Liquidity Taking Algorithms on the market is much more difficult. These algorithms, like a statistical arbitrage strategy, tend to take liquidity in general, but it is very difficult or impossible to actually distinguish the method behind certain algorithms in the market. The firms that execute these algorithms cannot share their profitable strategies with researchers just to find what the actual effect is on the market. This is why researcher mostly focus on Algorithmic Trading in general, combining both Market Making and Liquidity Taking Algorithms into account.
- Since the usage of Algorithms in trading the liquidity in the market has significantly increased. Indicating that even though there are liquidity takers and liquidity providers, in the end, the market is better of in terms of market liquidity by having AT incorporated into the market.

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