Market makers in illiquid markets

How does information asymmetry provide liquidity in High Frequency Trading?

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Table of Contents

1. Abstract

High Frequency Traders claim to improve market quality by providing liquidity and reducing bid-ask spreads. Opponents state that HFT exploits their technology advantage and creating an unfair market situation compared to non HFT. When looking closer it indeed seems that HFT makes markets more efficient by continuous quoting and therefore improving quality. Pre- and post-entry HFT data shows a bid-ask spread reduction which leads to lower risks and cost of equity. Small-caps however need additional support by regulatory and unnatural trading activity to benefit from HFT.

2. Introduction

High Frequency Traders (HFT), are they devils or disruptors? According to some they are responsible for market behavior like the 2010 Flash Crash, to others they are the ones that create and seize opportunities in financial markets. It does seem that HFTs can heavily influence price changes, for example by back running on sell off orders being sold in smaller chunks (Korajczyk & Murphy, 2015). But are they exploiting information asymmetry and because of that disrupting the market in a negative way or do they create liquidity so that more traditional companies can benefit from market volatility? And if so, do their actions create the same sort of liquidity in small-cap markets compared to large-cap markets? The answers to these questions might tell us if HFT is a blessing or the proverbial curse.

In 2005 stock exchanges became fully automated. This increased automation reduced the human role and gave way for a new type of electronic market makers, the algorithm traders (AT) (Brogaard, et al., 2013). In 2009 automated trading was already responsible for 73% of executed orders in the United States. The level of automation made it easier and cheaper to execute (large) orders while the algorithms determine price, quantity and venue routing (Hendershott, et al., 2010). One type of automated trader attracted the most attention: the high-frequency trader (HFT). In the absence of a formal definition most associate HFT with extremely fast computers running algorithms coded by developers. These traders typically do not work at the large sell-side banks, but at privately held firms. They trade with many small positions and normally do not carry positions overnight. HFTs are characterized as a new breed of intermediary, but their position as providers of improved market quality or hurting the market by exploiting information asymmetry is fiercely debated between practitioners and academics (Menkveld, 2016). To get a clear understanding of the *modus operandi* of High Frequency Traders and if this would also apply to illiquid (small-cap) markets the following sections will be covered;

1. A theoretical description of the markets and methods of HFT;
2. The determination of asset pricing and returns;
3. The bid ask spread for a number of assets traded on the London Stock Exchange;
4. A hypothetical theory on the application of the HFT methods in small-cap markets;
5. The conclusion and limitations on this research.

The main focus of this research lies in the theoretical part of finance and specifically HFT versus liquidity, therefore empirical investigations are presented in short and used as an indication of automated trading behavior.

3. Research question

Based on a broader perspective and research regarding information asymmetry and HFT companies the following research question has been derived;

How does information asymmetry provide liquidity in High Frequency Trading?

To answer this research question the following subquestions have been formed:

Subquestion 1: What is information asymmetry?

Subquestion 2: What is liquidity?

Subquestion 3: What is High Frequency Trading?

Apart from the mentioned research questions which should shed light on HFT in general there are some additional raised issues. Next to the explanation of the actual work methods and effects of HFT on financial markets these should give more information on the hypothetical questions if HFT would also be effective in low liquidity markets.

4. Literature Review

4.1 Theory

4.1.1 Information asymmetry

Information asymmetry occurs when one party to an economic transaction possesses greater knowledge than the other party. As George Akerlof stated information asymmetry can seriously harm markets. It doesn't matter how rational people might be, when there is an information gap between buyers and sellers markets could break down. If buyers can't separate relatively good and bad products, buyers are only willing to pay average prices which result in good products leaving the market (Akerlof, 1970). It is assumed that all traders have access and make use of the same information which creates an equilibrium. If all traders have access to the same information and if *ex ante* and *ex post* markets are available releasing extra information should have no effect on value due to the fact that a single trader is too small to make a difference. The question arises why traders should do anything when they can't make a profit of it (Milgrom & Stokey, 1982). Information asymmetry results into higher transaction costs and therefore raise the required rate of return and lowers the stock price. From the management standpoint it is desirable to reduce asymmetry and maximize shareholder value (Bartov & Bodnar, 1996). Information asymmetry also has effect on valuation in the case of divestment, e.g. corporate spin-offs which enhance information asymmetry but improve overall valuation (Krishnaswami & Subramaniam, 1999).
According to the Efficient Markets Hypothesis there should be no arbitrage opportunities because differences in information in regards to pricing of assets will be in perfect equilibrium. Ask and demand will solve any difference in pricing competition. However, this is impossible or else traders would not be compensated for their efforts in gathering information. When there are no inefficiencies there would not be any profits to be made by the market and thus no reason to be 'in the markets' (Grossman & Stiglitz, 1980). The Grossman and Stiglitz Paradox argue the generally accepted theories Capital Asset Pricing Method (CAPM) and Arbitrage Pricing Theory (APT). These theories rely on symmetric information and the assumption that information is only relevant for the market as a whole. Individual idiosyncratic risk can be diversified away so by holding a portfolio with

enough stocks everything looks symmetric (O'Hara, 2003). A factor that could trigger information asymmetry are (scheduled) announcements, e.g. information about company earnings available to some traders, but not all. More asymmetry implies a bid-ask spread increase and a market liquidity decrease. However, information disclosure may lead to increased volumes despite the liquidity reduction (Kim & Verrecchia, 1994). Enhanced price informativeness generated by aggregated investor trading impacts firm value and should lead to higher stock prices. This is the result of more information being available and thus leading to less asymmetry, higher specific stock liquidity and reduced spread. Higher liquidity results in lower expected returns and therefore higher stock prices and firm value (Wang & Zhang, 2015). An important characteristic of market microstructures is that trades reveal information. This could create information asymmetry, HFT can get non-public information on trades sooner than non-HFT because of their speed advantage and colocation trading venues (Muhle-Karbe & Webster, 2017). Acting on existing trade information is also known as frontrunning often seen as the reason that HFT exploits their unfair advantage. Although the HFT firm Optiver (2010) states that frontrunning is not an issue in HFT and HFT even reduces this method it could theoretically be used to detect asymmetry and make use of this opportunity (Scopino, 2015).

4.1.2 Market liquidity

Markets have two main functions when looking at asset pricing, namely liquidity and price discovery. Liquidity is the link between the buyer-seller connection where the spread is the traders' transaction cost. A relatively larger liquidity spread, and thus cost for the investor, could have a negative impact on asset pricing due to the lower net returns (O'Hara, 2003). To be able to trade for a price as close as possible to market prices is an important and desirable feature of financial markets. Liquidity is described by three measures; 1) size, 2) price and 3) time. Illiquidity sources are influenced by transaction costs (bid-ask spreads) and price pressure when the assets needs to be sold and buyers are not available which induces extra risk (Jones, 2013). By posting quotes for buy as well as sell orders market makers provide liquidity to the financial markets. Because of these market makers investors are always able to trade financial instruments (Rijper, et al., 2010). In illiquid markets it is harder to sell large positions and the transaction costs are higher which results in more risk. A higher risk ratio reduces asset prices and requires investors to demand more compensation. Market liquidity is linked to funding liquidity (the availability of funding) which, when becoming constrained, could lead to a crisis (Amihud, et al., 2012).

In addition to looking at liquidity on an individual stock basis, one could also look at the aggregated market liquidity in correlation with trading activity. These are influenced by inventory and asymmetric information but also by short term interest rates as well as trading days. Research revealed that spreads increased dramatically in down markets but decrease marginally in rising markets (Chordia, et al., 2001). Whilst not causing extreme price movements itself, HFT does provide liquidity even in the case of permanent price changes. However, when there are extreme price movements for multiple stocks at once HFT demands liquidity. The cause of this switch is that supplying liquidity is more risk averse than the liquidity demanding strategies (Brogaard, et al., 2017). Illiquidity is related to the execution costs. When a trader wants to execute an order he has to wait till a favorable price is available or act immediately at the current bid or ask price. The quoted price includes a premium for direct execution. This effectively means that the measure of (il)liquidity is the bid-ask spread (Amihud & Mendelson, 1986).

4.1.3 High Frequency Trading

In January 2005 stock exchanges became fully automated. This increased automation reduced the human role and gave way for a new type of electronic market makers, also known as High Frequency Traders (HFT). HFT predicts price changes over horizons of less than 3 to 4 seconds and executes in milliseconds while trading is mostly based on two sources of public information; macroeconomic news and limit book imbalances (Brogaard, et al., 2013). HFT is a part of algorithmic trading (AT), which is defined by making use of computer algorithms for order execution and cancellations. HFT traders are market professionals making large numbers of trades on a daily basis. HFT is often characterized by 1) high speed computer programs, 2) co-location services and data services to minimize network latency, 3) high speed order execution and cancellation and 5) leaving (almost) no unhedged orders overnight (Jones, 2013). Because of the high level of automation, costs for intermediaries have been lowered dramatically. By reducing friction and trading costs, technology could result in more efficient risk sharing, facilitate hedging, improve liquidity, creating more efficient pricing and in the end reduce firms' cost of capital (Hendershott, et al., 2010). HFT is not a new phenomenon, but an evolution of the securities markets triggered by the adoption of new technologies and more specific automated computer algorithms. In the last couple of years HFT raised significant attention due to the flash crash in 2010 (Gomber, et al., 2011). In general HFT conducts the following activities; 1) Market making, the continuous quoting to provide liquidity to traders and 2) Statistical arbitrage, identifying price efficiencies between securities or markets and trying to capitalize on those events. Both strategies focus on tiny profits and therefore need to be executed automatically. These strategies should result in more efficient markets by creating trading possibilities as well as arbitraging out price differences. There are more strategies that can be thought of, but, according to High Frequency Trading company Optiver, more creative methods based on exploiting client orders could be damaging to market quality (Rijper, et al., 2010). The switch from local locations, e.g. the New York Stock Exchange to trade US equities, to venues better equipped of handling HFT demands were driven by the need for low latency connections.

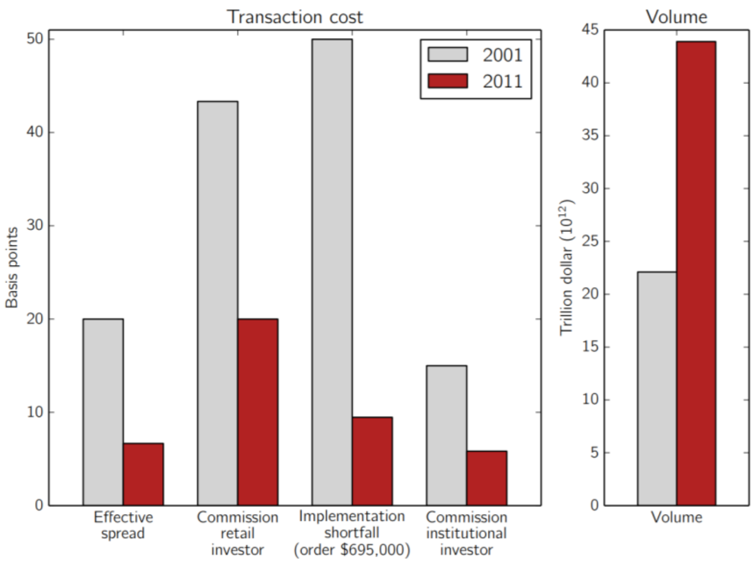


Figure 1: pre- vs post HFT entry US equity 2001-2011

Figure 1 shows the pre- and post HFT entry and the result on US equity between 2001-2011. Where institutional investors trade larger orders and split them into smaller chunks if necessary to minimize price impact, HFT focuses on high volume smaller orders. In this timeframe total trading volume has doubled while the spread and transaction costs reduced (Menkveld, 2016). The latency advantage has given room for discussion between academics and practitioners. By trading in milliseconds and exploiting this advantage, HFT would be able to predict when orders are going to arrive at different trading locations. Research in the UK showed that it doesn't seem that this is the case, at least not in short periods of time. However, discovered patterns show some, not decisive, evidence that over longer periods there might be an advantage over non-HFT traders (Aquilina & Ysusi , 2016). The Flash Crash of May 6th 2010 showed that the new technologies available makes the financial system more vulnerable but according to the Deutsche Bank the solution should not be relying on more regulatory measures. Restrictions on physical co-locations would be limited and an obligation to provide continuous liquidity would expose market makers to price risk in the case of a crash which could lead to financial instability. A more suitable solution would be to install circuit breakers that automatically pause market trading when the volatility would temporarily become too high (Chlistalla, 2011).

4.1.4 Asset pricing and return

Assets are priced based on fundamental value and the expected return. To determine the fundamental value of an asset multiple pricing methods are available, e.g. Present Value Model; the Gordon Growth Model, but also the Efficient Market Hypothesis that states that the market price reflects the actual value. To measure the appropriate return the Arbitrage Pricing Theory and the Capital Asset Pricing Model amongst others can be used. Most models connect expected return to the risk investors have to be compensated for with CAPM as the most widely used model (Krause, 2001). The Capital Asset Pricing Model of William Sharpe (1964) and John Lintner (1965) is used for various applications such as the estimation of cost of capital and evaluating portfolios. The ease of use makes it a desirable way to measure risk and return, however it is based on assumptions which also shows its flaws. The CAPM Model, based on the portfolio model of Harry Markowitz (1959), assumes that investors are risk averse and choose mean-variance portfolios focusing on minimizing variance and maximizing expected returns (Fama & French, 2004).

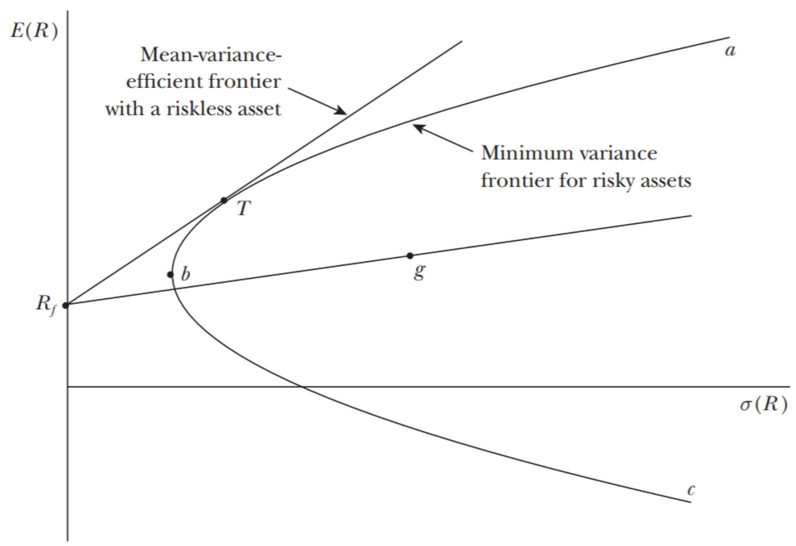


Figure 2: CAPM CML mean variance frontier

The formula for CAPM is $E(R) = Rf + ß*[E(RM) - Rf]$ where $E(R)$ is the expected return, Rf the risk-free rate, ß the stock beta and $[E(RM) - Rf]$ the market risk premium. When investing in small cap stocks another factor comes into play, the premium. As part of the Fama and French Three Factor Model (market premium, value premium and size premium) the SMB factor, or 'small minus big', the size premium is the return spread between small and large stocks. These smaller stocks carry a different systematic risk profile than large stocks which in turn has an effect on premium and expected returns (Chen & Zhao, 2009). According to the small firm effect companies with a small market capitalization outperform large-caps. Average returns on regular stocks are related to factors like size, sales growth and book-to-market equity. When observing small capitalization stocks the Three Factor Model (size, book-to-market ratio and return) explains abnormal returns, or anomalies. This model does have a downside as it is sensitive to time period effects (Fama & French, 1996). Where investors often focus on future earnings, calculated by the present value of future income, to decide if the asset is worth to invest in, the book-to-market ratio is a metric that provides information on the current situation. In other words, does the current market value for a specific stock match the book value. In the case of variances trading opportunities are available, e.g. value stocks. The book-to-market ratio can be found by dividing the book value of the firm by the market value of the firm.
Small-caps that invest a lot seem to suffer from low average returns. The Fama and French Five Factor Model research (2014) shows that small-cap portfolios are impacted by volatility (Fama & French, 2015). Liquidity and asset pricing are highly correlated. Amihud and Mendelson (1986) found a positive expected stock return-illiquidity correlation and Amihud (2002) a negative return-liquidity relation even when taking the Fama and French Three Factor model taking into account (Lam & Tam, 2011). Illiquidity affects small stocks more than large stocks, hence an illiquidity premium is in place (Amihud, 2002). Higher expected returns are required for high spread stocks but increasing the liquidity of stocks should result in lower spreads. This higher liquidity combined with lower spreads results in a higher firm value. Therefore financial incentives to improve liquidity could result in rising specific asset prices (Amihud & Mendelson, 1986). A model proposed by Acharya and Pedersen states that CAPM applies for returns net of illiquidity costs. This means that investors should take into account that less liquidity demands a higher required return. Therefore they created a model named liquidity adjusted CAPM which takes the illiquidity factor into account. Results show that persistent positive shocks to illiquidity are associated with low contemporaneous returns and high predicted future returns (Acharya & Pedersen, 2005).

4.1.5 Small cap liquidity

Small-cap stocks behave differently when compared to large-cap stocks. Portfolio theory shows that diversification in negatively correlated asset classes reduces portfolio variance and can improve portfolio performance (Petrella, 2005). Large-cap stocks are subject to global pricing more than small-cap stocks. They are more likely to be cross-listed and tradable on foreign equity markets. Small-caps tend to be traded more on local equity markets which adds to the lower level of liquidity (Huang, 2007). Algorithm Trading (AT) improves liquidity for large-cap stocks. Quoted spreads narrow under automated quoting. The narrower spreads are a result of a decline in adverse selection and more informative quotes. Research showed that there a no significant effects on small-cap stocks but this could be due to limited datasets (Hendershott, et al., 2010). The illiquid nature of small-cap stocks combined with a higher liquidity risk demand a higher cost of capital and required return for small-caps. These firms are allowed by Euronext to hire designated market makers (DMM's) who guarantee a minimal liquidity supply. The market makers hired by the small cap companies improve liquidity, reduce risk and generate higher returns (Menkveld & Wang, 2013).

4.1.6 Summary

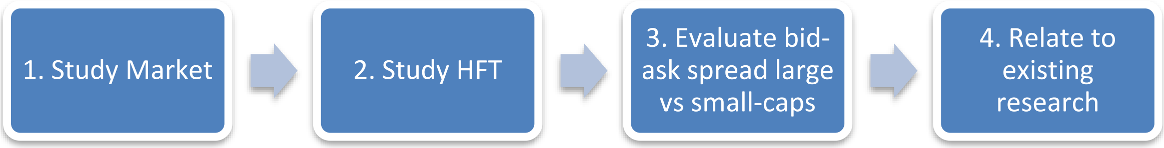
We speak of information asymmetry when one side has greater knowledge than the other side. This asymmetry could have negative impact on market stability (Akerlof, 1970). Information asymmetry leads to higher transaction costs, raise the required return and in effect reduces stock price. To maximize firm and thus shareholder value it is desired to minimize asymmetry (Bartov & Bodnar, 1996). Fundamental value of a stock can be calculated by using models as Present Value Method, the Gordon Growth Model or the Efficient Market Hypothesis (EMH) (Krause, 2001). However, according to the EMH there should be no arbitrage opportunities at all. All traders should have the same access resulting in equilibrium because all price inefficiencies are solved by ask and demand almost instantly. Traders need to be compensated for their efforts in gathering information which means that inefficiencies are inevitable to generate profits (Grossman & Stiglitz, 1980). Models like CAPM and APT, argued by Grossman and Stiglitz (1980) rely on symmetry and are based on the assumption that information is only relevant to the market as a whole. Individual idiosyncratic risk can be diversified away so by holding a portfolio with enough stocks everything looks symmetric. The two main factors of markets are liquidity and price discovery. The liquidity spread could have impact on asset pricing due to lower net returns (O'Hara, 2003). Liquidity is measured by size, price and time. When relevant pricing is not available the asset faces illiquidity resulting in price pressure and extra risk (Jones, 2013). In illiquid markets it is harder to sell large positions and the transaction costs are higher resulting in extra risk. A higher risk ratio reduces asset prices and requires investors to demand more compensation (Amihud, et al., 2012). When a trader wants to sell or buy an order a favorable price needs to be available or he has to act at the current bid-ask price. The quoted price includes a premium for direct execution. This means that the measure of (il)liquidity is the bid-ask spread (Amihud & Mendelson, 1986). HFT provides liquidity by continuous quoting, but in the case of extreme price movements for multiple stocks at once HFT demands liquidity. The reason for this is that supplying liquidity is more risk averse than the liquidity demanding strategies (Brogaard, et al., 2017). HFT is characterized by 1) computer algorithms, 2) co-location to minimize latency, 3) high speed order execution and 5) leaving no open positions overnight (Jones, 2013). The high level of automation reduces transactions costs and can result in more efficient risk sharing, improved liquidity, more efficient pricing and reduce firms' cost of capital (Hendershott, et al., 2010). HFT focuses mainly on; 1) Market making to provide liquidity and 2) making profits on price efficiencies by statistical arbitrage (Rijper, et al., 2010). Where institutional investors divide their large orders into smaller chunks to prevent price impact, HFT generates large volumes in smaller orders with tiny profits. While the trading volume increased significantly the spread and transaction costs reduced when looking at pre- vs. post HFT entry (Menkveld, 2016).

CAPM as a mean to measure risk and return is the most widely used model for asset pricing but is partially based on assumptions which shows its vulnerability (Fama & French, 2004). The question arises how CAPM, based on symmetry relates when linked to HFT thriving on asymmetry.

Fama & French's Three Factor Model adds the premium (market premium, value premium and size premium) to the equation and shows that small-cap portfolios are affected by volatility (Fama & French, 2015). Amihud (2002) states that the illiquidity of small stocks also adds a premium. Due to the impact of liquidity to CAPM Acharya and Pedersen constructed a model called liquidity adjusted CAPM (Acharya & Pedersen, 2005). A factor for the lower liquidity level of small-caps is the more localized equity markets. Large-caps are more likely to be cross-listed and tradable on foreign equity markets (Huang, 2007). Due to limited research on small-cap spreads show no significant effects have been found but this results are not decisive (Hendershott, et al., 2010). Liquidity in the Euronext small-cap market is artificially improved by having small firms hire designated market makers who guarantee minimum supply. In turn they improve liquidity, reduce risk and generate higher returns (Menkveld & Wang, 2013).

5. Research design

What needs to be researched is how HFT, by using information asymmetry, could theoretically benefit illiquid markets. To research the liquidity effect in markets with a specific size distribution the following research design has been set up;



1. **Study liquidity and price discovery**
   A literature study on the connection in regular (large-cap) markets when looking at liquidity, price discovery and asset pricing.
2. **Study High Frequency Trading**
   A literature study on HFT and their trading methods.
3. **Research current bid-ask spread percentage large-caps vs mid-cap vs small-caps**
   A comparison of 15 FTSE 100 stocks and 15 UK Small-caps. To examine the spread flow 15 mid-cap stocks are randomly selected from the FTSE Mid 250. The following steps are taken to gather data on 45 stocks:
   I. Select 15 large-caps (FTSE100) in the IG Markets trader terminal
   II. Select 15 mid-caps (FTSE Mid 250) in the IG Markets trader terminal
   III. Select 15 small-caps (FTSE Small Cap) in the IG Markets trader terminal
   IV. Calculate the bid-ask spread percentage based on current prices on London Stock Exchange
   V. Study execution price and trader type and relate to the mean bid-ask price on London Stock Exchange
4. **Relate to existing research**
   Connecting the data to existing literature and construct a possible theory.

The London Stock Exchange (LSE) gives limited public information on trades. The orderbook can be seen per day for a number of trader per stock. In this orderbook the type of trade is mentioned but historic trades are not. This data is used to 1) verify the indication of automated trades and 2) a change in spread for that specific trades (London Stock Exchange, 2019). Stocks are picked at random and not based on intraday popularity. The reason for this is that small-cap stocks are particularly illiquid and in the extensive stock list in the trader terminal (IG) there is not enough volume to sort small-caps based on popularity. Small-cap stocks lacking quoted prices are not taken into account.

6. Results

The stock data from the London Stock Exchange shows the liquidity and tradability issues when comparing markets and their quoted firms. The large-cap stocks are characterized by mostly automated executed orders (Appendice I. Stock data London Stock Exchange). The trader type is classified by LSE on execution, e.g. Automatic Order (AT), Uncrossing or Off-Book. Automatic orders are not HFT orders per definition, but are executed immediately and driven by algorithms and thus the closest to indicate the impact on the bid-ask spread in this research. The stocks traded in the FTSE100 index are in majority executed by automated trading algorithms. Liquidity is high and the bid-ask spread percentage is, for 12 of the 15 researched stocks within that limited time period, between 0.02 and 0.06 percent. Because only the last executed orders on the LSE have been taken into account small variances may be possible. The orderbook revealed that most executed orders have a relative small trade value below GBP 5.000. Larger trade values could have more effect on execution prices. The actual execution price can be found close to the mean of bid-ask spread per stock which implies fast execution and relative low volatility, the market price is not affected abnormally by the order itself. The order book shows that liquidity is high with orders executed every few seconds. The mid-cap stocks (FTSE Mid 250) show a larger spread compared to the FTSE100 stocks. Although trade value shows similar orders below GBP 5.000 the trader type is more often 'Off-book' instead of automated. The bid-ask spread percentage is almost 5 times as high as the percentage on large-caps. The lower level of automation and the amount of trades seems to have negative impact on narrowing the spreads but this is a preliminary finding. What can be seen, despite the small dataset, is that there is correlation between spread, automation and liquidity. The smaller the market capitalization, and with that the placement in a specific index, the higher the spread. The small-cap stocks in the FTSE Small Cap show a large number of listings without quoted prices. Only stocks have been selected that have a bid as well as an offer price. None of the trades researched were executed using automatic trading. The bid-ask spread varied from 1% up to 30% combined with a trade volume of zero to no more than 10 trades a day. Where the average bid-ask spread in this dataset on the large-caps is 0.08%, the average spread on the small-caps is 11.67%. The variance on the execution price for the last traded orders compared to the mean of the bid and ask price for a specific stock shows that the large-caps returns an average of 0.01%, but the small-caps 0.04%. While the bid-ask spread percentage for small-caps is 146 times larger than for the large-caps, the mean variance in execution is 4 times greater. What does stand out is the volatility, where in the large-caps the execution stays close to the mean, the small-cap execution shows several specific spikes up to 8%. This seems to confirm that quoted spreads narrow under automation, helped by the larger volume. Orders in small-caps can trigger greater price movement on execution due to the low number of trades.

7. Conclusion

7.1 Discussion

The goal of this research was to gain insights in the work methods and ethics of High Frequency Traders. The answer to the question if HFT improves market quality or exploits advantages and possibly destabilize the financial markets will still be depending on the side who is asked. However, this research does raise some question which might need further research. How do the Efficient Market Hypothesis and CAPM models correlate with HFT? The EMH tells us that the market price is the same as the fundamental value. So what is the driver for small size firms to get on the radar of

HFT? Although HFT claim to improve market efficiency, they need to make a profit. According to the assumption that markets are or will be in equilibrium when ask meets demand there first must be an effective market or enough demand to drive prices (bid-ask) closer. To create the demand a financial incentive is needed, or in other words, there must be a profit to be made. Investors would not be compensated for their efforts if there is no chance on profits. One interesting question might be to research how trading affects firm value. As HFT creates liquidity and therefore demand, the value rises, possibly resulting in a different book-to-market ratio which creates under- or overvalued firms, resulting in investment opportunities.

7.2 Limitations

The unwillingness (closed information) of the companies leaves room for interpretation. The complete dataset is based on desk research. Dark pool traders don't disclose information which makes it hard, if not impossible, to verify inside trades. Liquidity and price discovery have been researched extensively, however the link with small cap liquidity and HFT research is limited. Narrowing down liquidity and price factors on small cap trading would take more time to generate decisive academic outcomes. The liquidity adjusted CAPM could give better insights on illiquid small-cap requires returns. Due to the fact that the bid-ask spread as seen in the trader terminal orderbook changes continuously a large dataset would be needed to be able to compare large-caps and small-caps over time.

7.3 Conclusion

The rise of automated trading and in particular HFT made markets more efficient by improving liquidity and lowering transaction costs. HFT plays a double role in the financial markets by acting as a liquidity provider and thus helping the market quality, but also profiting of arbitrage opportunities (Rijper, et al., 2010). This effectively means that automated trading narrows quotes and lowers costs for the market as a whole, but demands an advantage in transaction speed to keep maintaining profitability. Therefore HFT will be focusing even more on those small margins to profit of asymmetry by looking for even faster ways to execution leaving non-HFT with less opportunities. One might say that this is indeed an unfair advantage. When evaluating the percentage of algorithm trades in the market non-HFTs seem to become a dying breed as they will not be able to match the innovations in IT. Given the developments in automation HFT does look like the future of trading by given the market the liquidity it needs to become truly efficient. Quoting prices, lowering the bid-ask spread and delivering market demand will drive informativeness. More information known to the public will result in prices that resemble the fundamental value better as stated in the Efficient Market Hypothesis.

Trades revealing information in market microstructures gives HFT the opportunity to build on their advantages towards traditional traders. They will always focus on getting information sooner than others, hence the never ending need for speed improvement (Muhle-Karbe & Webster, 2017). The gathered information gives room for quoting specific prices and possibilities for arbitrage and thus for providing liquidity. HFT essentially creates their own market opportunities. Needed methods to obtain this information will keep giving room for debate. The question if this same techniques would also work in small-cap markets should be researched more thoroughly. It is quite clear that more automation has its benefits on market tradability but it is expected that there are more factors that explain stock liquidity. Expected return is important for investors and the willingness to trade a stock. When an investor would trade a small-cap stock he needs to be sure that this stock can be sold at the right price and generating the required return. The illiquid nature of small-caps demands a premium to bear the risk involved. The main question would then be, how can HFT reduce risk? A possible solution would be to create more demand. As Amihud and Mendelson stated (1986) higher returns are required for high spread stocks, but lower spreads result in higher firm value. Instead of the currently hired designated markets makers to unnaturally support the small-caps other financial incentives could be a trigger to make small-cap markets more interesting for investors. This would mean that the risk-return ratio should become more attractive for investors. Theoretically continuous quoting by HFT could lower spreads and make the trade less risky. Demand could rise if traders were more confident that they can buy, but also sell the asset when the opportunity arises. A possible side-effect could be that more demand creates higher market prices as shown in theory (Wang & Zhang, 2015) but the market price would not reflect book value affecting the book-to-market ratio used by Fama and French (1996). The relative large bid-ask variances currently in the small-cap market may give a difference in the use of the Efficient Market Theory compared to the actual value. At some point in time, when price differences are arbitraged out by the market, a natural equilibrium will possibly emerge, but till that moment trading opportunities will be available. HFT can be a catalyst to improve liquidity, even in small-caps, but it seems that more market factors need to be taken into account. As they are all related to each other (return, liquidity, asset pricing) additional research would be necessary.

7.4 Recommendations

Conducting further research on the need of market maker support to provide liquidity in the small-cap market is recommended. Results show that small-cap markets rely on non-natural regulatory induced liquidity providers which makes it harder to build a sustainable equilibrium. Also the relation to small firm premiums and the effect on expected returns and volatility should be researched more in-depth. One might ask what the main driver would be to improve actual liquidity. Does quoting by automated traders have sufficient effect or would this give an unrealistic asset pricing when looking at fundamental value? Small-caps are known for their higher than average volatility. Further research would be necessary in the form of a longitudinal study.

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Appendices

I. Stock data London Stock Exchange FTSE100

Nr.	Company name	Index	Bid LSE	Offer LSE	Spread	Percentage	Execution price	Mean variance	Execut perc.	Trade Value	Latest Trade	Flag	Ratio
1	3i Group PLC	FTSE100	801,00	801,40	0,40	0,05%	801,6	-0,40	-0,05%	GBP 1.450,90	Automatic	ALGO	100%
2	Rolls-Royce Holdings PLC	FTSE100	815,00	815,40	0,40	0,05%	815,6	-0,40	-0,05%	GBP 2.560,98	Automatic	ALGO	90%
3	BAE Systems PLC	FTSE100	472,60	472,80	0,20	0,04%	472,5	0,20	0,04%	GBP 8.656,20	Automatic	ALGO	100%
4	Astra Zeneca PLC	FTSE100	6.069,00	6.071,00	2,00	0,03%	6069	1,00	0,02%	GBP 3.520,00	Off Book		70%
5	BT Group PLC	FTSE100	237,95	238,00	0,05	0,02%	237,9	0,07	0,03%	GBP 2.864,32	Automatic	ALGO	100%
6	Barclays PLC	FTSE100	155,10	155,74	0,64	0,41%	155,18	0,24	0,15%	GBP 775,90	Automatic	ALGO	100%
7	Coca-Cola HBC AG	FTSE100	2429	2430	1,00	0,04%	2430	-0,5	-0,02%	GBP 4.349,70	Automatic	ALGO	100%
8	GlaxoSmith Kline PLC	FTSE100	1514,6	1515	0,40	0,03%	1514,6	0,2	0,01%	GBP 5.270,81	Automatic	ALGO	80%
9	Marks & Spencer Group PLC	FTSE100	253,6	253,8	0,20	0,08%	253,7	0	0,00%	GBP 532,77	Off Book		90%
10	RELX PLC	FTSE100	1623	1623,5	0,50	0,03%	1623	0,25	0,02%	GBP 1.623,00	Automatic	ALGO	100%
11	Reckitt Bensinger Group PLC	FTSE100	5950	5952	2,00	0,03%	5952	-1	-0,02%	GBP 4.940,16	Automatic	ALGO	100%
12	Royal Dutch Shell PLC A	FTSE100	2377	2378	1,00	0,04%	2378,5	-1	-0,04%	GBP 17.221,86	Automatic	ALGO	100%
13	Smurfit Kappa Group PLC	FTSE100	2130	2134	4,00	0,19%	2134	-2	-0,09%	GBP 629,88	Automatic	ALGO	100%
14	Standard Life Aberdeen	FTSE100	260,95	261,1	0,15	0,06%	261	0,025	0,01%	GBP 854,77	Automatic	ALGO	100%
15	British American Tobacco PLC	FTSE100	2577,5	2579	1,50	0,06%	2576,53	1,72	0,07%	GBP 46.555,61	Off Book		90%
			Average spread			**0,08%**		Average variance	**0,01%**				
C	Bid GBX												
D	Offer GBX												
E	spread (offer-bid)												
F	spread percentage												
G	Execution price												
H	Difference execution price comp. to offer-bid												
I	percentage execution price variance to offer price												
J	Last trade type												
K	Trade flags by LSE												
L	Ratio trade type last 10 trades												

II. Stock data London Stock Exchange FTSE Mid250

Nr.	Company name	Index	Bid LSE	Offer LSE	Spread	Percentage	Execution price	Mean variance	Execut perc.	Trade Value	Latest Trade	Flag	Ratio
1	Alliance Trust	FTSE MID 250	698	700	2,00	0,29%	700	-1	-0,14%	GBP 2.792,00	Automatic	ALGO	50%
2	Bellway PLC	FTSE MID 250	2646	2651	5,00	0,19%	2649	-0,5	-0,02%	GBP 4,36	Automatic	ALGO	100%
3	CLS Holdings PLC	FTSE MID 250	213,5	218	4,50	2,06%	218	-2,25	-1,03%	GBP 387,90	Automatic	ALGO	100%
4	Capita PLC	FTSE MID 250	114,75	115,2	0,45	0,39%	114,95	0,025	0,02%	GBP 710,39	Automatic	ALGO	100%
5	Fidelity European Values	FTSE MID 250	210,5	212,5	2,00	0,94%	212	-0,5	-0,24%	GBP 235,32	Off Book		70%
6	G4S	FTSE MID 250	200,3	200,7	0,40	0,20%	200,3	0,2	0,10%	GBP 200,30	Automatic	ALGO	100%
7	Just Eat PLC	FTSE MID 250	598,8	599,6	0,80	0,13%	599	0,2	0,03%	GBP 658,90	Automatic	ALGO	90%
8	KAZ Minerals PLC	FTSE MID 250	527,2	528	0,80	0,15%	527,8	-0,2	-0,04%	GBP 4.486,30	Automatic	ALGO	100%
9	Plus500 Ltd	FTSE MID 250	1479	1481	2,00	0,14%	1481	-1	-0,07%	GBP 1.451,38	Automatic	ALGO	60%
10	Saga Ltd	FTSE MID 250	104,8	105,1	0,30	0,29%	104,9	0,05	0,05%	GBP 475,20	Automatic	ALGO	100%
11	Serco Group PLC	FTSE MID 250	100,2	100,4	0,20	0,20%	100,8	-0,5	-0,50%	GBP 340,70	Off Book		70%
12	Superdry PLC	FTSE MID 250	483,4	484,4	1,00	0,21%	484,8	-0,9	-0,19%	GBP 276,34	Automatic	ALGO	100%
13	Ted Baker PLC	FTSE MID 250	1538	1542	4,00	0,26%	1540	0	0,00%	GBP 1.093,40	Automatic	ALGO	60%
14	Vivo Energy PLC	FTSE MID 250	124,4	129,98	5,58	4,29%	129,98	-2,79	-2,15%	GBP 129,98	Automatic	ALGO	100%
15	Workspace Group PLC	FTSE MID 250	816,5	818,5	2,00	0,24%	818,5	-1	-0,12%	GBP 818,50	Automatic	ALGO	80%
			Average spread			**0,67%**		Average variance	**-0,29%**				
C	Bid GBX												
D	Offer GBX												
E	spread (offer-bid)												
F	spread percentage												
G	Execution price												
H	Difference execution price comp. to offer-bid												
I	percentage execution price variance to offer price												
J	Last trade type												
K	Trade flags by LSE												
L	Ratio trade type last 10 trades												

III. Stock data London Stock Exchange FTSE Small Cap

Nr.	Company name	Index	Bid LSE	Offer LSE	Spread	Percentage	Execution price	Mean variance	Execut perc.	Trade Value	Latest Trade	Flag	Ratio
1	4d Pharma PLC	FTSE SMALL CAP	98,2	109,5	11,30	10,32%	107,75	-3,9	-3,56%	GBP 2.155,00	Off Book		0%
2	1spatial PLC	FTSE SMALL CAP	33	36	3,00	8,33%	34,5	0	0,00%	GBP 1.725,00	Off Book		0%
3	AIQ Limited	FTSE SMALL CAP	20	24	4,00	16,67%	0	0	0,00%	GBP 0,00	No trading		0%
4	Agriterra	FTSE SMALL CAP	7	10	3,00	30,00%	0	0	0,00%	GBP 0,00	No trading		0%
5	Air Partner PLC	FTSE SMALL CAP	80	89,8	9,80	10,91%	85	-0,1	-0,11%	GBP 2.125,00	Off Book		0%
6	BSD Crown Ltd	FTSE SMALL CAP	20	23	3,00	13,04%	23	-1,5	-6,52%	GBP 1,84	Uncrossed		0%
7	BlackRock Income & Growth	FTSE SMALL CAP	149	182	33,00	18,13%	0	0	0,00%	GBP 0,00	No trading		0%
8	EU Supply PLC	FTSE SMALL CAP	10	12	2,00	16,67%	10	1	8,33%	GBP 1.100,00	Off Book		0%
9	FIH Group PLC	FTSE SMALL CAP	290	310	20,00	6,45%	293,75	6,25	2,02%	GBP 2.317,69	Off Book		0%
10	GAN PLC	FTSE SMALL CAP	47	50	3,00	6,00%	47,5	1	2,00%	GBP 4.750,00	Off Book		0%
11	Infrastrata PLC	FTSE SMALL CAP	1,2	1,22	0,02	1,64%	1,22	-0,01	-0,82%	GBP 1.610,00	Off Book		0%
12	JP Morgan Euro Trust	FTSE SMALL CAP	333	337	4,00	1,19%	333	2	0,59%	GBP 989,01	Uncrossed		0%
13	Provexis PLC	FTSE SMALL CAP	0,25	0,33	0,08	24,24%	0,3	-0,01	-3,03%	GBP 10.500,00	Off Book		50%
14	Quiz PLC	FTSE SMALL CAP	30,5	31,4	0,90	2,87%	30,84	0,11	0,35%	GBP 4.771,87	Off Book		80%
15	Safestay PLC	FTSE SMALL CAP	32	35	3,00	8,57%	33,45	0,05	0,14%	GBP 98,01	Off Book		0%
C	Bid GBX		Average spread			**11,67%**		Average variance	**-0,04%**				
D	Offer GBX												
E	spread (offer-bid)												
F	spread percentage												
G	Execution price												
H	Difference execution price comp. to offer-bid												
I	percentage execution price variance to offer price												
J	Last trade type												
K	Trade flags by LSE												
L	Ratio trade type last 10 trades												