AGGRESSIVE AND DEFENSIVE HIGH-FREQUENCY TRADING AND ITS IMPACT ON LIQUIDITY OF GERMAN STOCK MARKET

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Abstract

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Algorithmic trading and especially high frequency trading is the concern of the current research studies as well as legislative authorities. It is also the subject of criticism mostly from low frequency traders and long-term institutional investors. This is due to several cases of market manipulation and flash crashes in the previous years. Advocates of this trading mechanism claim that it has large positive influence on the market, such as liquidity growth by lowering spreads and others. This paper is focused on testing the relationship between market liquidity of shares traded on Frankfurt Stock Exchange and HFT activity on European stock markets. Author proposes own methodology for measuring dynamics in HFT activity, without knowledge of original market messages. Liquidity is measured by various from of price spreads. Econometrical methods for panel regression are used to determine these relations. Results of this paper will reveal the relevance of the HFT trader's main argument about creating liquidity and hence reducing market risks related with high spreads and low number of limit orders.

Keywords: high-frequency trading, liquidity, spread, effective spread, realized spread, weighted spread, relative spread

INTRODUCTION

Algorithmic trading and more specifically high frequency trading became the most common trade realization method on developed markets with large volumes of trading. It is not only part of trading decision process, but it is also an important tool of order submission process, risk assessment, data management and market predictions. Algorithms have found their place in many segments of world markets including equity, bond, derivatives and commodity markets. In the world largest exchange markets electronic order submission replaced the floor trading or is at least playing crucial part in the trading. Electronic trading brought much more effectivity on markets and represents the cheaper solutions than replicated work of floor traders or specialists (Hendershott, 2011b). This part financial industry is related with the development in other fields. Mathematicians create new models for

effective asset pricing, price prediction, data mining and risk optimization. Hardware engineers design computers that are capable of superfast computation and more importantly data transmission. Co-location is one of the crucial conditions for HFT traders. Hence they put their servers as close to the exchanges as possible. The connection between particular exchanges has become such important that direct cable lines were constructed between them and next steps are even more astonishing. Construction of beacon towers is planned between exchanges in the U.S., which will save precious milliseconds of data transfer and assure better access to information for HFT traders. HFT can be defined as a subset of algorithmic trading, or more precisely the use of computer programs for entering of trading orders with the computer algorithm. Further, HFT is distinguished from general algorithmic trading in terms of holding periods and trading purposes (Zhang, 2010). The initial purpose of algorithmic

trading was to deal with price impacts caused by large block trades. Algorithms were created to break up the block orders into several pieces, which were then executed separately. The purpose was to time each partial order, so the price impact will not bring additional costs to the trader (Bertsimas, 1998). Readers can refer to (McGowan, 2012) for deeper background of HFT.

The goal of this paper is to examine an impact of these changes and high frequency trading (HFT) on liquidity of securities traded on German Stock Exchange. Liquidity of traded instruments is considered to be one of indicators of market stability. It is based on sufficient trading activity in all market situations and possibility of finding counterpart to the trade at acceptable price. Limit orders are the main means of liquidity creation. Each exchange has its own rules, but mostly, market participants are paid for placing limit orders and creating liquidity. They are also required to pay commissions for placing market orders and closing open limit positions and hence lowering liquidity. Market makers use these opportunities to create profit by constant liquidity provisioning (Aldridge, 2013). This is only the simplified description of much more complex price discovery process. The theory suggests, that the more limit orders are placed on the market the lower is the difference between bid and ask price. Thus, spreads are the appropriate indicator of market liquidity (Kendall, 2007). In this paper spreads will be used as proxy for the measurement of market liquidity.

Argument for the high-frequency algorithms, that it decreases spreads and increases liquidity, has been the leading evidence of all HFT advocates. Research is mostly focused on the US markets, where HFT activity is much more imminent. First papers that focused on the related topics are studies concerning the liquidity providers (companies submitting limit orders) and liquidity takers. They have assumed either liquidity suppliers are perfectly competitive (Glosten, 1994) or that their commissions are declining with the number of liquidity suppliers (Biais, 2000). The provision given to the liquidity providers in market making position, who are obliged to take a position in trade have been priced as an option (Copeland, 1983) and these option costs have been optimized by effective market monitoring (Foucault, 2003). Fees and provisions for HFT market makers move in certain patterns in intraday periods (Foucault, 2013). Dynamic liquidity provisions for market makers are strongly affecting their willingness to undertake risk in accordance to their capital situation. If market makers have enough capital, they provide optimal amount of liquidity. This leads to reduction of price peaks and rapid changes in volatility. Whereas if they lack capital or the trading is too costly then market makers undersupply liquidity (Weill, 2007). And the undersupply of liquidity is much more evident under the circumstances when market makers face

market manipulation and other predatory activities (Attari, 2005).

Studies have been carried out to analyze adjustment of the automated trading strategies to the conditions of limit order book in supplying or taking liquidity. The confirmation of relationship between spreads and market makers activity brought first significant results. Specialist firm-level spreads are getting wider when specialists hold large positions or loose money (Comerton-Forde, 2010). Co-movement of liquidity is stronger among stocks listed on NYSE, which are traded by the same specialist company (Coughenour 2004). Current theoretical concept postulates that time variation of market liquidity is the function of limited market-maker capital (Gromb 2002; Brunnermeier, 2009). The most of liquidity models are based on three explaining factors: fixed costs, asymmetric and private information and inventory structure.

It has been proven that algorithmic trading has narrowed down spreads on New York Stock Exchange, especially after automatic quote dissemination (Hendershott, 2011a). They also stated that bid-ask spreads of large blue-chip companies are reduced along with adverse selection, trade-related price discovery and quote informativeness after the enhanced implementation of automated trading. Co-location as the basic requirement of the efficient HFT business and useful proxy indicator for HFT activities have given many evidences that after enabling very close access to the exchange servers the reduction in price spreads has been significant in many cases; i.e. on Australian Securities Exchange (Frino, 2013). Other evidences confirming positive relationship between spreads and HFT activity are Brogaard, (2011); Brogaard (2014); Hasbrouck (2013); Hendershott (2009). Predictive market models have been created to simulate the liquidity behavior under the influence of automated market maker. (Slamka, 2013).

This paper is using methodology introduced by (Hendershott, 2011b). These models for different kind of spreads are enhanced with other explaining variables describing market activity. Calculations are conducted on the most traded stocks from London Stock Exchange (LSE). The paper is structured as follows. Section Material and Methods describes analyzed data and introduces some basic relationships among used variables. Next, it summarizes used methodology and the structure of models. Section Results shows main results of the paper and Section Discussion presents a set of possible setbacks and future challenges of this research. Conclusions derived from the results are placed in last section. They are compared with the results in former research.

MATERIALS AND METHODS

As was stated before, most of research concerning high-frequency trading and its influence on market

liquidity has been conducted on US markets. Therefore, I have decided to focus my attention on European markets, where algorithmic trading is similarly developed but the proper research is still lacking. Next section clarifies stock selection process and the description of variables creation and methods used for their further analysis.

Data

Activity of algorithmic trading might be theoretically measured for any kind of asset, which is traded on market, where this trading is allowed. However, there is no point to test influence of HFT activity if there is no activity at all or clustered into short intervals. Especially in cases like this, when this activity is not measured directly. We have focused on the stocks, where the average daily traded volume (from previous year) exceeded 10 million EUR. Second, market capitalization had to be greater than 2 million EUR. This would assure that trading with chosen securities would have effect on the whole market. Only primary issues were included. Third, trading activity was required to be distributed over the observed period. This was satisfied if there were at least 10,000 out of 65,959 observation with at least one trade. Some were excluded just because there were no data available. Using these criterions I reduce the selection to 26 most traded stocks on German Stock Exchange. Analyzed period is from April 15,2015 to October 19,2015. This interval is same for all securities. All trading days in selected interval were included except of September 22. On this day Volkswagen emission scandal erupted and increased market volatility followed. That could bias characteristics of chosen variables.

One minute observations have been used in all variables. This frequency was used because it is the most dense available. First 5 and last 20 minutes of each day were also excluded, due to effects of opening and closing auction. Major problem that occurred during these periods were negative spreads. All other periods with negative spreads were excluded. These were mostly before some major information announcements. Table I characterizes all variables and their average comparative statistics of all selected shares. All data were acquired from Bloomberg database.

Negative profits with negative skewness confirm overall downward trend, which was present during whole period. Number of outstanding limit orders (na and nb) and volume of these orders (va and vb) suggests that in average, supply of liquidity was sufficient, however there seems to be lack of sell orders. This can also be explained by decreasing trend. There was no such need to replace sell orders, because everybody was rather buying at market prices. Five types of spread are used to proxy liquidity status. Namely bid-ask spread (s), relative spread (gs), share volume-weighted quoted half-spread (qs), effective spread (es) and realized spread (rs). First two are strictly positive, which was assured by omitting turbulent market periods. Next three can gain negative values due to order imbalance in limit order book and tendency of traders to cross the spread in certain market situations. Volatility is lower than standard deviation of returns, which is caused by different methodology for estimating volatility of the share returns. Nevertheless, it is still bit exaggerated. This is mainly induced by market microstructure noise and bid ask bounce, which are common in high frequency data (Bandi and Russell, 2008). Changes in HFT activity are stationary varying around 0 with small positive changes and less dense greater negative changes, which suggest sudden withdrawals of algorithmic traders from the market.

I: *Comparative statistics of 26 selected shares from Frankfurt Stock Exchange.*

Variable	Mean	Maximum	Minimum	Stand. Dev
Price (P)	46.6696	54.1715	37.3986	4.0899
Profit (r) (%)	–0.0003	2.20	–3.95	0.0513
Number of trades (nm)	7.4763	156	0	5.9483
Number of sell orders (na)	158.0224	852.1538	14.3846	65.4087
Number of buy orders (nb)	155.0741	794.3840	13.1923	63.1371
Volume of trades (vm) (thousands)	3.3689	810.8693	0	5.5341
Volume of sell orders (va) (thousands)	6.8398	816.1790	0	6.6291
Volume of buy orders (vb) (thousands)	308.8365	2,718.1674	37.0941	119.1975
Spread (s)	0.0392	0.4711	0.0104	0.0158
Relative spread (gs)	0.0012	0.0102	0.0004	0.0004
Weighted spread (qs)	0.0144	0.1631	-0.1270	0.0315
Effective spread (es)	0.0007	0.0067	-0.0004	0.0002
Realized spread (rs)	0.0005	0.0149	-0.0258	0.0005
Order imbalance (oi)	0.1918	0.4216	0.0573	0.0457
Volatility (σ)	0.0004	0.0164	0.00003	0.0003
Difference of HFT activity (hft)	0.0011	1.2091	–0.7697	0.1499

For all variables Jarque-Bera test did not deny normal distribution.

Methodology

First of all measure for HFT activity has to be defined. This factor is usually derived from the real messages traffic between an exchange and HFT traders. However, these data are very seldom accessible. Proxy variables based on quantity of trades, volume of trading and average trade size are used instead. Most commonly used method is based on negative value of average trade size or an order (Hendershott *et al.*, 2011a). High- frequency traders submit significantly smaller orders in order of more efficient order management. This helps them to keep their position at the top of limit order book and rise the probability of gaining profits from spreads (Gsell, M., and Gomber, P., 2009). I have proposed enhanced version of this measurement using not only size of the trade, but also number of trades. Number of orders and number of trades are increasing when algorithmic trading activity is rising. It is mainly due to separation of large orders with large price impact into several smaller orders (Aldridge I., 2013). Proposed method is not feasible for estimating HFT activity, but rather its dynamics over time. Difference in HFT activity is measured as logarithm of reverse relative change of average trade size (in number of shares) multiplied by relative change in number of trades.

$$hft_{i,t} = ln \left(\frac{\left(vol_{i,t-1} + \overline{\left(\frac{vol}{n}\right)}_{i,t,h} \right)(n_{i,t}+1)}{\left(vol_{i,t} + \overline{\left(\frac{vol}{n}\right)}_{i,t,h} \right)(n_{i,t-1}+1)} \frac{(n_{i,t}+\bar{n}_{i,t,h})}{(n_{i,t-1}+\bar{n}_{i,t,h})} \right) \qquad (1)$$

where is volume of trading of share *i* in time *t*. It is identified as the sum of volume of market orders ($vm_{i,t}$), volume of limit sell orders ($va_{i,t}$) and volume of limit buy orders ($vb_{i,t}$). Number of orders of share *i* in time *t* is denoted as . It is again given by sum of number of trades ($nm_{i,t}$), number of limit sell orders ($na_{i,t}$) and number of limit buy orders ($nb_{i,t}$). One extra trade (calculated as the mean of average sizes of trades in last *h* observations) is added to the ratio of the change in average size of trade (or order). This will assure that function will be defined even in cases of complete market inactivity. Average number of trades (again calculated from last *h* observations) is added to second ratio. Without this change, relative change in number of trades would be higher for lower absolute changes. If changes of aggressive HFT activity need to be calculated, only volume of market orders ($vm_{i,t}$) and number of trades ($nm_{i,t}$) are used. On the other hand, when changes in defensive HFT activity are needed, it would be calculated only from volume of limit orders ($va_{i,t}$ and $vb_{i,t}$) and number of limit orders ($na_{i,t}$ and $nb_{i,t}$).

As was mentioned before the classical approach using bid ask spreads had indicated dubious relationship with activity of algorithmic traders. Hence, I have to apply other measures used to characterize liquidity (Hendershott *et al.*, 2011b). First alternative was relative spread ($gs_{i,t}$) defined as the bid-ask spread divided by market price. Second option was share volume-weighted quoted half-spread calculated as

$$qs_{i,t} = \frac{Bid\_price_{i,t} \cdot vb_{i,t} - Ask\_price_{it} \cdot va_{i,t}}{(vb_{i,t}+va_{i,t}) \cdot 2p_{i,t}} \qquad (2)$$

where p_{it} is the current market (trade) price of stock i at time t. This carries more information than bid-ask spread and relative spread, becauces it tells us not only the prices of best limit orders, but also actual size of these outstanding orders. Efective spread is calculated as difference between the midpoint of the bid ask prices and the transaction price. For certain stock i is the effective spread calculated as

$$es_{i,t} = q_{i,t} \frac{p_{i,t} - m_{i,t}}{m_{i,t}} \qquad (3)$$

where $m_{i,t}$ is representing midpoint price (middle between best bid price and best ask price), $q_{i,t}$ is indicator variable that equals 1for buyer-initiated trades and –1 for seller-initiated trades (Bessembinder, 2003). This spread reflects also position of market price regarding to the bid and ask price, which highlights the insufficient liquidity on either side of limit order book.

Revenue to liquidity providers is included by using 5-minute realized spread, which assumes the liquidity provider is able to close position at the price midpoint 5 minutes after the trade (Hendershott, 2011b). Proportional realized spread is stated as:

$$rs_{i,t} = q_{i,t} \frac{p_{i,t} - m_{i,t+5min}}{m_{i,t}} \qquad (4)$$

All these five alternatives for liquidity measurement were used as explained variable in models using changes in HFT activity and other control variables as explanatory variables. Explained variable have been used in form of first differences to avoid unstationarity (Brooks, 2014). Panel regression model was inspired by model used by Hendershott (2011a) with addition of volatility of analyzed shares $\sigma_{i,t}$ and difference of logarithmic returns of analyzed shares $dr_{i,t}$.

$$y_{i,t} = \alpha_i + \beta_1 hft_{i,t} + \beta_2 \sigma_{i,t} + \beta_3 dr_{i,t} \\ + \beta_4 RV_{m,t} + \beta_5 turn_{i,t} + \beta_6 af_{i,t} + \epsilon_{i,t} \qquad (5)$$

Frino *et al.* (2013) used realized volatility of share returns. In this case, other method has been used. Volatility of certain share have been calculated as $\sigma_{i,t} = ln(H_{i,t}/L_{i,t})$, where $H_{i,t}$ is highest share price during *t* observation and $L_{i,t}$ the lowest one. Control variables are market volatility ($RV_{m,t}$), turnover ($turn_{i,t}$) and inactivity indicator ($af_{i,t}$). Market volatility is calculated as realized volatility of one minute returns of German stock market index DAX (moving window of 60 observations prior *t*). Inactivity indicator is a dummy variable which indicates observations when there were 0 trades. More specifically, no market orders occurred.

After specifying model, statistical test concerning panel models were conducted. First of all, test for poolability (Baltagi, 2008) confirmed that there are significant differences between coefficient estimations for individual shares. Hence panel regression is necessary and data cannot be pooled. Next Hausman test for model specification rejected random effects model (Hausman, 1978). Serial correlation has been examined with likelihood-based conditional LM test (Baltagi and Li, 1995), locally robust LM test (Bera, Sosa-Escudero and Yoon, 2001), Breusch-Godfrey test for panel models and Wooldridge's first-difference test (Wooldridge, 2010). First three tests did not reject the presence of serial correlation. The fourth test did so. Presence of cross-sectional dependence has been rejected with both Pesaran CD test and Breusch-Pagan LM test (Pesaran, 2004). Unit root was rejected for explained variables and for residuals using augmented Dickey-Fuller test for panel data (Im, Pesaran, and Shin, 2003). Last, heteroskedastic error terms have not been rejected using Breusch-Pagan test for panel data (Wooldridge, 2010).

Based on these results estimator for panel models with fixed effects have been chosen as appropriate option. Covariance matrix has been estimated by heteroskedasticity consistent HAC estimator for fixed effects (Arellano, 1987), which also deals with the serial correlation (Stock and Watson, 2008).

These results were then compared with results of OLS estimation of the model (5) with robust error terms estimator to deal with present heteroscedasticity. Heteroscedasticity was tested with Breusch-Pagan test. No problem with unstationarity of residuals was present. Multicolinearity of regressors has been rejected by variation inflation factor (Brooks, 2014).

RESULTS

Estimations of panel model (5) were conducted for all five chosen types of spreads. In all cases has been confirmed that with rising activity of high-frequency traders, spreads are becoming narrower and thus markets of tested shares are becoming more liquid. Results can be seen in Table II. HFT market makers are able to supply liquidity in most of cases. This also means that any aggressive behavior of some algorithmic traders (liquidity takers) has smaller effect on market liquidity, than positive effects created by liquidity providers. These results are consistent with results of similar research papers (Hendershott *et al.*, 2011a; Chaboud, *et al.*, 2014; Jarnecic, and Snape, 2014). Estimation of models showed only small explanatory power. Nevertheless, low values of coefficient of determination are common in this field of research (Aldridge, 2013). This is mostly due to all the additional noises which are accompanied in the high frequency data. Explanation of the changes in spreads value was not the goal of this paper anyway. The goal was to test the significance of relationship between HFT activity and the size of spreads, which was proven in all cases. The most suitable measure seems to be effective spread, with highest coefficient of determination. Control variables were also significant in the model, except of market volatility. Volatility of the returns had positive effect on the spreads in all cases (negative on the liquidity)

Same estimations were realized also for aggressive and defensive HFT activity. Defensive HFT activity does not seem to have significant impact on changes in liquidity supply. This may be due to fact that this activity is dominantly performed by market makers, who are supplying liquidity continuously. Or at least are supposed to. Hence there are not many

II: *Coefficient estimations of changes of HFT activity for various types of spread*

	Type of Spread				
Model	**Bid – Ask**	**Relative**	**Weighted**	**Effective**	**Realized**
Total HFT activity					
Coefficient of HFT activity	−8.7351*** (0.1182)	−0.2162*** (0.0034)	−11.3801*** (0.2921)	−0.0189*** (0.0018)	−0.0037 (0.0062)
Adjusted R² (%)	0.3348	0.2914	0.1038	1.1764	0.0136
Defensive HFT activity					
Coefficient of HFT activity	−0.0747*** (0.8622)	−0.2182*** (0.0033)	−14.1622*** (0.2924)	−0.0133*** (0.0024)	−0.0058 (0.0071)
Adjusted R² (%)	0.3158	0.2815	0.1042	1.1726	0.0138
Aggressive HFT activity					
Coefficient of HFT activity	−4.8744*** (0.2555)	−0.000003** (0.0013)	0.000042 (0.1231)	−0.000110*** (0.0009)	0.000011*** (0.0026)
Adjusted R² (%)	0.5871	0.2242	0.6734	2.3912	0.1447

*** indicates the 1 % level of significance, ** indicates the 5 % level of significance.
All coefficients and their standard deviations are expressed in thousandths.

changes in their performance. Nevertheless, all the coefficients were also negative for all types of spreads as can be seen in Table II. Effect on bid ask spread is much smaller than in previous case, but relative spread is hardly different. Also coefficients for other three types of spreads have not changed significantly.

On the other hand models with changes in aggressive HFT had (relatively) greater explanatory power. Also in these cases were all the coefficients negative. Surprisingly coefficients for bid ask spread and effective spread are much lower than for the cases of defensive HFT. That suggests that aggressive trading which is supposed to withdraw liquidity from the market have tendency to lower the spreads more. On the other hand realized spread seems to be larger after the period with increased HFT activity. That could mean increasing immediate liquidity but loss of liquidity in longer period, caused by inability of market makers to replace limit orders on the top of the order book and maintain sufficient level of liquidity.

The best model was explaining changes in effective spreads with adjusted coefficient of determination 0.02391. This model can be seen in Table III. Hence, it can be claimed, that there is significant positive relationship between HFT activity and liquidity.

Set of linear regression estimations of the model (5) have been performed for each stock and for all types of spread. This method might not be the most accurate one for high frequency data, but is sufficient for the control purposes. Negative effect of HFT on the size of spreads was confirmed in little more than half of the selected stocks. Effective and realized spreads show mostly positive effects as can be seen in Table IV. That can be explained in a way, that nominally the spreads are getting smaller in increasing presence of algorithmic traders, however only small limit orders are kept on the top of the order book and the real liquidity is moved further from the market price. These results confirmed outcomes from panel regression in first three cases, but positive effects for effective and realized spread are in strong contradiction with previous analysis.

Defensive HFT have the same influence on the properties of spreads (including coefficients and their directions) as shown in Table IV. Relations of these results with results from panel regressions are similar as for overall HFT activity.

In cases of aggressive orders of algorithmic traders, results were the same for first two types of spreads, however effective spread confirmed positive effect on liquidity for all analyzed stocks. But realized spreads are increasing in nearly all cases. This might again signalize that market makers are unable to add sufficient liquidity after an increased aggressive trading. Effective spreads are shrinking in these periods, so market makers are able to respond immediately. But in next 5 minutes their activity is not sufficient.

Directions of coefficients are the same as in panel regression and confirm acquired results.

DISCUSSION

Five methods for measuring spreads were applied in this paper. This is standard approach to proxy market liquidity (Hendershott, 2011b). Further research can focus on other measurements of market liquidity, which would better reflect its depth. More specifically focus can be pointed at the shape of the limit order book and distribution of orders in it. This way, real top of the order book can be distinguished from the imaginative top with no depth. Next, estimation of maximal absolute distance of limit orders from market price would establish properties of effective working trading systems.

Deeper comparison between aggressive HFT activity and defensive market making would help to justify the benefits and risks of this phenomenon. Also interaction between these two sides of the algorithmic trading would be worth of proper analysis, which would justify their role in the liquidity creating and taking process. Measuring of HFT activity is crucial for this field of research, but is difficult to estimate, without data from the stock exchanges including all messages or at least share of messages from HFT traders and market makers on all messages. Measuring this by proxy variables, as was performed in this paper, is feasible but always carries a high probability of mistake. Research in the time effects of changes in market making efficiency and activity of algorithmic traders would be beneficial for the purposes of identifying levels of market liquidity, stability and volatility.

It would be also interesting to address the willingness of HFT market makers to make market during more volatile periods or during periods of increased activity of traders, who are placing aggressive orders.

III: *Model estimation for aggressive HFT activity and effective spreads*

Variable	hfta	dr	σ	af
Coefficient estimation	−0.1112*** (0.0077)	23.0422*** (4.5856)	3.1823*** (8.3602)	0.1101*** (0.0138)
Adjusted R² (%)	2.3912			
F-statistic	8409.77			

*** indicates the 1 % level of significance, ** indicates the 5 % level of significance All coefficients and their standard deviations are expressed in thousandths.

IV: *Table IV. OLS estimations of coefficients of HFT activity changes for various types of spread for 26 shares traded on Frankfurt stock exchange*

Model	Bid – Ask	Relative	Weighted	Effective	Realized
			Type of Spread		
			Total HFT activity		
Coefficient of HFT activity	–5.0163 (14.739)	–0.1452 (0.3183)	–8.1873 (15.1962)	0.0165 (0.0432)	0.0035 (0.0562)
Significance*	15	14	15	6	6
Average adj. R² (%)	0.9993	1.0078	0.6492	2.3645	0.1342
			Defensive HFT activity		
Coefficient of HFT activity	–5.0079 (14.6844)	–0.1454 (0.3169)	–8.2076 (15.3103)	0.0213 (0.0434)	0.0013 (0.0550)
Significance*	15	15	15	5	6
Average adj. R² (%)	0.9983	1.0069	0.6528	2.3699	0.1340
			Aggressive HFT activity		
Coefficient of HFT activity	–0.4113 (0.9868)	–0.0094 (0.0203)	0.1877 (1.4743)	–0.0475 (0.0410)	0.0654 (0.0171)
Significance*	13	12	6	26	2
Average adj. R² (%)	0.6364	0.6494	0.4110	2.6679	0.1291

*Number of shares with significant negative coefficients of HFT activity.
All coefficients and their standard deviations are expressed in thousandths.

CONCLUSIONS

Algorithmic trading and especially high frequency trading is the issue that is often discussed by researchers and legislative authorities. It is also the subject of criticism as a mechanism of market manipulation, but simultaneously it is positively rated because of its influence on market liquidity. This paper is focused on testing the relationship between changes of market liquidity of shares traded on Frankfurt Stock Exchange and the changes in HFT activity. Tests have been conducted on larger stocks that are frequently traded. In most cases tested relations were proven to be positive. This confirms the results of other studies focused on market liquidity (Brogaard, 2011; Brogaard, 2014; Hasbrouck, 2013, Hendershott, 2011b). Changes in aggressive HFT seems to have stronger effect on the reduction of spreads than defensive market making, but have greater tendency to increase spreads in long run.

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