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Liquidity of the European stock markets under the influence of HFT

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Abstract

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 mostly low frequency traders and long-term institutional investors. This is mostly 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 futures traded on EUREX Exchange and HFT activity on European derivative markets. Econometrical methods for time series analysis 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 of all the market risks related with high spreads and low number of limit orders.

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Keywords: "liquidity; high-frequency trading; spreads; reggression"

1. Introduction

Algorithmic trading and more specifically high frequency trading became the most popular trade realization method. It is not only part of trading decision process, but it is also an important tool of order submission process, risk evaluation, data management and market environment 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. Electronic trading brought much more effectivity on markets and represents the cheaper solutions than replicated work of floor traders or specialists (Hendershott, 2011). This phenomenon is related with the development in other fields. Mathematicians create new

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models for effective asset pricing, price prediction, data mining and risk optimization. Hardware engineers designe computers that are capable of superfast computation and more important 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 a important that direct cable lines were constructed between them and next steps are even more astonishing. They plan to build beacon towers 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 of large block trades. Algorithms were created to break up the order into several pieces, which were then executed separately. The purpose of that was to time each partial order then 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 London Stock Exchange. Liquidity of traded instruments is considered to be one of market stability indicators. It is based on sufficient trading activity in all market situations. Market orders as well as limit orders are the main means of liquidity creation. Each exchange has its own rules, but mostly the market participants are paid for placing limit orders and hence creating liquidity. They are also required to pay commissions for placing market orders which closing opened 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 most limit orders are placed on the market the lowest is the difference between bid and ask. Thus, spreads are the great indicator of market liquidity. In this paper spreads will be used as proxy for the measurement of market liquidity (Kendall , 2007).

Argument for the high-frequency algorithms is that it decreases spreads and increases liquidity have been the leading evidence of all advocates of HFT. However, the research is mostly focused on the US markets, where the 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). Dynamic liquidity provisions of market makers are strongly affecting of their willingness to undertake risk in accordance to their capital situation. If market makers have enough capital they provide the socially optimal amount of liquidity, which leads to reduction of price peaks and rapid changes in volatility, whereas if they lacks 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 adjusting 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 bring first significant results. Specialist firm-level spreads are getting wider when specialists hold large positions or lose 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 narrow down spreads on New York Stock Exchange, especially after automatic quote dissemination (Hendershott, 2011). They also confirm that bid-ask spreads of large blue-chip companies is reduced simultaneously 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 was significant in many cases; i.e. on Australian Securities Exchange (Frino, 2013). Other evidences confirm 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, 2011). 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 2 describes analyzed data and introduces some basic relationships among used variables. Section 3 summarizes used methodology and the structure of models. Section 4 shows main results of the paper and Section 5 presents a conclusion derived from the results, which are compared with the results in former research.

2. 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. We have focused on the stocks, where the average daily traded volume exceeded 10 million GBP. Using this criterion we chose 22 most traded stocks on London Stock Exchange. The analyzed period is from September 16 2014 to March 30 2015. One minute observations have been used in all variables. Table 1 characterizes all factors used for further calculations.

Table 1. List of variables

Variable	Definition
r	one minute return of the stock market price
num	number of market orders during one minute
num_b	number of limit bid orders during one minute
num_a	number of limit ask orders during one minute
vol	traded volume during one minute (in number of shares)
vol_b	number of shares in bid limit orders during one minute
vol_a	number of shares in ask limit orders during one minute
val	traded volume during one minute (in money value)
val_b	money value of bid limit orders during one minute (in mil.)
val_a	money value of ask limit orders during one minute (in mil.)
size	one minute average number of shares in one market order
size_b	one minute average number of shares in one bid limit order
size_a	one minute average number of shares in one ask limit order
RV	realized volatility
spread	bid-ask spread calculated from one minute average prices
HFT	high-frequency trading activity

We applied data from both side of order book to adopt the influences from bid as well as ask side of price spreads. It is important to include these variables, because HFT activity as we measure it is only a ratio and it is important to identify whether the number of trades and volume of trading is actually high.

Realized volatility as the denomination of market volatility (McAleer, 2008) have been calculated from past 60 market price returns as

$$RV = \sum_{i=1}^{n} r_i^2 \tag{1}$$

Increasing volatility can be caused by endogenous and exogenous factors. Usually algorithmic trading is blamed for these events (Martinez, 2011); however it needs not to be true at all the time. Some research indicates the opposite relationship (Zhou, 2013).

It is rather difficult to address the real HFT activity on the certain market, unless you have full access to the database from an exchange. We use proxy variable which is derived from the fact that, AT firms usually trade large volumes in small pieces and their activities are connected with large number of trades and more specifically messages (Hendershott, 2011).

In the Table 2. are demonstrated average correlations between tested variables. Activity of HFT is strongly negatively correlated with average size of trades, which confirms the assumptions that algorithmic trading is realized via small orders. Spreads do not have any relevant interaction with selected variables. The relationship between HFT and spreads does not seem to be significant. In this case simple bid-ask spread was used. That is reason why we will apply different kinds of spread measures while testing the impact of HFT on liquidity.

Table 2. Correlation matrix of analyzed variables

	num	*num_b*	*num_a*	*vol*	*vol_b*	*vol_a*	*Size*	*size_b*	*size_a*	*RV*	*spread*	*HFT*
num	1,00	0,71	0,68	0,16	0,05	0,03	-0,02	-0,03	-0,04	0,01	0,05	0,04
num_b		1,00	0,78	0,26	0,22	0,19	0,13	0,11	0,13	0,01	0,05	-0,13
num_a			1,00	0,26	0,18	0,25	0,13	0,11	0,13	0,01	0,05	-0,13
vol				1,00	0,67	0,71	0,89	0,58	0,64	0,00	0,00	-0,66
vol_b					1,00	0,66	0,63	0,88	0,59	0,00	0,01	-0,83
vol_a						1,00	0,68	0,58	0,88	0,00	0,01	-0,75
size							1,00	0,56	0,63	0,00	-0,01	-0,65
size_b								1,00	0,59	0,00	0,02	-0,87
size_a									1,00	0,00	0,02	-0,78
RV										1,00	0,01	0,00
spread											1,00	-0,03
HFT												1,00

Other variables are mostly correlated within the groups and they also do not have any impact on realized volatility of given stock prices. Even though there was no correlation between HFT activity and spreads, there is an obvious pattern in the some of the data samples of chosen stock prices suggesting that during the time interval at the end of researched period there was large HFT activity connected with the low spreads.

3. Methodology

First of all we have to define how to measured HFT activity. 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. We have used formula derived from Hendershott et.al (2011) methodology.

$$HFT_{it} = -\frac{val_{it} + val\_b_{it} + val\_a_{it}}{num_{it} + num\_b_{it} + num\_a_{it}} \tag{2}$$

As was mentioned before the classical approach to spreads had indicated dubious relationship with activity of algorithmic traders. Hence, we have to apply other measures used to characterize liquidity. First alternative was relative spread defined as the bid-ask spread divided by market price (*gspread*). Second option was share volume-weighted quoted half-spread calculated as

$$qspread_{it} = \frac{Bid\_price_{it} \cdot vol\_b_{it} - Ask\_price_{it} \cdot vol\_a_{it}}{\left(vol\_b_{it} + vol\_a_{it}\right) \cdot 2p_{it}} \tag{3}$$

where p_{it} is the current market (trade) price of stock i at time t. Bid price, ask price and trade price are calculated as ine minute averages. Efective spread is calculated as difference between the midpoint of the bid ask prices and the transaction price. For certain stock is the effective spread calculated as

$$espread_{it} = q_{it} \frac{p_{it} - m_{it}}{m_{it}} \tag{4}$$

where m_{it} is representing midpoint price, qit is indicator variable that equals 1for buyer-initiated trades and -1for seller-initiated trades (Bessembinder 2003).

We include revenue to liquidity providers 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, 2011). Proportional realized spread is stated as:

$$espread_{it} = q_{it} \frac{p_{it} - m_{i,t+5\min}}{m_{it}} \tag{5}$$

All these five alternatives for liquidity measurement were used as explained variable in models using HFT activity and other related variables as explanatory variables. First model was rather simple one using only HFT activity as explaining variable.

$$y_{it} = \beta_0 + \beta_1 HFT_{it} + \varepsilon_{it} \tag{6}$$

Second model was enhanced with variables denoting number of trades and volume of trading to distinguish between the cases when the average size of trades is small and overall market activity high and those cases when the activity is low. Realized volatility was also added to the model, following Frino et.al (2013).

$$y_{it} = \beta_0 + \beta_1 HFT_{it} + \beta_2 vol_{it} + \beta_3 num_{it} + \beta_4 RV_{it} + \varepsilon_{it} \tag{7}$$

Last model uses all variables from the second section of this paper. They were included to the model to better assess the activity on both sides of limit order book.

$$\begin{aligned} y_{it} = \beta_0 &+ \beta_1 HFT_{it} + \beta_2 vol_{it} + \beta_2 vol\_b_{it} + \beta_2 vol\_a_{it} + \beta_3 num_{it} + \beta_3 num\_b_{it} + \beta_3 num\_a_{it} \\ &+ \beta_3 size_{it} + \beta_3 size\_b_{it} + \beta_3 size\_a_{it} + \beta_3 r_{it} + \beta_4 RV_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

These models were estimated for all liquidity proxies and for all 22 chosen stocks. Newey-West Bartlett HAC estimator was used for coefficient estimation to solve problems with heteroscedasticity and autocorrelation Newey et al. (1994).

4. Results and Discussion

Estimation of the previous models showed only small explanatory power. Nevertheless, low values of coefficient of determination are nothing devastating in this field of research. Results for the model (6) can be seen in Table 3. Simple model has proven the hypothesis that rising HFT activity has negative effect of spreads and thus increasing liquidity. The most suitable measure seems to be effective spread, with highest coefficient of determination. Their values are rather low in the statistical point of view. However, if we compare it with other research papers in this field, results are not much different. This is mostly due to all the additional noises which are accompanied in the high frequency data. We were not trying to explain the spreads value any way. Our goal was to test the significance of relationship between HFT activity and the size of spreads, which was proven in most of cases.

Table 3. Number of positive, negative and non-significant coefficients for variable HFT in model (6).

	positive	negative	non-significant	avg R^2
spread	1	11	10	0,7260
qspread	0	22	0	0,4386
gspread	2	9	11	0,7070
espread	3	19	0	10,0887
rspread	2	19	1	2,2077

Model (7) is analyzed in Table 4. The model confirmed the results from the previous case. Only the models with the highest significance suggest that the relationship has an opposite direction.

Table 4. Number of positive, negative and non-significant coefficients for variable HFT in model (7).

	positive	negative	non-significant	avg R^2
spread	1	21	0	1,0878
qspread	2	20	0	2,3399
gspread	2	20	0	1,5489
espread	17	5	0	22,2914
rspread	4	18	0	4,5864

Model (8) is analyzed in Table 5. with mixed results. Interestingly, the effective spreads models are now in favor of negative coefficients (positive effects on liquidity). The uncertainty of the results is due to inclusion of order book information. These factors mostly confirmed the hypothesis that higher number of trades and lower average size of the trades have a negative effect on the size of spreads.

Table 5. Number of positive, negative and non-significant coefficients for variable HFT in model (8).

	positive	negative	non-significant	avg R^2
spread	11	11	0	1,8214
qspread	1	21	0	7,2155
gspread	19	2	1	3,2203
espread	8	14	0	28,6042
rspread	17	5	0	5,8701

5. Conclusion

Algorithmic trading and especially high frequency trading is the issue that pays attention of current 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 the market liquidity. This paper was focused on testing the relationship between market liquidity of futures traded on EUREX Exchange and HFT activity on European derivative markets. The model results are mixed and it is influenced by the way of volatility measurements. Although, the mixed results the effect of HFT on market liquidity is positive. The reason of mixed findings might be caused by the usage of proxies for measurement of liquidity because of limited public information about the analyzed market. This way of liquidity measurement will be the subject of our future investigation.

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