The Nexus of High-Frequency Trading, Market Fragmentation and Market Liquidity: A Cross-Market Equilibrium Analysis

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Abstracts: This paper addresses the ongoing debate regarding the social benefits of two significant recent changes in the equity market microstructure: high-frequency trading (HFT) and trade fragmentation. Employing a unique, extraordinarily large dataset of millisecond time-stamped trades and quotes from 2008 to 2016, enriched with data from the London Stock Exchange (LSE) and three multilateral trading facilities (MTFs)—CHIX, Bats, and Turquoise, this study evaluates how HFT and fragmentation simultaneously impact market liquidity through a cross-market simultaneous equations model approach. The analysis reveals novel findings at the intersection of HFT and fragmentation, identifying an interlinkage that influences, at least partially, the extent of their individual effects on liquidity. The results demonstrate that HFT enhances liquidity across trading venues, with advanced low-latency features at the exchange level significantly narrowing both quoted and effective spreads. CHIX, in particular, stands out for attracting HFT due to its superior low-latency technology since its inception. Market fragmentation harms the primary exchange's liquidity while improving that of alternative trading exchanges. Further, cross-market liquidity and HFT activities suggest that HFT market-making activities are interconnected across markets, with HFT liquidity supply being higher at exchanges where spreads are wider. The impact of HFT is also time-invariant; it not only sustains but also improves market liquidity during periods of financial crisis. Additionally, HFTs concentrate on the primary exchange during periods of higher volatility. A statistically significant market-wide HFT component positively affects HFT activities across markets. Among other determinants, fragmentation positively affects HFT—the higher the fragmentation, the more HFT activity.

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1 Introduction

Over the past two decades, the advent of sophisticated computing technology has brought about pathbreaking changes in financial marketplaces (Biais and Foucault, 2014; O'Hara, 2015). Machine intelligence has empowered human civilization to perform tasks with ease, speed, and at low cost, but it has also raised concerns about welfare-damaging, inequitable competition between humans and machines. One such change in market microstructure that has attracted considerable attention from regulators, practitioners, and academics is high-frequency trading (HFT). In today's equity market, a large share of trading volume is conducted by HFTs (Boehmer, Fong and Wu, 2021), and there has been public debate since 2009 about its effects (Menkveld, 2016). The rise of machines has also led to the proliferation of machine-friendly trading venues and their high-speed connecting channels. Two remarkable financial market regulation changes in the recent past, Reg NMS (in the US) and MiFID (in the EU), broke the long-dominated concentration rule and opened up the avenue for dispersing trades across venues. However, the effects of new exchange competition and trade fragmentation on market quality have also raised concerns (O'Hara and Ye, 2011; Degryse, De Jong and Kervel, 2015).

As academics, practitioners, and regulators strive to address these issues, the hidden mechanisms of the high-frequency trading world are becoming more visible. It has been conjectured that HFT and market fragmentation have ridden on each other in their advancement. Menkveld (2014, 2016) argue, "...the two most salient trends in securities markets since the turn of the century—order flow fragmentation and HFT entry—are intimately related and both driven by technology and regulation. ... There is arguably a symbiotic relationship between new electronic venues and HFTs. These new venues need HFTs to insert aggressively priced bid and ask quotes, and HFTs need the new venues to satisfy their requirements in terms of automation, speed, and low fees." This paper explores this novel aspect of market complexity and investigates how HFT and market fragmentation interact and impact market quality. In doing so, it focuses on the European equity market, which has experienced both the influx of HFT and market fragmentation and, to the best of our knowledge, has not been the subject of a study on this issue to date.

The MiFID regulation repealed the concentration rule[2] in the European equity market, allowing

[2]The concentration rule led to a situation where a single stock exchange dominated each member state in the EU.

new electronic trading venues to compete with traditional stock exchanges. Following this, exchanges invested heavily in technology (Linton and Mahmoodzadeh, 2018) to reduce latency[3], and several alternative exchanges were launched. As a result, order flow has become spread across multiple trading floors, leading to a fragmented market. High-frequency traders, who use low-latency strategies (Hasbrouck and Saar, 2013), have benefited from this investment in technology. The regulation has facilitated the creation of high-frequency trading (HFT) market access across European equity markets.

The current marketplace is highly fragmented, and market participants can employ smart order routing (SOR) techniques to find liquidity across multiple trading venues. The potential counterparties for HFT market-makers have a large selection of trading venues on which they can trade. To interact with this order flow, HFTs must be present on all these trading venues (The Netherlands Authority for the Financial Markets, 2016). O'Hara (2015) argues that HFT is strategic because it maximizes against market design, other HFTs, and other traders, and HFTs need to optimize in a market that contains other HFT players. The cross-market HFT presence makes limit order books linked across markets, and so too, order flows and price behavior. I address this added cross-market complexity in HFT research in this paper by analyzing the impact of HFT and market fragmentation on market liquidity. In doing so, I use a novel approach that can tackle the simultaneity of HFT activities across markets.

I primarily examine how HFT and fragmentation affect market liquidity in a cross-market setting. The research setup I use to examine the primary research question also allows me to investigate other related issues such as the drivers of HFT within and across markets, the nature of exchange competitions, etc. To answer these questions, I use millisecond time-stamped TRTH data from the LSE and three alternative electronic exchanges. The dataset covers the entire post-MiFID period until 2016. I develop daily measures for liquidity, HFT, and fragmentation across the four markets included in the sample. I also develop some consolidated measures to reflect the level and evolution of exchange competition over time. I estimate the simultaneous equations model using the three-stage least squares method for the full sample as well as its suitable subsamples classified based on both cross-sectional and time-series dimensions.

[3]According to Hasbrouck and Saar (2013), latency is viewed as the time it takes to learn about an event, generate a response, and have the exchange act on the response.

The results suggest that HFT enhances liquidity across markets, significantly narrowing both quoted and effective spreads due to lower latency at the exchange level. Particularly, CHIX stands out in attracting HFT due to its market model and better response to the market demand for advanced low-latency technology compared to its rivals since its inception. Additionally, the findings indicate that while market fragmentation reduces liquidity at the primary exchange, it increases it at alternative trading venues. The evidence also suggests that trader preferences for technological differentiation at the exchange level play a crucial role in modern markets.

The results concerning cross-market liquidity and HFT activities suggest that HFT market-making activities are interconnected across markets, with HFT liquidity supply being higher at a particular exchange when spreads are wider there and narrower at others. This finding is supplemented by the observation that a market-wide HFT component positively influences exchange-level HFT activities. Additionally, volatility impacts HFT activity differently across trading venues: it decreases HFT activity in alternative exchanges but increases it in the primary exchange. Moreover, fragmentation is positively correlated with HFT activity—the higher the fragmentation, the greater the observed HFT activity. Among other factors, order sizes, relative tick sizes, and volatilities have a significant impact on HFT activities. Additionally, HFTs concentrate in the primary exchange during periods of higher volatility.

Analyses extended to large and small stocks provide evidence that HFT remains active in highly liquid stocks even when spreads are narrow. To stay competitive, HFTs must frequently update their quotes in these liquid stocks, necessitating that they continue to supply liquidity even when it becomes less profitable. The time-varying analysis confirms that the overall direction of the associations between HFT and liquidity, and market fragmentation and liquidity, remains relatively stable over the sample period, albeit with some time-varying impacts.

The rest of the paper is structured as follows. Section 2 links this study with the existing body of literature. Section 3 describes the data and measures and presents descriptive evidence. Section 4 explains the research strategies and discusses the main results. Section 5 concludes.

2 Relevant Literature

This paper covers three related aspects: i) HFT, its drivers, and speed competition across exchanges; ii) market fragmentation; and iii) their impact on market liquidity. I briefly mention here some studies that are more relevant to this study[4].

The evidence provided in several studies (Hendershott, Jones and Menkveld, 2011; Hasbrouck and Saar, 2013; Boehmer, Fong and Wu, 2015) on the relationship between AT/HFT and market quality shows that AT/HFT improves liquidity. The papers studying the impact of market fragmentation on market quality (O'Hara and Ye, 2011; Gresse, 2017; Degryse et al., 2015) mostly support the view that market fragmentation improves liquidity. The novelty of my paper is that I study both HFT and market fragmentation across markets using a panel dataset for a relatively long period compared to those mostly used in the literature.

The spirit of this paper is close to the papers that study HFT and market fragmentation across markets, like Upson and Van Ness (2017) and Brogaard, Hendershott and Riordan (2014), but the approach and measures that I use are different from those they used in their research. This paper also joins the strands of HFT literature related to: i) examining HFT liquidity supply and demand within and across markets (Hendershott and Riordan, 2013; Carrion, 2013; Menkveld, 2013); ii) studying HFT in LSE-listed stocks (Brogaard, Hendershott, Hunt and Ysusi, 2014; Jarnecic and Snape, 2014); and iii) studying exchange competition (He, Jarnecic and Liu, 2015; Riordan, Storkenmaier and Wagener, 2011). The motivation of papers (Riordan and Storkenmaier, 2012; Frino, Mollica and Webb, 2014; Murray, Pham and Singh, 2016; Frino, Mollica, Monaco and Palumbo, 2017; Brogaard, Hagströmer, Nordén and Riordan, 2015) examining the impact of speed on market environments supports the analysis conducted in this paper.

3 Market, Data, Variables and Measures

3.1 Market Background

Two of the most striking recent changes in global equity market design, which have proliferated trading venues, are the adoption of 'Regulation National Market System (RegNMS)' in the US in 2005

[4]I refer to Hossain (2023) and Hossain (2022) for a detailed discussion of the literature related to this study.

and the enactment of MiFID in Europe in 2007, following the developments in the US. The adoption of MiFID in 2007 (and MiFID II in 2018) has proliferated trading venues across the European equity market. One of the vital changes it brought into effect was abolishing the monopoly power of traditional exchanges in trading securities and liberalizing them into many trading platforms like regulated markets (RMs), multilateral trading facilities (MTFs), and systematic internalisers (SIs). These platforms have different market structures and reporting systems defined under MiFID directives[5].

In broad terms, RMs and MTFs operate similarly, providing an electronic multilateral platform for users. These trading venues generally match orders on a non-discretionary basis according to pre-defined rules that establish price and time priority. RMs and MTFs are required to publish pre-trade quotes and report details of executed trades to the market (CFA Institute, 2011). Both RMs and MTFs can organize primary listings. However, RMs facilitate the listing of regulated instruments, while MTFs do the same for unregulated ones. In practice, only RMs offer primary listing services. MTFs prefer not to do so and may be viewed as equivalent to electronic communication networks (ECNs) in the US (Gresse, 2017). Firms choose the RM for listing, and once listed, MTFs may organize trading for that firm. SIs are investment firms that internalize order flow to deal on their own account on an organized, frequent, and systematic basis. Trades executed through SIs are reported as over-the-counter (OTC) trades. Some large RMs in the European equity market include the LSE Group (operator of the London Stock Exchange and Borsa Italiana), NYSE Euronext (operating exchanges in France, Belgium, the Netherlands, Portugal, and the United Kingdom), and Deutsche Börse Group (operator of the Frankfurt Exchange and the Xetra trading system).

The LSE runs electronic order books on which buy and sell orders are continuously matched from open to close according to price-time priority rules. Automated trading sessions start at 8:00 and close at 16:30 local time. As a supply-side response, significant investments have been made by the LSE in technology to meet the growing HFT demand for low-latency[6] trading over the last two decades. The implementation of the Millennium trading platform has improved its latency to 113 microseconds, compared to 600 milliseconds before the year 2000 (Linton and Mahmoodzadeh,

[5]In order to capture 'dark pool' operators and other similar trading systems, a new category of trading venue called Organised Trading Facility (OTF) was introduced for non-equity instruments in MiFID II, which came into effect on January 3, 2018.

[6]The turnaround time between a message from a trader and its receipt at the exchange platform

2018). Besides RMs, the main MTFs are CHIX, BATS, and Turquoise. These exchanges are well-equipped with modern latency-based technologies and have become main rivals of primary exchanges like the LSE. Significant market share has been lost by the LSE to these exchanges in recent years (Hossain, 2023).

MTFs also run transparent order books in which anonymous orders are matched continuously during the same trading hours as primary exchanges. MTFs differ in terms of the speed of execution, the number of securities traded, and trading fee structure (Degryse et al., 2015). Their market models are adapted to the needs of high-frequency traders by offering low-latency trading with high throughput rates. Most MTFs follow a so-called maker/taker fee model, offering a transaction rebate to those who provide liquidity (the market maker) while charging customers who take that liquidity. The LSE also followed the maker/taker fee model before switching back to a traditional fee schedule on September 1st, 2009.

3.2 Data

In constructing the sample, the STOXX 800[7] is taken as stocks' universe, and as many samples as possible are obtained from there[8]. The primary source of data is Thomson Reuters Tick History (TRTH)[9], a product of the Securities Industry Research Centre of Asia-Pacific (SIRCA), which is compiled from the Global Thomson Reuters exchange feeds. Two resilient London-based recording devices provide the millisecond timestamp to each recorded message. The primary analysis of the TRTH data structure reveals that time synchronization of trades and respective quote messages is

[7]Please see the section 'Tables and Figures' at the end for the referred tables and figures.

[8]STOXX 800 constitutes the largest 800 market capitalized stocks in Europe. Table 1: Panel A shows the STOXX 800 composition at the end of 2016. It reports that the top 50% of stocks on the list come from only three primary trading venues: the London Stock Exchange, Deutsche Börse (Xetra), and Euronext Paris, with LSE-listed stocks making up more than 50%. Table1 (Panel B) shows the market share of both primary and alternative lit trading venues in European equity markets. Among the trading venues, CHIX, BATS, and Turquoise facilitate most of the lit trading besides the primary platforms. Remarkably, the present market share of CHIX exceeds that of any other trading venue. These three alternative trading venues/MTFs are chosen for measuring trade dispersion outside of the listing exchange LSE.

[9]One of the challenges of HFT and fragmentation research across markets is identifying the same security across trading venues. TRTH provides unique identification symbology known as the Reuters Instrument Code (RIC). The RIC structure is complex, with several parameters—defined by a stock's primary listing venue, trading venues, currency denominations, etc.—arranged in a specific order to form a RIC. The International Securities Identification Number (ISIN) provides the unique identification of a stock across exchanges. ISIN and RIC are used to identify sample stocks across exchanges (See Table 3) for a better explanation, which illustrates how a stock with a unique ISIN but different RICs is identified across exchanges.

not uniform across trading venues. TRTH provides better quotes and trades time synchronization for trading venues physically closer to the IDN Collection LAN in London (e.g., LSE, CHIX, BATS, Turquoise) compared to those located remotely outside of London (e.g., Deutsche Börse (Xetra), Euronext Paris). This issue raises significant challenges in determining trades and quotes-based measures of transaction cost, particularly for the effective spread.

Considering the TRTH time synchronization issue, sample choices are narrowed down to the UK-based LSE-listed stocks included in STOXX 800. To address the fragmented environment of these stocks appropriately, CHIX, BATS, and Turquoise are selected as their alternative venue counterparts. These four trading venues facilitated around 99% of lit trading during the period 2014–2016 for the stocks primarily listed on the LSE, and this pattern is quite regular over the sample period (see Table 1, Panel C). Trades and quotes data have been available from TRTH since 1996 for most primary trading venues, while data for alternative trading venues in the MiFID zone started to be available from mid-2008. Among the 220 primarily selected stocks from the LSE, TRTH provides data support for only 204 stocks[10].

TRTH supplies quotes and trades records through two main files: the Time and Sales (TS) and the Market Depth (MD). The Time and Sales file provides transaction records and the best quote updates, while the Market Depth file includes the queue of bid and ask limit prices and respective quantities (displayed in the limit order book). The records in Market Depth can be extracted to 25 best limit prices (based on their availability), of which up to the best 10 levels are extracted. These two files are downloaded and processed for all stocks primarily selected in the sample (see Table 2: Panel A). This process requires substantial computing resources and data processing time. Approximately 885 files of Market Depth data, each containing 70 million records, and 300 files of Time and Sales data, each containing 110 million records, were processed on average in several phases before obtaining the usable output.

At this point, a primary analysis shows that among those 204 securities, some are not compatible for further analysis due to reasons like delisting, takeovers or mergers with other firms or liquidation at some point or do not have enough data coverage for all four trading venues for unknown reasons, and we set a final filter to ensure uniform data coverage of the selected stocks and exclude them if they do not satisfy the following conditions: (i) data availability in LSE at least from

[10]Table 2 shows the TRTH data availability for the sample stocks across trading venues.

2006; (ii) data availability in alternative trading venues from 2008 or at least from the 1st quarter of 2009[11]. We are left with 149 stocks after setting the final filter. To be in the safe side and to avoid the possible econometric pitfalls of an unbalanced panel estimation, we reduce our sample again to 132 stocks so that all stocks in our sample can confirm uniform coverage over the study period. Our final sample is a balanced panel of 132 stocks with the coverage of 2624 days each (Table 4). We also rely on the Thomson Reuters's Datastream for the relevant data, which are not supported from TRTH but used in this study (e.g. daily market capitalization).

3.3 Variables and Measures

Market liquidity measures used in this study include the spread ($spread_{it}$), the effective spread ($espread_{it}$), the realized spread ($rspread_{it}$), the price impact ($price\_impact$), and market depth ($depth_{it}$). Alternative proxies for measuring HFT are used, such as a modified Hendershott et al. (2011) proxy (hft_{it}) and the order-to-trade ratio ($ord\_to\_trad_{it}$). The Herfindahl-Hirschman Index ($HHItrd$), the most commonly used definition of market concentration in the literature, is used as the proxy for order fragmentation across markets. All measures are developed on the four trading venues at three different levels (where applicable) of the limit order book (BBO, 5 best, and 10 best LOB quotes)[12]. All measures are developed using intraday millisecond trades and quotes records for the automated trading sessions (8:00–16:30 London time) of the respective exchanges. Additionally, some consolidated measures across trading venues are developed, which are explained below.

EBBO. European Best Bid and Offer (EBBO) is a hypothetical aggregate measure of the best bid and offer prices for LSE-listed stocks across trading venues, equivalent to the NBBO (National Best Bid and Offer) in the US. Snapshots of the transparent limit order books of all four trading venues are taken at 500-millisecond intervals during trading hours between 8:10 and 16:25. The first 10 minutes and the last 5 minutes of the automated trading sessions are excluded to avoid undue price pressure from the opening and closing sessions. At each snapshot, the best bid (the highest among the four local bid prices) and the best offer (the lowest among the four local offer prices) are

[11]Table 2 (Panel B) shows the reduced list of quarterly data used to construct the panel for the period 2005–2016
[12]For a detailed discussion on variable measures, please refer to Hossain (2022) and Hossain (2023)

defined, and both do not necessarily have to come from the same trading venue.

%EBBO. The %EBBO measures the frequency by which a trading venue uniquely or jointly contributes to the EBBO. A trading venue's contribution to both the lowest ask price and the highest bid price is included in the %EBBO. The joint/simultaneous trading venue participation rate (single/double/triple/quadruple) refers to the number of trading venues contributing to the EBBO each time. For a unique contribution, the unique venue participation rate measures which exchange contributes to the EBBO. In the presence of HFTs, these measures are expected to reveal the order flow competition across trading venues.

Unlike RegNMS, MiFID does not impose consolidated tape and trade-through rules for European markets; rather, it allows some aspects to be decided by the market. For example, MiFID directives detail the 'obligation to execute orders on terms most favorable to the client'. This provision requires firms to take relevant steps to ensure the best possible execution for clients and consider 'price, costs, speed, likelihood of execution and settlement, size, nature or any other consideration relevant to the execution of the order'. The %EBBO shows the extent to which limit order books are linked across European markets in providing competitive quotes.

Quotes update speed. The average quotes update speed shows the average time between two quotes updates and is measured by dividing the number of quotes updates by the length of the automated trading sessions (measured in seconds). The measure is expected to reflect the speed aspect of exchange competition.

Descriptive statistics

This section presents descriptive evidence regarding HFT and market liquidity across four markets for the period from December 2005 to December 2016, after winsorizing the extreme 1% values on both tails. To facilitate cross-sectional comparison, the full sample is divided into five equal quintiles based on market capitalization. Descriptive analyses show both aggregate and quintile-based measures (mean, median, and standard deviation) and monthly trends over the sample period. The descriptive evidence provided on the EBBO, %EBBO, and quotes update speed is based on a subsample of 45 stocks that became fragmented across the main four trading venues in the initial post-MiFID period, and for which the maximum data support from TRTH is available for the period thereafter.

Tables 13 and 14 report the quarterly summary of the %EBBO for the unique and joint venue participation rates in the EBBO, and Figures 1a and 1b show the quarterly trends of the same measures, respectively. Starting from a rate of 100% in the first quarter of 2008, the unique trading venue participation rate began to decline, while the level of joint participation in the %EBBO increased over the period. During the period from 2008 to 2010, the average single, double, triple, and quadruple venue participation rates were 54%, 23%, 13%, and 10%, respectively, and remained perfectly symmetrical on both sides of the order book throughout the years. It is apparent that the joint participation rate in the %EBBO increased over the period but never exceeded 50%. The trends in venue participation rates indicate that order flow competition in European markets intensified over the years.

The rivalry between the LSE and CHIX is clearly evident in Table 14, which reports how the LSE lost its market share to alternative exchanges over the sample period. Since the competition for order flows in European equity markets started at the end of 2007, CHIX has dominated the provision of the best bid and ask prices. To remain competitive for HFTs, the LSE made significant investments in low-latency technology and upgraded the trading system in several phases during the period from 2006 to 2011. As seen in Table 14, the LSE began to regain some of its lost market share starting in 2013. Among the competing venues, CHIX dominated the contribution to the EBBO. Turquoise was next after the LSE and CHIX in contributing to the EBBO. The EBBO participation rate of the exchanges was apparently symmetrical on both sides of the order book.

Figure 1c depicts the trends of quotes update speed across four markets. The trends of both quotes update speed and %EBBO moved together consistently throughout the sample period—the higher the quotes update speed, the more the exchanges shared in the %EBBO—indicating that exchanges providing better low-latency technology attract more traders/market-makers relying on speed. Since the enactment of MiFID, the quotes update speed in CHIX was the highest until 2012, after which the LSE started to take the lead back. Turquoise also appears to have become more competitive over the years, in contrast to BATS, which lost its competitiveness in the same period.

The summary statistics of HFT proxies across four markets are presented in Tables 5 and 6, and Figures 3b and 3a show the trends of the respective measures over the period. Among the exchanges, the average HFT intensity measured by all proxies is the highest in CHIX. The average per-minute message rate ($hft2$) for the LSE, CHIX, BATS, and Turquoise are 84, 116, 69, and 67, respectively. The evidence also shows that HFTs predominantly relied on large stocks, a common feature observed across exchanges. The rising trends of HFT were consistent across exchanges throughout the sample period. CHIX was found to be more competitive than the LSE in the initial post-MiFID period (2008–2011), and in the latter period, the LSE appeared to regain its position. This phenomenon is also consistent with the %EBBO pattern already mentioned.

The descriptive statistics of liquidity measures are presented in Tables 7 and 8, and Figures 4 and 5 show the trends of the same measures across four markets. Among the exchanges, the LSE provided the tightest quotes, particularly for small stocks over the period. Moreover, both quoted and effective spreads in large stocks were low in the LSE in the initial period of market fragmentation, which eventually disappeared in the latter period due to fierce exchange competition. Large stocks are the most fragmented, and it seems that competition in order flows impacted them the most. As can be seen, effective half-spreads for large stocks were low in almost all trading venues other than BATS, especially in the latter period of the sample (2013–2016). Figure 9 also shows that trends in quotes update speed and quoted spreads across trading venues moved together consistently, particularly in large stocks—the higher the quotes update speed, the lower the spreads were.

Figures 7 and 8 show the trends in average quoted depth and trade size across four markets. For the LSE, both quoted depth and trade sizes started to decrease sharply in the pre-MiFID period (2005–2008), particularly in large stocks, and the trend continued throughout the post-MiFID period. For alternative trading venues, both quoted depth and trade sizes were consistently smaller than those of the LSE and declined throughout the period. Figure 8 depicts the evolution of trade size in large stocks and shows that over the years trade size has been declining monotonically across trading venues, indicating the increasing HFT intensity over the years.

Tables 9, 10, 11, and 12 show the decomposition of effective spreads into realized spreads and price impacts across four trading venues, and Figure 6 depicts the trends of these measures. The decomposition is based on four hypothetical post-trade quotes adjustment intervals (10 seconds, 30 seconds, 1 minute, and 5 minutes). As can be seen, price impacts and realized spreads decreased across trading venues over the period, and realized spreads were negative in all markets for all measures except for BATS. The evidence suggests that trade execution quality improved across exchanges over the years.

The overall descriptive evidence shows that over the years, quoted and effective spreads narrowed and HFT intensity increased across exchanges. It appears that HFT played a substantial role in integrating the fragmented European market using the available low-latency structure. As a result, both quoted and effective spreads converged to low levels across trading venues over the post-MiFID period. The subsequent sections address the issue more systematically.

4 Methods, Results and Discussions

4.1 A Simultaneous Equations Model Approach

This study builds upon the analysis conducted by Hossain (2023) by employing a methodology designed to address potential endogeneity among liquidity, HFT, and market fragmentation measures. Market liquidity and HFT influence each other through at least two mechanisms: (i) the long-term decline in spread-based transaction costs, which may be due to the low market-making costs of HFTs, and (ii) the increasing competition among HFT firms, driven by substantial investments in high-speed trading technology. Additionally, evidence suggests that both liquidity and volatility levels affect HFT participation in the market. From a demand perspective, the proliferation of modern low-latency trading venues can be seen as a response by trading venues to market demand. The implementation of the simultaneous equations model is conducted in two phases. First, data from the primary exchange (LSE) is used to estimate the model in this section. The next section 4.2 presents the models' estimation across all four trading venues.

Market liquidity appears to play a significant role as one of the determinants of order flow fragmentation, as more liquid stocks tend to be more fragmented. While it is more likely that liquidity influences the fragmentation decision rather than the other way around, it is widely accepted in the literature that market fragmentation also impacts liquidity. In recent years, the most active channel affecting quoting and trading activities across markets has been HFT. In response to the rising demand for HFT, the supply side has rapidly increased the number of electronic exchanges with low-latency technology across the European equity market. This has resulted in a clear simultaneity among HFT, market fragmentation, and liquidity.

To tackle the simultaneity among HFT, market fragmentation, and market quality, a simultaneous equations model is considered, which is a relatively new approach in market microstructure research. Buti, Rindi and Werner (2011) and Aitken, Cumming and Zhan (2014) argue that market quality, fragmentation, and HFT are jointly determined in equilibrium, and they employed simultaneous equations models in their studies. Hasbrouck and Saar (2013) also uses a similar approach in a simpler setting, attempting to determine the impact of low latency on market quality.

The argument here is that market quality (MQ_{it}), HFT (HFT_{it}), and market fragmentation ($MFrag_{it}$) are determined in equilibrium, and three equations are defined accordingly, one for each variable. The variables MQ_{it}, HFT_{it}, and $MFrag_{it}$ are included on the right-hand side as they are found to be determinants of each other in the literature. This setup is expected to overcome the limitations usually found in IV-GMM specifications. The three-equation simultaneous model is:

$$\begin{aligned} MQ_{it} = {} & \alpha_{i_{(mq)}} + \sum_{m=1}^{M} \gamma_{(mq)_m} + \beta_{1_{(mq)}} HFT_{it} + \beta_{2_{(mq)}} MFrag_{it} + \beta_{3_{(mq)}} \overline{MQ}_{-it} \\ & + \beta_{4_{(mq)}} \log(mktcap)_{it} + \beta_{5_{(mq)}} \log(voltintra)_{it} + \beta_{6_{(mq)}} inv(price)_{it} + \epsilon_{it_{(mq)}}, \end{aligned} \tag{1}$$

$$\begin{aligned} HFT_{it} = {} & \alpha_{i_{(hft)}} + \sum_{m=1}^{M} \gamma_{(hft)_m} + \beta_{1_{(hft)}} MQ_{it} + \beta_{2_{(hft)}} MFrag_{it} + \beta_{3_{(hft)}} \overline{HFT}_{-it} \\ & + \beta_{4_{(hft)}} \log(size)_{it} + \beta_{5_{(hft)}} \log(value)_{it} + \beta_{6_{(hft)}} rtk_{it} + \beta_{7_{(hft)}} \log(mktcap)_{it} \\ & + \beta_{8_{(hft)}} \log(voltintra)_{it} + \epsilon_{it_{(hft)}}, \end{aligned} \tag{2}$$

$$\begin{aligned} MFrag_{it} = {} & \alpha_{i_{(frg)}} + \sum_{m=1}^{M} \gamma_{(frg)_m} + \beta_{1_{(frg)}} HFT_{it} + \beta_{2_{(frg)}} MQ_{it} + \beta_{3_{(frg)}} \overline{MFrag}_{-it} \\ & + \beta_{4_{(frg)}} \log(value)_{it} + \beta_{5_{(frg)}} \log(mktcap)_{it} + \beta_{6_{(frg)}} \log(voltintra)_{it} + \epsilon_{it_{(frg)}}, \end{aligned} \tag{3}$$

where indices i and t represent stocks and days respectively, MQ_{it} represents one of the two log-normalized market liquidity measures ($spread\_bps$, $espread$), HFT_{it} represents the HFT proxy ($hft2$), $MFrag_{it}$ represents the market fragmentation proxy ($HHItrd$), $\overline{MQ}_{-it}$ represents the average market liquidity level over all stocks in the same size group excluding stock i, $\overline{MFrag}_{-it}$ represents the average market fragmentation level over all stocks in the same size group excluding stock i, $\overline{HFT}_{-it}$ represents the average HFT intensity over all stocks in the same size group excluding stock i, $\log(mktcap)$ is the log-normalized market capitalization, $\log(voltintra)$ is the log-normalized intraday mid-price range volatility, $inv(price)$ is the inverse of the daily average price, $\log(size)$ is the log-normalized trade sizes, $\log(value)$ is the log-normalized trading volumes, rtk_{it} is the relative tick size, α_i is the firm fixed effects, $\sum_{m=1}^{M} \gamma_m$ is the time (month) fixed effects, and indices $_{(mq)}$, $_{(hft)}$, and $_{(frg)}$ refer to the respective coefficients of the equations MQ_{it}, HFT_{it}, and $MFrag_{it}$ respectively.

The analysis is conducted using a balanced panel of 132 stocks as described in the data section. Besides the full sample, the analysis is performed separately on large and small stocks to examine the cross-sectional impact and on three subsamples divided into equal periods: 2008-2010, 2011-2013, and 2014-2016 to observe the time-varying impact. The estimation method employed is the GMM approach (H3SLS), which is robust to unknown heteroscedastic error structures. This three-stage method is asymptotically equivalent to 3SLS when disturbances are homoscedastic (Greene, 2003). It enhances estimation efficiency over the two-stage method (Zellner and Theil, 1962) and is relevant to this study in two ways. First, the European equity market structure necessitates a simultaneous equations model, potentially leading to non-zero contemporaneous covariance in the structural disturbances among MQ_{it}, HF_{it}, and $MFrag_{it}$. Second, using disproportionate instruments for HFT_{it}, $MFrag_{it}$, and MQ_{it} results in both identified and over-identified equations in the system. In both cases, 3SLS maintains full information characteristics.The coefficients estimated through three-stage least squares are also reported alongside the H3SLS (GMM) estimates to compare their robustness. All estimations include monthly time-fixed effects for each of the 108 months from January 2008 to December 2016, along with stock-level fixed effects.

Results and Discussion

Tables 15, 16, and 17 report the estimates for the whole sample, large and small stocks, and three sub-sample periods, respectively, where only quoted spreads and effective half-spreads are used as dependent variables. Table 15 presents two sets of estimates using GMM and 3SLS for each liquidity measure, while the others only report GMM estimates. The discussions on estimates for the models 1, 2, and 3 are presented in order.

Market Liquidity (MQ_{it})

Table 15 shows that all the coefficients estimated through GMM and 3SLS for each model are highly significant. As expected, the 3SLS estimates are generally stronger than those obtained using GMM. However, there is one exception where the coefficient of MQ_{it} in column (III) is not significant, but the corresponding 3SLS estimates are highly significant. Among the three equations, the first one is the most interesting, showing the impact on liquidity. Columns I, IV, VII, and X report the estimated coefficients for quoted spreads and effective half-spreads, respectively. It shows that higher HFT is associated with narrower quoted and effective spreads, whereas higher fragmentation is associated with wider quoted and effective spreads. Other estimates show that the average liquidity level in the same group of other stocks, firm sizes measured by market capitalization, volatility, and price level are also determinants of liquidity. Higher market liquidity in the same size group and higher volatility are associated with wider spreads, whereas larger firm sizes (market capitalization) and higher price levels are associated with narrower spreads. The results confirm the evidence documented using OLS in Hossain (2022)]with stronger estimates.

The estimates in Table 16 (columns I, IV, VII, X) confirm the same sign of the estimates as observed in the full sample across large and small stock groups, though with different magnitudes. This implies that both HFT and fragmentation in smaller cap stocks seem to have a more pronounced effect. The coefficients in Table 17 (columns I, IV, VII) show that the impact of both HFT and market fragmentation on liquidity has narrowed and even turned non-significant during 2014-2016 for market fragmentation. This might be due to the fact that fragmentation has reached its saturation stage for the employed stocks, where variations in fragmentation do not create enough space to explain the changes in liquidity econometrically.

High Frequency Trading (HFT_{it})

The coefficient estimates of equation 2 are reported in Table 15 (columns II, V, VIII, XI). These estimates explain the factors influencing HFT intensity and extend the understanding of the bi-directional causality between HFT, market fragmentation, and liquidity. It can be seen that there are some indirect impacts that channel to liquidity through HFT. The coefficient of MQ_{it} is positive, implying that there are one or more mechanisms associating wider quoted and effective spreads with higher HFT. This likely indicates the phenomenon where HFTs post non-marketable limit orders as part of their regular market-making activities. Aitken, Harris and Harris (2015) found similar results and argued accordingly. Evidence suggests HFT participation is not only limited to the BBO (AMF, 2017). HFTs also post quotes around the BBO and even in the deeper levels of the order book, depending on market conditions, consistent with the evidence provided in Hossain (2022).

The estimate of $MFrag_{it}$ implies that a higher fragmentation level is also associated with higher HFT intensity, as expected. As can be seen, market-wide factors ($\overline{HFT}_{-it}$) play a significant role in determining HFT, supporting the argument and methodology of HFT instruments development on market-level HFT activities (Hasbrouck and Saar, 2013). Among other factors, larger firm size and larger trading volume are associated with higher HFT. On the contrary, higher volatility, higher relative tick sizes, and higher trade sizes are indicative of lower HFT.

Table 16 provides more insight into the determinants of HFT activities across stocks. A higher estimate of the coefficient MQ_{it} for small stocks may indicate that spreads in non-marketable limit orders become wider when HFTs post them for relatively illiquid stocks. Other results also show that larger stocks are associated with more intense market-wide factors, relative tick sizes, and trade sizes. Volatility in small and large stocks appears to have different impacts on HFT, though estimates seem not significant in GMM. Higher volatility in large stocks tends to reduce HFT intensity, which is consistent with the explanation of Hasbrouck and Saar (2013). It is argued that during periods of high illiquidity, HFT creates externalities by participating more in illiquid stocks. Similar evidence is also observed in Hossain (2023) that HFT provided more liquidity during 2008-2009 when it was scarce. However, the same estimates for effective spreads are negative, implying that mere HFT participation by providing non-marketable quotes may not benefit in reducing the actual trading cost. Table 17 (columns III, VI, IX) shows a similar effect observed in Table 15 over the periods, with a few exceptions. HFT appears to provide more intense non-marketable quotes during 2014-2016, which is consistent with a less intense HFT impact on liquidity (column VII) in the same period.

4.2 A Cross-Market Equilibrium Analysis

In this final part of the analysis, a cross-market simultaneous equations model approach is used to examine the relationship between HFT, market fragmentation, and liquidity. A multi-market setup is expected to overcome the endogeneity arising from simultaneity within and across markets. The endogeneity within a market is well-acknowledged in the HFT literature (Hendershott et al., 2011; Hasbrouck and Saar, 2013; Boehmer et al., 2015). The concept of endogeneity within a market suggests that an exogenous shock in liquidity might establish a more (or less) attractive environment for, and lead to an increase (or decrease) in HFT activities. However, the same argument can be made for endogeneity across markets, which seems more intuitive considering the existing equity market structure, especially in Europe. This research design aligns with the recommendations and evidence of recent HFT literature (O'Hara, 2015; The Netherlands Authority for the Financial Markets, 2016)[13].

The simultaneous equations model that is currently estimated expands and redefines to include all trading venues in the sample: LSE, CHIX, BATS, and TURQ. The original model comprises three equations (1-3), each representing one of the three endogenous variables: liquidity (MQ_{it}), HFT (HFT_{it}), and market fragmentation ($MFrag_{it}$). The market fragmentation variable ($MFrag_{it}$) is excluded in the revised setting because equations are developed for each venue that integrate the fragmented markets of cross-listed stocks. Consequently, the redefined model for the four trading venues consists of eight equations. The first four equations position the liquidity variable (MQ_{it}) on the left-hand side, while the remaining four position the HFT variable (HFT_{it}) similarly.

The cross-market simultaneous equations model is :

$$\begin{aligned} MQ_{1it} = {} & \alpha_{i_{(mq)1}} + \sum_{m=1}^{M} \gamma_{(mq)_{1m}} + \beta_{1_{(mq)1}} HFT_{1it} + \beta_{2_{(mq)1}} HHItrd_{it} + \beta_{3_{(mq)1}} \overline{MQ}_{-1it} \\ & + \beta_{4_{(mq)1}} ln(mktcap)_{it} + \beta_{5_{(mq)1}} ln(voltintra)_{1it} + \beta_{6_{(mq)1}} inv(price)_{it} + \epsilon_{it_{(mq)1}}, \end{aligned} \tag{4}$$

[13] Figure 2 presents some of the evidence provided in The Netherlands Authority for the Financial Markets (2016) regarding cross-market HFT activity in European markets

$$
\begin{aligned}
MQ_{2it} = \alpha_{i_{(mq)2}} + \sum_{m=1}^{M} \gamma_{(mq)_{2m}} + \beta_{1_{(mq)2}} HFT_{2it} + \beta_{2_{(mq)2}} HHItrd_{it} + \beta_{3_{(mq)2}} \overline{MQ}_{-2it} \\
+ \beta_{4_{(mq)2}} ln(mktcap)_{it} + \beta_{5_{(mq)2}} ln(voltintra)_{2it} + \beta_{6_{(mq)2}} inv(price)_{it} + \epsilon_{it_{(mq)2}},
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
MQ_{3it} = \alpha_{i_{(mq)3}} + \sum_{m=1}^{M} \gamma_{(mq)_{3m}} + \beta_{1_{(mq)3}} HFT_{3it} + \beta_{2_{(mq)3}} HHItrd_{it} + \beta_{3_{(mq)3}} \overline{MQ}_{-3it} \\
+ \beta_{4_{(mq)3}} ln(mktcap)_{it} + \beta_{5_{(mq)3}} ln(voltintra)_{3it} + \beta_{6_{(mq)3}} inv(price)_{it} + \epsilon_{it_{(mq)3}},
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
MQ_{4it} = \alpha_{i_{(mq)4}} + \sum_{m=1}^{M} \gamma_{(mq)_{4m}} + \beta_{1_{(mq)4}} HFT_{4it} + \beta_{2_{(mq)4}} HHItrd_{it} + \beta_{3_{(mq)4}} \overline{MQ}_{-4it} \\
+ \beta_{4_{(mq)4}} ln(mktcap)_{it} + \beta_{5_{(mq)4}} ln(voltintra)_{3it} + \beta_{6_{(mq)4}} inv(price)_{it} + \epsilon_{it_{(mq)4}},
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
HFT_{1it} = \alpha_{i_{(hft)1}} + \sum_{m=1}^{M} \gamma_{(hft)_{1m}} + \sum_{v=1}^{4} \beta_{v_{(hft)v}} MQ_{vit} + \beta_{5_{(hft)1}} \overline{HFT_{-1it}} + \beta_{6_{(hft)1}} HHItrd_{1it} \\
+ \beta_{7_{(hft)1}} ln(size)_{1it} + \beta_{8_{(hft)}} ln(volume)_{1it} + \beta_{9_{(hft)1}} rtk_{1it} + \beta_{10_{(hft)1}} ln(mktcap)_{it} \\
+ \beta_{11_{(hft)1}} ln(voltintra)_{1it} + \epsilon_{it_{(hft)1}},
\end{aligned} \tag{8}
$$

$$
\begin{aligned}
HFT_{2it} = \alpha_{i_{(hft)2}} + \sum_{m=1}^{M} \gamma_{(hft)_{2m}} + \sum_{v=1}^{4} \beta_{v_{(hft)v}} MQ_{vit} + \beta_{5_{(hft)2}} \overline{HFT_{-2it}} + \beta_{6_{(hft)2}} HHItrd_{2it} \\
+ \beta_{7_{(hft)2}} ln(size)_{2it} + \beta_{8_{(hft)2}} ln(volume)_{2it} + \beta_{9_{(hft)2}} rtk_{2it} + \beta_{10_{(hft)2}} ln(mktcap)_{it} \\
+ \beta_{11_{(hft)2}} ln(voltintra)_{2it} + \epsilon_{it_{(hft)2}},
\end{aligned} \tag{9}
$$

$$
\begin{aligned}
HFT_{3it} = \alpha_{i_{(hft)3}} + \sum_{m=1}^{M} \gamma_{(hft)_{3m}} + \sum_{v=1}^{4} \beta_{v_{(hft)v}} MQ_{vit} + \beta_{5_{(hft)3}} \overline{HFT_{-3it}} + \beta_{6_{(hft)3}} HHItrd_{3it} \\
+ \beta_{7_{(hft)3}} ln(size)_{3it} + \beta_{8_{(hft)3}} ln(volume)_{3it} + \beta_{9_{(hft)3}} rtk_{3it} + \beta_{10_{(hft)3}} ln(mktcap)_{it} \\
+ \beta_{11_{(hft)3}} ln(voltintra)_{3it} + \epsilon_{it_{(hft)3}},
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
HFT_{4it} = {} & \alpha_{i_{(hft)4}} + \sum_{m=1}^{M} \gamma_{(hft)_{4m}} + \sum_{v=1}^{4} \beta_{v_{(hft)_v}} MQ_{vit} + \beta_{5_{(hft)4}} \overline{HFT_{-4it}} + \beta_{6_{(hft)4}} HHItrd_{4it} \\
& + \beta_{7_{(hft)4}} ln(size)_{4it} + \beta_{8_{(hft)4}} ln(volume)_{4it} + \beta_{9_{(hft)4}} rtk_{4it} + \beta_{10_{(hft)4}} ln(mktcap)_{it} \\
& + \beta_{11_{(hft)4}} ln(voltintra)_{4it} + \epsilon_{it_{(hft)4}},
\end{aligned} \tag{11}
$$

where indices i, t, v represent stocks, time (days), and trading venues respectively, v takes the values $1, 2, 3, 4$ corresponding to LSE, CHIX, BATS, and Turquoise respectively. MQ_{vit} represents one of two log-normalized liquidity measures, quoted spreads ($spread_bps$) or effective half-spreads ($espread$); HFT_{vit} represents the HFT proxy ($hft2$); $HHItrd_{it}$ serves as the market fragmentation proxy. $\overline{MQ}{-}vit$ denotes the average market liquidity level across all stocks in the same size group, excluding stock i at venue v, while $\overline{HFT}{-}vit$ indicates the average HFT intensity for the same exclusion criteria. Log-normalized market capitalization is captured by $ln(mktcap)$; $ln(voltintra)vit$ measures the log-normalized intraday mid-price range volatility; $invprice$ is the inverse of daily average prices; $ln(size)vit$ and $ln(value)vit$ represent the log-normalized trade size and trading volume, respectively; $rtickvit$ denotes the relative tick size. The firm fixed effect is denoted by α_i, and the time (month) fixed effects by $\sum_{m=1}^{M} \gamma_m$. The coefficients of the equations for MQ_{vit} and HFT_{vit} are indexed by (mq) and $(hft)v$, respectively. Market-wide measures on liquidity ($\overline{MQ}{-}vit$) and HFT ($\overline{HFT}_{-vit}$) for each venue are based on similarly sized stock groups, classified by market capitalization.

Model identification and the order condition. To meet the order condition, the number of exogenous variables that appear elsewhere in the equation system must be at least as large as the number of endogenous variables in the equation. The number of endogenous variables in equations (4)–(7) and (8)–(11) are two and five, respectively. The control variables specified in models (4)–(7) should be considered exogenous. Models (4)–(7) and (8)–(11) use the same control variables as specified in section 4.1 for Models (10) and (11), respectively. All models share three common exogenous variables: $ln(mktcap)$, $inv(price)$, and $HHItrd_{it}$. The rest—$\overline{MQ_{-vit}}$, $\overline{HFT_{-vit}}$, $ln(size)$, $ln(voltintra)$, $ln(volume)$, and $rtick$—are based on the respective market and differ from each other. The system has, in aggregate, more excluded exogenous variables than required by the order condition, and therefore meets the order condition. The rank condition ensures that there is a unique solution to this set of equations. In practical terms, the rank condition is difficult to establish in large equation systems. Practitioners typically take it as given (Greene, 2003).

The models in equations (4) to (11) were estimated as a system using a panel dataset that includes variables from all four trading venues (LSE, CHIX, BATS, and Turquoise) for 149 stocks over 2060 days, from October 2008 to December 2016. Suitable subsamples classified on both cross-section and time-series dimensions are also used. The three-stage least squares method is employed, an approach that enhances estimation efficiency over the two-stage method (Zellner and Theil, 1962) and possesses full information characteristics when the use of disproportionate instruments results in both identified and over-identified equations in the system.

The impact of HFT and market fragmentation on market quality

The results of the simultaneous equations model estimation for the full sample are detailed in Table 18. Panel A displays the market quality equations for liquidity (equations 4–7), with Columns I–IV detailing quoted spreads, and Columns V–VIII focusing on effective half-spreads.

The main variables of interest, HFT (HFT_{it}) and market fragmentation ($HHItrd_{it}$), exhibit highly statistically significant estimates across all equations. Notably, all HFT estimates consistently show a negative sign for both liquidity measures, with CHIX presenting the strongest HFT estimates among the trading venues. Conversely, the market fragmentation variable, while also statistically significant, displays varying signs across venues: negative in alternative venue equations—$MQ_{(chix)it}$, $MQ_{(bats)it}$, $MQ_{(turq)it}$—and positive in the primary venue equation ($MQ_{(lse)it}$).

The results suggest that HFT enhances liquidity across trading venues, with varying impacts—the more conducive the exchange-level environment is for HFT, the narrower both the quoted and effective spreads become. CHIX, in particular, stands out in attracting HFT due to its advanced low-latency technology since its inception. This evidence aligns with the findings of Hendershott et al. (2011), Hasbrouck and Saar (2013), and Boehmer et al. (2015), who explore the causal relationship between HFT and market quality. Additional support is provided by various studies assessing the impact of external HFT shocks on market liquidity[14]. Furthermore, our findings indicate that while market fragmentation reduces liquidity at the primary exchange, it increases it at alternative trading

[14]Refer to Frino et al. (2014), Murray et al. (2016), Frino et al. (2017), Riordan and Storkenmaier (2012), and Brogaard et al. (2015).

venues. At the primary venue, LSE, the advantages of concentrated markets—scale economics and network externalities—outweigh the benefits of market fragmentation seen in competitive exchange environments. Conversely, the opposite is true for alternative exchanges. The evidence suggests that trader preferences for technological differentiation play a crucial role in contemporary markets. This study offers unique insights into the complex interplay between the dual impacts of exchange co-existence from a multi-venue perspective. To the best of my knowledge, no other research to date reconciles these opposing effects as presented here. Importantly, the findings challenge the notion, suggested by O'Hara and Ye (2011) and Gresse (2017), that market fragmentation universally improves liquidity, particularly in primary exchanges, though the analytical approach here also differs from those in their studies.

All estimates for control variables are highly statistically significant and exhibit the expected signs. Average exchange-level liquidity appears to have varying positive impacts on stock-level liquidity across exchanges—the lower the exchange-level liquidity, the stronger the effect. Other contributing factors include a lower inverse price level and intraday volatility, as well as higher market capitalization, all of which contribute to improved liquidity.

Drivers of HFT

Columns I-IV and V-VIII of Panel B (Table 18) present the results for HFT equations (8)–(11), estimated for quoted spreads and effective half-spreads, respectively. The estimates for liquidity (MQ_{vit}), average market-wide HFT ($\overline{HFT}{-vit}$), market fragmentation ($HHItrdit$), trade sizes ($ln(size)vit$), relative tick sizes ($rtickvit$), trade volume ($ln(volume)vit$), market capitalization ($ln(mktcap)vit$), and intraday mid-price range volatility ($ln(voltintra)vit$) are highly statistically significant across equations, with two exceptions reported in column V. The primary variables of interest, market liquidity ($MQvit$) and market fragmentation ($HHItrd_{it}$), highlight the relationships among HFT, market quality, and fragmentation across different markets. The estimates for market liquidity, represented by quoted and effective spreads for LSE ($MQ_{(lse)it}$) and CHIX ($MQ(chix)it$), display positive signs in equations specific to these markets and negative signs for other venues. Conversely, all estimates for market liquidity in equations for BATS ($MQ(bats)it$) and Turquoise

($MQ(turq)_{it}$) show positive signs across exchanges. For the other variables, estimates for average market-wide HFT, market fragmentation, and trade volume are positive, while those for market capitalization, trade sizes, and relative tick sizes are negative across all equations.

These results concerning cross-market liquidity and HFT activities suggest that liquidity levels at the LSE and CHIX influence HFT activity across trading venues. Specifically, HFTs supply liquidity to the LSE when quoted and effective spreads are wider at the LSE and narrower at CHIX, and vice versa for CHIX. Similarly, wider spreads at BATS and Turquoise also appear to increase HFT activities at both the LSE and CHIX. In the case of BATS and Turquoise, HFTs supply liquidity to both markets when spreads are narrower at the LSE and CHIX and wider in these respective markets.

The findings imply at least two significant conclusions: first, HFT market-making activities are interconnected across markets; second, HFTs provide liquidity primarily when spreads are wider. This evidence aligns with the research of Hendershott and Riordan (2013) and Carrion (2013), who found that HFTs supply liquidity when it is scarce and demand liquidity when it is plentiful. They observed that HFTs/ATs are less inclined to submit new orders or cancel existing ones and more likely to initiate trades when spreads are narrow, reacting swiftly to market events, especially under wide spread conditions. These observations also support the cross-market HFT strategies described in The Netherlands Authority for the Financial Markets (2016) and Menkveld (2013).

The results in Table 18 reveal a statistically significant, market-wide HFT component that positively affects HFT activities across markets. Fragmentation is positively correlated with HFT activity—the higher the fragmentation, the more HFT activity is observed. Order size is inversely related to HFT—the smaller the order size, the greater the HFT activity. These findings are consistent with those of Hendershott et al. (2011) and Aitken et al. (2014), who also reported a relationship between HFT and smaller order sizes. Additionally, relative tick size significantly influences HFT activities—the lower the relative tick size, the higher the HFT activity. Contrarily, O'Hara (2015) found that HFTs tend to leave orders in the book longer and trade more aggressively when the relative tick size is larger. Volatility impacts HFT activity differently across trading venues: higher volatility decreases HFT activity in alternative exchanges but increases it in the primary exchange. During periods of high volatility, HFTs prefer executing their strategies on the primary exchange, aligning with He et al. (2015), who noted that trading concentrates on primary exchanges during market stress. These results also support the findings in Hossain (2023) concerning the relationships between HFT, relative tick sizes, order sizes, order volume, and market capitalization.

Large and small stocks

Significant differences in liquidity and HFT across quintiles, as shown by descriptive analyses, have led to the division of the full sample (149 stocks) into two equal subsamples: a small-cap group (75 stocks below the median market capitalization) and a large-cap group (74 stocks above the median market capitalization). This division allows for an examination of how firm size influences the results obtained for the full sample. The system of equations (4)–(11) is estimated for both groups using quoted and effective half-spreads as dependent variables, mirroring the approach used for the full sample. The results are reported in Table 19 for large stocks and Table 20 for small stocks, with Panel A detailing market quality equations (4)–(7) and Panel B covering HFT equations (8)–(11). Columns I-IV present estimates for quoted spreads, and columns V-VIII for effective half-spreads. To avoid redundancy, only results that differ from those of the full sample are discussed. All estimates are highly statistically significant for both groups of stocks, showing almost identical coefficient signs as those obtained for the full sample. The market liquidity equations for both large and small stocks reveal no significant differences in the main variables of interest—HFT and market fragmentation—compared to the full sample results. However, the estimates for large stocks against quoted spreads in Panel B (Table 19) for the LSE and CHIX, which appear in columns I and II, differ from those of the full sample, displaying a consistent negative sign across equations. The estimates for effective half-spreads remain aligned with those of the full sample.

These results indicate that HFT remains active in highly liquid stocks, even when spreads are narrow. Descriptive evidence reveals that the average quoted spreads in large stocks are approximately 60% smaller than in small stocks. To stay competitive, HFTs must frequently update their quotes in these liquid stocks, necessitating that they continue to supply liquidity even when it becomes less profitable. It is also important to note that the stocks included in the samples are among the highest market capitalized stocks on the LSE, predominantly from the FTSE 100 and FTSE 250 indices. The small stocks classified in the subsamples do not necessarily exhibit the characteristics of typical small stocks mentioned in the literature, which may account for the similar estimates observed across different stock groups

Time-varying effects

The analysis is expanded to assess whether the effects of high-frequency trading and market fragmentation on liquidity, as well as the determinants of HFT liquidity supply, vary over time. The original sample is segmented into three subsamples (2008–2010, 2011–2013, and 2014–2016), each consisting of 149 stocks and covering a three-year period. The system of equations (4)–(11) is estimated for each subsample using the same liquidity measures as in previous sections. These subsamples are uniformly classified over the sample period without any specific motivation. The results are reported in Table 21, with Panel A presenting the estimates for market quality equations (4)–(7) and Panel B for HFT equations (8)–(11). Columns I–IV and V–VIII provide estimates for quoted spreads and effective half-spreads, respectively. To conserve space, only the estimates for the primary variables of interest are reported; however, the unreported estimates are also significant at the 1% level and exhibit the expected signs

The coefficient estimates for equations (4)–(7) in Panel A across the three subperiods are all statistically significant at the 1% level and exhibit the same signs as those reported in Table 18 for the full sample, with the exceptions occurring in columns II and VI. Notably, during the initial period of alternative trading venues' operations (2008–2010), one estimate for CHIX is significant only at the 5% level. This outlier does not impact the overall findings. In the latter period of the sample (2014–2016), the estimates for HFT appear stronger, while those for market fragmentation show weaker associations across markets.

The results indicate that the overall direction of the associations between HFT and liquidity, and market fragmentation and liquidity, remains relatively stable over the sample period, albeit with some time-varying impacts. Panel B presents the coefficient estimates for HFT equations, revealing several time-varying effects. For LSE, notable estimates include $MQ_{(lse)it}$ for the period 2014–2016 (column I). For CHIX, $MQ_{(lse)it}$ (column II) and $MQ_{(chix)it}$ (columns II and VI) during 2008–2010, and $MQ_{(chix)it}$ (column II) for 2011–2013 stand out. BATS shows variability in $MQ_{(lse)it}$ estimates (columns III and VII) for 2008–2010, and similar estimates (column VII) for 2011–2013 and 2014–2016. For Turquoise, $MQ_{(chix)it}$ in column VIII for 2011–2013 is significant. These fluctuations are primarily associated with LSE and CHIX, suggesting that varying spread levels at these competitive exchanges influence HFTs' liquidity supply across markets over time

The estimates for the period 2008–2010 highlight the intense market competition in European equity markets following the adoption of MiFID. During these years, CHIX, BATS, and Turquoise emerged as key alternative trading venues, beginning to compete directly with the incumbent LSE. Among these Multilateral Trading Facilities (MTFs), CHIX was particularly advanced in offering low latency trading platforms. Descriptive evidence indicates that during this period, spreads at CHIX were the narrowest for large stocks, maintaining this position until the end of 2013, when LSE regained the lead. In response to early losses in market share in 2008, the LSE undertook several initiatives between 2007 and 2011 to upgrade its trading system. Consequently, results from 2008 to 2010 show that HFT liquidity supply was positively correlated with the narrower spreads observed at CHIX across markets. Conversely, during the same period, liquidity at LSE, as measured by quoted spreads, did not similarly influence HFT liquidity supply across markets.

However, from 2011 to 2013, narrower spreads at LSE began to positively affect HFT liquidity supply across alternative trading venues, while the impact of CHIX's quoted spreads weakened across other markets. Between 2014 and 2016, narrower spreads in both LSE and CHIX were associated with increased HFT liquidity supply across trading venues.

5 Conclusion

To establish the interrelationship between high-frequency trading (HFT), market fragmentation, and market liquidity, the study employs a unique cross-market simultaneous equations model that incorporates measurement variables from all venues with cross-listed stocks where HFTs are actively engaged as part of their market strategies. This methodology aims to assess the impact of HFT on market liquidity, acknowledging the symbiotic relationship between HFT and market fragmentation, as well as the endogeneity that exists between HFT and market liquidity. Using a millisecond time-stamped intraday dataset, a panel of 132 LSE-listed stocks spanning from 2008 to 2016, this study provides evidence that HFT enhances liquidity across markets, significantly narrowing both quoted and effective spreads due to lower latency at the exchange level. Particularly, CHIX stands out in attracting HFT due to its market model and better response to the market demand for advanced low-latency technology compared to its rivals since its inception. Additionally, the findings indicate that while market fragmentation reduces liquidity at the primary exchange, it increases it at alternative trading venues. The evidence also suggests that trader preferences for technological differentiation at the exchange level play a crucial role in modern markets.

The results concerning cross-market liquidity and HFT activities suggest that HFT market-making activities are interconnected across markets, with HFT liquidity supply being higher at a particular exchange when spreads are wider there and narrower at others. This finding is supplemented by the observation that a market-wide HFT component positively influences exchange-level HFT activities. Additionally, volatility impacts HFT activity differently across trading venues: it decreases HFT activity in alternative exchanges but increases it in the primary exchange. Moreover, fragmentation is positively correlated with HFT activity—the higher the fragmentation, the greater the observed HFT activity.

Analyses extended to large and small stocks provide evidence that HFT remains active in highly liquid stocks even when spreads are narrow. To stay competitive, HFTs must frequently update their quotes in these liquid stocks, necessitating that they continue to supply liquidity even when it becomes less profitable. The time-varying analysis confirms that the overall direction of the associations between HFT and liquidity, and market fragmentation and liquidity, remains relatively stable over the sample period, albeit with some time-varying impacts.

HFTs employ a diverse range of trading strategies (Biais and Foucault, 2014; Hagströmer and Nordén, 2013). The HFT proxy used in this study does not necessarily reflect the activities of any specific HFT but rather captures a mixture of strategies. The evidence provided here suggests the relative dominance of a subset of HFTs who employ strategies that strengthen market environments, particularly those indicative of market-making HFTs. The evidence from this study holds significant implications for regulators and trading platform providers, particularly in Europe. Indiscriminate regulations aimed at hindering HFT activities could severely harm the trading environment and the welfare of market participants. Encouraging exchanges to enhance HFT-friendly platforms and improve high-speed connectivity could increase market competition and reduce trading costs, while advancing low-latency technology may enable exchanges to capture greater market share.

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Tables

Table 1: The universe of Sample Stocks

This table shows the decomposition of large-cap stocks across European countries (Panel A) as presented in the STOXX 800 index at the end of year 2016, and relative position of the European lit trading venues based upon total European equity trading volumes (Panel B) and trading volumes of LSE listed stocks (Panel C).

Panel A : STOXX 800's Composition		
Country (primary listing venues)	No. of Instruments	(%)
UK (LSE)	220	27.50
France (Euronext Paris)	95	11.88
Germany (Xerta)	84	10.50
Switzerland (Six Swiss)	61	7.63
Sweden	60	7.50
Italy	47	5.88
Spain	37	4.63
The Netherlands	28	3.50
Denmark	25	3.13

Panel B: Market Share of European Lit Trading Venues (Jan 2014 to Dec 2016)		
Exchanges	Turnover (Eurobn)	(%)
Batx CXE	5500.47	18.48
LSE	3514.16	11.81
Paris	3239.61	10.89
Deutsche Borse	3060.42	10.28
Turquoise	3051.43	10.25
Milan	2111.71	7.10
Bats BXE	1732.77	5.82
SIX Swiss	1531.50	5.15
Amsterdam	1474.64	4.96
Madrid	1020.24	3.43
Stockholm	954.50	3.21
Swiss Exchange	424.97	1.43
Copenhagen	352.76	1.19
Brussels	322.49	1.08

Panel C: Market Share of Europen Lit trading Venues for LSE listed stock (Jan 2014 to Dec 2016)		
Exchanges	Turnover (Eurobn)	(%)
LSE	2736.05	56.19
Bats CXE	1003.66	20.61
Turquoise	729.17	14.97
Bats BXE	355.05	7.29
Aquis	30.96	0.64
Equiduct	8.04	0.17
ICAP Securities	6.4	0.13

Source: Fidessa (https://fragmentation.fidessa.com/)

Table 2: TRTH's data support over the sample period

This table shows the data availability (from TRTH) for the LSE listed stocks primarily selected for the sample (across major trading venues). Panel A reports the data availability for the LSE and other three alternative trading venues, BATS, CHIX, Turquoise (TURQ), since 2008. Panel B reports the data availability for the stocks finally selected for the sample.

PANEL A

Post MiFID TRTH DATA availability for LSE stocks included in STOXX 800				
Year	BATS	CHIX	LSE	TURQ
Jan05–Dec07	0	0	180*	0
Jan-08	n.a.**	n.a.	182	n.a.
Jan-09	159	159	184	156
Jan-10	160	160	185	162
Jan-11	165	166	190	167
Jan-12	183	183	192	171
Jan-13	189	189	194	174
Jan-14	197	197	198	197
Jan-15	204	203	204	203
Jan-16	205	204	205	204

* availability varies over the period

** not available

PANEL B

Unbalanced panel constructed by taking eligible stocks from PANEL A					
year	Qtr	LSE	CHIX	BATS	TURQ
2005	1	118	n.a	n.a	n.a
2005	2	122	n.a	n.a	n.a
2005	3	131	n.a	n.a	n.a
2005	4	136	n.a	n.a	n.a
2006	1	138	n.a	n.a	n.a
2006	2	139	n.a	n.a	n.a
2006	3	140	n.a	n.a	n.a
2006	4	142	n.a	n.a	n.a
2007	1	143	n.a	n.a	n.a
2007	2	146	n.a	n.a	n.a
2007	3	149	n.a	n.a	n.a
2007	4	149	n.a	n.a	n.a
2008	1	149	n.a	n.a	n.a
2008	2	149	138	n.a	n.a
2008	3	149	143	n.a	70
2008	4	149	149	136	75
2009	1	149	149	148	85
2009	2	149	149	149	147
2009	3	149	149	149	148
2009	4	149	149	149	148
2010	all	149	149	149	149
2011	all	149	149	149	149
2012	all	149	149	149	149
2013	all	149	149	149	149
2014	all	149	149	149	149
2015	all	149	149	149	149
2016	1	149	149	149	149

Table 3: Reuters Instrument Code (RIC) structure

This table explains how a stock is identified across exchanges in the TRTH data request environment. This illustration is based on an excerpted TRTH data request snapshot of HSBC HOLDINGS, an LSE listed UK based company. Under uniform symbology, RIC structure of a stock comprises two parts: the unique root part which is 'HSBA' in this example and the listing/trading venue extension (upper case 'L','BS', 'TQ' and 'CHI' for LSE, BATS, Turquoise and CHIX respectively) that comes after a period '.'. If a stock is traded in the primary exchange, the first part of the RIC only includes the ticker root while an additional lower case letter referring an unique primary venue (lower case 'l' for LSE) is added with the root if it is traded on any other exchanges. Accordingly, 'HSBA.L', refers the RIC of the primary exchange LSE, and 'HSBAl.CHI', 'HSBAl.BS' and 'HSBAl.TQ' refer that for alternative exchange CHIX, BATS and Turquoise respectively. The ISIN is unique for a stock and can be used to link all RICs defined against a stock. The lower section of this table shows a real TRTH data request environment.

RIC	ISIN	Exchange	Name	First Date	Last Date	Underlying RIC
HSBAl.BS	GB0005405286	BTE	HSBC HOLDINGS	23/10/2008	26/10/2017	HSBA.L
HSBAl.TQ	GB0005405286	TRQ	HSBC HOLDINGS	1/8/2008	26/10/2017	HSBA.L
HSBAl.CHI	GB0005405286	CHI	HSBC HOLDINGS	5/4/2008	26/10/2017	HSBA.L
HSBA.L	GB0005405286	LSE	HSBC HOLDINGS	1/1/1996	26/10/2017	HSBA.L

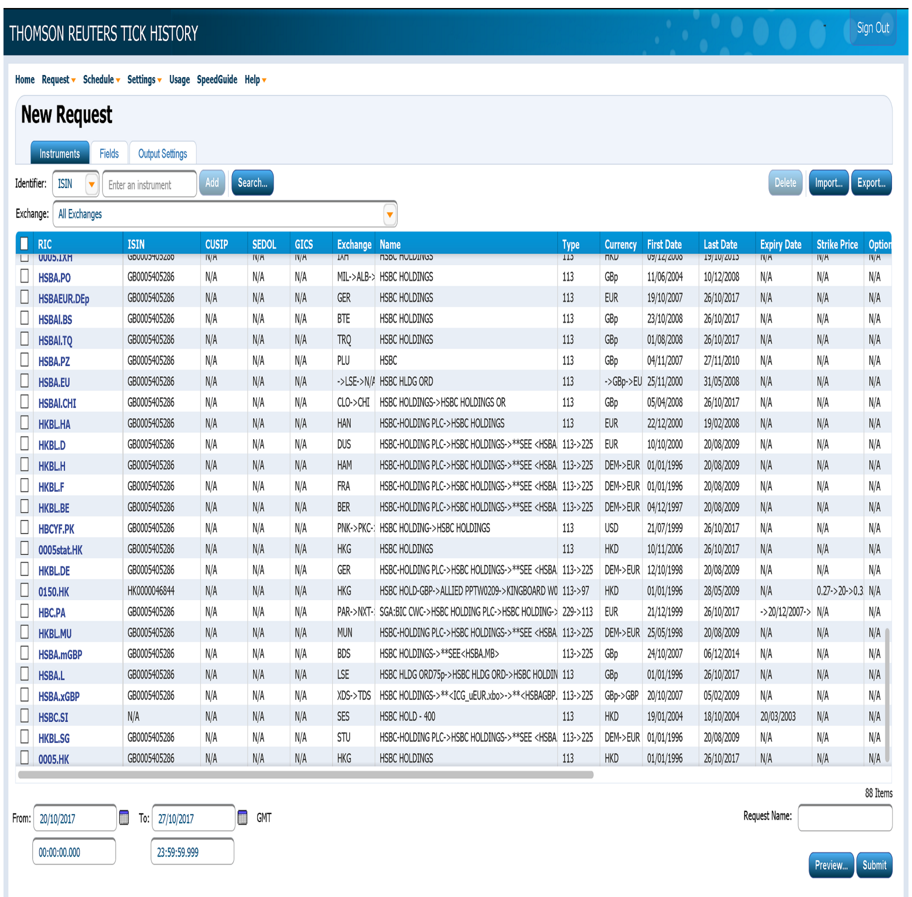


Table 4: List of the sample securities

The table lists all 132 LSE listed securities (by their RICs) included in the sample for the period 2005 to 2016 with the number of trading days coverage.

RIC	Days	RIC	Days	RIC	Days	RIC	Days	RIC	Days	RIC	Days
AAL	2624	BWY	2624	GOG	2624	JMAT	2624	PZC	2624	SPX	2624
ABF	2624	BYG	2624	GPOR	2624	KGF	2624	RAT	2624	SRP	2624
ADN	2624	CCL	2624	GRG	2624	KIE	2624	RB	2624	SSE	2624
AHT	2624	CLLN	2624	GRI	2624	LAND	2624	RBS	2624	STAN	2624
ANTO	2624	CNA	2624	GSK	2624	LGEN	2624	REL	2624	SVS	2624
AV	2624	CNE	2624	HIK	2624	LLOY	2624	RIO	2624	SVT	2624
AVV	2624	COB	2624	HLMA	2624	LSE	2624	ROR	2624	SXS	2624
AZN	2624	CPG	2624	HMSO	2624	MCRO	2624	RR	2624	TATE	2624
BAB	2624	CPI	2624	HSBA	2624	MGGT	2624	RRS	2624	TLW	2624
BARC	2624	CRDA	2624	HSV	2624	MKS	2624	RSA	2624	TPK	2624
BATS	2624	DGE	2624	HSX	2624	MRW	2624	RTO	2624	TSCO	2624
BBA	2624	DOM	2624	ICP	2624	MTO	2624	SBRY	2624	UBM	2624
BDEV	2624	DRX	2624	IGG	2624	NEX	2624	SDR	2624	ULE	2624
BLND	2624	DTY	2624	IHG	2624	NG	2624	SGC	2624	ULVR	2624
BLT	2624	ECM	2624	III	2624	NXT	2624	SGE	2624	UTG	2624
BNZL	2624	ELM	2624	IMI	2624	OML	2624	SHB	2624	UU	2624
BOY	2624	EMG	2624	INCH	2624	PFC	2624	SHP	2624	VOD	2624
BP	2624	EZJ	2624	INF	2624	PFG	2624	SMDS	2624	WEIR	2624
BRBY	2624	FGP	2624	INVP	2624	PNN	2624	SMIN	2624	WG	2624
BT	2624	GFS	2624	ITRK	2624	PRU	2624	SMWH	2624	WMH	2624
BVIC	2624	GKN	2624	ITV	2624	PSN	2624	SN	2624	WPP	2624
BVS	2624	GNK	2624	JLT	2624	PSON	2624	SNR	2624	WTB	2624

Table 5: Descriptive statistics for HFT proxies across venues: LSE and CHIX

This table presents the descriptive statistics for HFT proxies calculated on the millisecond-time stamped data for LSE and CHIX. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			LSE						CHIX					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
$hft1$	messages per minute (best 10 depth levels)	Mean	100.36	23.77	38.97	72.39	103.80	266.31	136.59	27.78	47.24	87.99	137.37	382.44
		Median	47.62	17.95	30.57	56.44	90.99	171.75	69.65	20.18	34.02	69.81	113.63	276.53
		StdDev	157.77	23.22	38.25	67.59	84.81	271.25	208.13	27.99	44.18	66.96	93.11	343.19
$hft2$	messages per minute (best 5 depth levels)	Mean	83.72	19.35	32.61	60.80	89.36	219.40	115.73	24.98	41.32	75.05	118.97	318.24
		Median	41.10	14.42	26.09	49.34	80.49	149.97	60.85	18.06	30.11	59.78	97.67	236.66
		StdDev	126.10	19.37	30.18	52.20	68.56	213.53	168.72	24.96	37.16	55.60	80.33	272.31
$hft3$	messages per minute (BBO)	Mean	39.32	9.57	15.67	28.33	43.50	100.91	48.67	11.65	18.19	32.03	50.28	131.16
		Median	20.38	7.48	12.87	23.91	40.04	76.56	27.76	9.14	14.57	27.27	43.95	101.99
		StdDev	54.32	8.98	13.09	21.76	30.81	88.30	64.84	9.76	13.83	20.59	29.12	100.26
$ordtotrd$	number of messages per executed order (order to trade ratio)	Mean	22.02	28.05	19.51	20.45	21.18	20.73	53.33	92.32	49.77	41.92	41.65	41.07
		Median	19.06	19.97	17.28	18.46	20.40	19.83	35.99	52.67	34.10	31.26	33.96	35.34
		StdDev	21.25	36.67	15.59	14.76	13.57	13.84	91.07	182.09	63.23	34.24	27.06	22.51
$hft1h$	GBP volume (100) per message (best 10 depth levels) time (-1)	Mean	-6.93	-2.24	-3.73	-5.14	-7.51	-16.21	-0.83	-0.29	-0.55	-0.81	-1.04	-1.47
		Median	-1.96	-0.88	-1.37	-1.77	-2.38	-3.60	-0.70	-0.22	-0.48	-0.75	-0.96	-1.33
		StdDev	15.51	4.19	5.87	8.42	10.93	29.12	0.65	0.27	0.38	0.47	0.53	0.73
$hft2h$	GBP volume (100) per message (best 5 depth levels) time (-1)	Mean	-7.54	-2.80	-4.17	-5.53	-8.04	-17.37	-0.95	-0.32	-0.62	-0.93	-1.20	-1.71
		Median	-2.33	-1.10	-1.64	-2.05	-2.72	-4.19	-0.81	-0.24	-0.54	-0.87	-1.11	-1.56
		StdDev	16.22	5.30	6.32	8.78	11.36	30.28	0.74	0.29	0.41	0.52	0.60	0.83
	observations (stock*day)		439583	90046	88374	87239	86786	87138	324334	64743	65175	64952	64484	64980

Table 6: Descriptive statistics for HFT proxies across venues: BATS and Turquoise

This table presents the descriptive statistics for HFT proxies calculated on the millisecond-time stamped data for BATS and Turquoise. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			BATS						Turquoise					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
$hft1$	messages per minute (best 10 depth levels)	Mean	77.42	15.21	25.63	45.68	75.30	222.58	76.08	15.51	25.47	47.88	74.67	207.74
		Median	35.16	11.35	18.12	33.94	58.10	157.87	34.88	12.19	19.28	33.90	55.87	152.82
		StdDev	127.95	16.24	29.43	39.79	60.55	214.90	116.43	13.77	26.59	49.28	63.64	185.25]
$hft2$	messages per minute (best 5 depth levels)	Mean	68.98	14.66	24.02	41.17	67.87	194.84	67.60	14.89	23.50	42.74	66.39	182.53
		Median	32.46	11.07	17.36	31.18	52.43	141.80	32.04	11.77	18.18	30.85	50.16	134.98
		StdDev	108.71	15.17	25.77	34.37	54.25	178.95	101.24	12.92	22.32	43.51	55.22	160.56
$hft3$	messages per minute (BBO)	Mean	33.27	9.37	13.92	21.53	32.45	88.03	33.74	9.21	13.68	22.10	32.43	87.59
		Median	18.11	7.38	10.81	17.18	26.39	66.87	18.46	7.34	11.10	18.13	26.77	65.44
		StdDev	45.29	8.42	11.84	16.04	22.96	71.41	46.51	7.63	10.61	15.99	21.93	74.79
$ordtotrd$	number of messages per executed order (order to trade ratio)	Mean	98.21	152.48	94.92	87.01	80.26	78.06	59.31	83.30	45.63	54.46	58.14	56.23
		Median	54.01	72.88	56.53	48.44	48.12	52.01	34.94	39.06	29.16	31.99	36.30	39.50
		StdDev	200.02	332.55	161.99	166.68	140.96	118.31	99.78	171.83	64.94	85.77	78.36	56.24
$hft1h$	GBP volume (100) per message (best 10 depth levels) time (-1)	Mean	-0.47	-0.16	-0.26	-0.43	-0.63	-0.86	-0.79	-0.36	-0.58	-0.76	-0.95	-1.25
		Median	-0.33	-0.13	-0.21	-0.35	-0.51	-0.69	-0.61	-0.28	-0.50	-0.63	-0.78	-1.03
		StdDev	0.49	0.15	0.20	0.35	0.46	0.70	0.69	0.30	0.40	0.55	0.70	0.92
$hft2h$	GBP volume (100) per message (best 5 depth levels) time (-1)	Mean	-0.52	-0.17	-0.27	-0.47	-0.69	-0.96	-0.87	-0.37	-0.62	-0.83	-1.06	-1.40
		Median	-0.36	-0.13	-0.22	-0.38	-0.57	-0.78	-0.67	-0.29	-0.53	-0.69	-0.86	-1.16
		StdDev	0.54	0.15	0.22	0.38	0.51	0.76	0.77	0.32	0.43	0.60	0.78	1.01
	observations (stock*day)		301585	58860	60333	60950	60478	60964	298676	56255	57828	61216	61491	61886

Table 7: Descriptive statistics for liquidity measures across venues: LSE and CHIX

This table presents the descriptive statistics for absolute quoted spread ($spread\_abs$) in GBX, relative quoted spreads ($spread\_bps$) in basis points (bps), volume weighted effective half-spreads ($espread$) in bps, average quoted depth at best price ($depth1$) in GBP100, average cumulative depth upto three best price ($depth3$) in GBP100. All measures are developed on millisecond time-stamped trades and quotes data for LSE and CHIX and appropriate averages are taken to convert them daily. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			LSE						CHIX					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
$spread\_abs$	absloute quoted spread (GBX)	Mean	1.44	2.54	1.40	1.13	1.19	0.90	1.77	3.77	1.71	1.21	1.27	0.90
		Median	0.89	1.20	0.95	0.84	0.80	0.77	0.95	1.52	1.05	0.87	0.84	0.80
		StdDev	2.32	4.41	1.40	1.05	1.33	0.74	3.59	6.95	2.12	1.81	1.53	0.90
$spread\_bps$	percentage quoted spread (bps)	Mean	20.39	44.13	22.18	15.05	11.64	8.09	24.88	63.11	26.64	15.56	11.48	7.65
		Median	13.79	30.70	18.41	13.48	11.01	7.61	13.61	40.83	19.52	13.00	10.63	6.45
		StdDev	23.71	40.62	13.50	7.77	4.52	4.83	40.03	72.61	21.91	12.96	6.19	6.14
$espread$	effective half- spread (bps)	Mean	7.16	14.78	7.50	5.42	4.47	3.37	7.74	18.26	8.34	5.16	4.04	2.89
		Median	5.09	9.98	6.30	4.94	4.33	3.15	4.72	11.48	6.09	4.43	3.86	2.35
		StdDev	8.50	15.26	4.73	2.87	1.77	2.27	11.75	21.50	7.09	3.71	1.82	2.45
$depth1$	average depth (BBO level/GBP 100)	Mean	415.98	70.53	134.85	252.09	492.27	1146.17	161.02	33.88	58.69	110.17	217.45	385.17
		Median	182.62	58.05	98.32	189.16	383.08	620.19	89.78	30.87	51.56	93.69	186.67	303.01
		StdDev	1291.87	52.33	127.28	214.74	417.22	2722.34	201.63	17.65	34.72	65.53	129.04	313.04
$depth3$	average cumulative depth (best three levels/GBP 100)	Mean	1781.55	265.08	526.51	1050.53	2200.43	4936.16	679.75	98.80	195.02	429.48	934.68	1741.92
		Median	792.94	225.70	402.43	832.48	1843.02	3050.27	333.68	89.05	164.06	352.90	802.42	1422.42
		StdDev	5077.64	182.06	435.92	805.45	1638.94	10577.23	900.43	58.89	126.42	291.27	580.22	1334.61
	observations (stock*day)		439583	90046	88374	87239	86786	87138	324334	64743	65175	64952	64484	64980

Table 8: Descriptive statistics for liquidity measures across venues: BATS and Turquoise

This table presents the descriptive statistics for absolute quoted spread ($spread\_abs$) in GBX, relative quoted spreads ($spread\_bps$) in basis points (bps), volume weighted effective half-spreads ($espread$) in bps, average quoted depth at best price ($depth1$) in GBP100, average cumulative depth upto three best price ($depth3$) in GBP100. These measures are developed on millisecond time-stamped trades and quotes data for BATS and Turquoise and appropriate averages are taken to convert them daily. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			BATS						Turquoise					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
$spread\_abs$	absloute quoted spread (GBX)	Mean	2.34	4.81	2.54	1.66	1.68	1.12	1.93	3.76	2.00	1.47	1.49	1.06
		Median	1.24	2.03	1.50	1.13	1.01	0.98	1.12	1.69	1.21	1.05	0.97	0.91
		StdDev	4.37	8.50	2.86	1.71	2.08	1.08	3.11	5.89	2.18	1.50	1.81	0.97
$spread\_bps$	percentage quoted spread (bps)	Mean	31.78	77.77	37.90	21.06	14.21	9.44	26.28	60.27	31.14	20.23	13.65	9.38
		Median	17.95	53.65	28.70	17.47	12.93	8.04	15.51	41.82	21.83	15.21	11.95	7.50
		StdDev	45.62	79.20	30.53	14.70	6.54	7.66	33.90	54.89	27.88	19.01	8.19	10.24
$espread$	effective half- spread (bps)	Mean	9.75	23.15	11.46	6.53	4.73	3.34	8.01	17.10	9.32	6.45	4.70	3.36
		Median	5.72	15.65	8.52	5.54	4.47	2.84	5.05	11.44	6.41	4.92	4.22	2.68
		StdDev	13.59	23.62	9.69	4.39	1.95	2.58	10.07	16.69	8.75	5.71	2.82	3.56
$depth1$	average depth (BBO level/GBP 100)	Mean	97.15	26.85	38.18	61.87	126.54	229.51	100.19	31.55	45.74	73.48	132.56	207.71
		Median	51.55	24.70	34.01	50.27	101.42	164.98	64.27	28.81	40.76	60.96	112.43	167.32
		StdDev	175.23	12.58	20.51	40.55	88.18	337.85	130.39	15.28	21.52	42.86	80.88	229.62
$depth3$	average cumulative depth (best three levels/GBP 100)	Mean	376.07	75.79	123.44	228.73	505.75	934.64	353.85	75.34	129.33	240.67	485.90	797.58
		Median	177.62	63.46	104.49	176.92	399.14	682.28	196.13	70.59	108.61	192.07	406.58	634.22
		StdDev	589.82	65.73	87.53	170.21	383.39	1016.78	450.24	39.89	78.52	166.22	333.06	699.37
	observations (stock*day)		301585	58860	60333	60950	60478	60964	298676	56255	57828	61216	61491	61886

Table 9: Descriptive statistics for realized half-spread measures across venues: LSE and CHIX

This table presents the descriptive statistics for realized half-spreads based on four hypothetical post-trade quote adjustment intervals. These measures are developed on millisecond time-stamped trades and quotes data for LSE and CHIX and weighted by the respective trade volume (number of shares) to convert them daily. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			LSE						CHIX					
variable	Description (units)		All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
	share volume	Mean	0.98	3.54	0.66	0.27	0.21	0.16	0.73	3.56	0.68	-0.08	-0.27	-0.23
$rspread1$	wighted 10-sec	Median	0.13	1.08	0.32	0.05	0.02	-0.04	-0.26	0.66	-0.08	-0.36	-0.36	-0.31
	realized spread (bps)	StdDev	5.65	11.54	2.93	1.78	1.25	1.09	7.22	15.07	4.02	2.16	1.02	1.27
	share volume	Mean	0.43	2.56	-0.02	-0.23	-0.15	-0.10	0.46	3.18	0.30	-0.37	-0.45	-0.35
$rspread2$	wighted 30-sec	Median	-0.15	0.41	-0.17	-0.28	-0.22	-0.16	-0.39	0.32	-0.37	-0.54	-0.47	-0.36
	realized half-spread (bps)	StdDev	5.59	11.48	3.01	1.88	1.32	1.05	7.06	14.74	3.99	2.10	1.03	1.21
	share volume	Mean	0.13	2.05	-0.39	-0.51	-0.35	-0.20	0.27	2.80	0.04	-0.54	-0.56	-0.39
$rspread3$	wighted 1-minute	Median	-0.28	0.08	-0.41	-0.44	-0.34	-0.20	-0.45	0.10	-0.51	-0.63	-0.53	-0.37
	realized half-spread (bps)	StdDev	5.68	11.65	3.18	2.03	1.43	1.07	7.02	14.67	3.99	2.12	1.11	1.21
	share volume	Mean	-0.21	1.12	-0.86	-0.72	-0.43	-0.18	0.08	1.99	-0.23	-0.58	-0.48	-0.29
$rspread4$	wighted 5-minute	Median	-0.32	-0.30	-0.60	-0.48	-0.31	-0.12	-0.36	-0.09	-0.52	-0.54	-0.39	-0.25
	realized half-spread (bps)	StdDev	6.09	12.36	3.87	2.53	1.77	1.30	7.20	14.98	4.50	2.50	1.50	1.34
	observations (stock*day)		439583	90046	88374	87239	86786	87138	324334	64743	65175	64952	64484	64980

Table 10: Descriptive statistics for realized half-spread measures: BATS and Turquoise

This table presents the descriptive statistics for realized half-spreads based on four hypothetical post-trade quote adjustment intervals. These measures are developed on millisecond time-stamped trades and quotes data for BATS and Turquoise and weighted by the respective trade volume (number of shares) to convert them daily. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			BATS						Turquoise					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
	share volume	Mean	1.43	5.40	1.65	0.30	0.03	-0.09	0.84	3.46	1.00	0.32	-0.18	-0.17
$rspread1$	wighted 10-sec	Median	0.11	1.86	0.63	0.07	-0.01	-0.13	-0.24	0.63	-0.05	-0.33	-0.36	-0.29
	realized spread (bps)	StdDev	8.91	18.08	6.72	2.84	1.30	1.31	6.92	13.34	6.36	3.95	1.69	2.12
	share volume	Mean	1.26	5.13	1.46	0.10	-0.11	-0.15	0.54	2.93	0.64	0.00	-0.39	-0.29
$rspread2$	wighted 30-sec	Median	0.04	1.61	0.47	-0.05	-0.09	-0.16	-0.36	0.26	-0.31	-0.50	-0.47	-0.33
	realized half-spread (bps)	StdDev	8.93	18.19	6.62	2.94	1.38	1.32	6.87	13.23	6.40	3.92	1.80	2.25
	share volume	Mean	1.11	4.82	1.27	-0.04	-0.20	-0.18	0.38	2.67	0.45	-0.19	-0.52	-0.31
$rspread3$	wighted 1-minute	Median	-0.01	1.42	0.35	-0.13	-0.14	-0.16	-0.41	0.08	-0.45	-0.58	-0.53	-0.33
	realized half-spread (bps)	StdDev	8.97	18.24	6.76	3.04	1.52	1.38	7.00	13.42	6.53	4.02	2.12	2.48
	share volume	Mean	0.90	3.82	1.04	-0.06	-0.14	-0.09	0.27	2.02	0.32	-0.23	-0.46	-0.14
$rspread4$	wighted 5-minute	Median	0.07	1.14	0.33	-0.07	-0.04	-0.05	-0.32	0.00	-0.40	-0.47	-0.40	-0.19
	realized half-spread (bps)	StdDev	9.13	18.30	7.48	3.78	2.14	1.76	8.04	14.34	7.78	5.21	4.19	4.54
	observations (stock*day)		301585	58860	60333	60950	60478	60964	298676	56255	57828	61216	61491	61886

Table 11: Descriptive statistics for price impact/adverse selection cost measures: LSE and CHIX

This table presents the descriptive statistics for price impacts/adverse selection costs based on four hypothetical post-trade quote adjustment intervals. These measures are developed on millisecond time-stamped trades and quotes data for LSE and CHIX and weighted by the respective trade volume (number of shares) to convert them daily. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			LSE						CHIX					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
	share volume	Mean	6.17	11.21	6.84	5.16	4.27	3.21	7.00	14.66	7.65	5.25	4.30	3.12
$price\_impact1$	wighted 10-sec price	Median	4.74	8.52	5.86	4.67	4.06	2.96	4.87	10.09	6.21	4.66	4.04	2.69
	impact (bps)	StdDev	5.64	9.41	4.01	2.58	1.66	1.77	8.82	16.01	5.47	3.47	1.78	1.81
	share volume	Mean	6.73	12.20	7.52	5.66	4.63	3.46	7.27	15.06	8.03	5.54	4.49	3.24
$price\_impact2$	wighted 30-sec price	Median	5.12	9.23	6.38	5.04	4.35	3.21	5.08	10.46	6.51	4.89	4.20	2.78
	impact (bps)	StdDev	6.23	10.31	4.58	3.01	1.93	2.03	8.95	16.14	5.68	3.57	1.92	1.96
	share volume	Mean	7.03	12.72	7.90	5.93	4.83	3.57	7.46	15.45	8.29	5.71	4.60	3.28
$price\_impact3$	wighted 60-sec price	Median	5.32	9.63	6.67	5.26	4.50	3.31	5.18	10.77	6.69	5.00	4.27	2.81
	impact (bps)	StdDev	6.59	10.87	4.93	3.27	2.12	2.17	9.19	16.52	5.91	3.63	2.06	2.05
	share volume	Mean	7.37	13.65	8.36	6.14	4.91	3.55	7.66	16.32	8.56	5.75	4.52	3.18
$price\_impact4$	wighted 5-min price	Median	5.41	10.21	6.96	5.36	4.51	3.22	5.08	11.14	6.72	4.89	4.10	2.67
	impact (bps)	StdDev	7.44	12.30	5.71	3.78	2.46	2.40	10.17	18.33	6.70	4.18	2.35	2.23
observations (stock*day)			439583	90046	88374	87239	86786	87138	324334	64743	65175	64952	64484	64980

Table 12: Descriptive statistics for price impact/adverse selection cost measures: BATS and Turquoise

This table presents the descriptive statistics for price impacts/adverse selection costs based on four hypothetical post-trade quote adjustment intervals. These measures are developed on millisecond time-stamped trades and quotes data for BATS and Turquoise and weighted by the respective trade volume (number of shares) to convert them daily. The sample consists of 149 stocks divided into 5 equal quintiles based on market capitalization for the period 2005–2016. Table 2 (Panel B) is refereed to see the periodical data coverage in the sample in detail.

			BATS						Turquoise					
			All	Small	Q2	Q3	Q4	Large	All	Small	Q2	Q3	Q4	Large
	share volume	Mean	8.31	17.74	9.79	6.23	4.69	3.42	7.18	13.64	8.34	6.13	4.89	3.54
$price\_impact1$	wighted 10-sec price	Median	5.40	12.06	7.56	5.35	4.33	2.95	5.11	9.54	6.42	5.08	4.40	2.93
	impact(bps)	StdDev	10.89	19.46	8.29	3.92	2.02	2.21	7.87	13.21	7.26	4.28	2.61	2.69
	share volume	Mean	8.50	18.05	10.00	6.43	4.83	3.49	7.49	14.18	8.70	6.45	5.11	3.67
$price\_impact2$	wighted 30-sec price	Median	5.56	12.42	7.81	5.52	4.42	2.99	5.37	10.08	6.77	5.35	4.58	3.06
	impact(bps)	StdDev	11.11	19.81	8.53	4.10	2.17	2.32	8.15	13.68	7.31	4.56	2.87	2.95
	share volume	Mean	8.65	18.37	10.20	6.58	4.92	3.51	7.66	14.49	8.90	6.64	5.25	3.70
$price\_impact3$	wighted 60-sec price	Median	5.65	12.73	7.98	5.62	4.47	3.00	5.52	10.36	6.99	5.49	4.67	3.10
	impact(bps)	StdDev	11.31	20.11	8.72	4.30	2.32	2.39	8.42	14.10	7.48	4.73	3.22	3.24
	share volume	Mean	8.88	19.35	10.45	6.62	4.87	3.44	7.81	15.16	9.09	6.75	5.24	3.56
$price\_impact4$	wighted 5-min price	Median	5.55	13.30	8.07	5.52	4.34	2.87	5.53	10.79	7.09	5.43	4.52	3.00
	impact(bps)	StdDev	12.44	22.14	9.65	5.05	2.82	2.75	9.85	16.05	8.65	6.09	4.96	5.13
observations(stock*day)			301585	58860	60333	60950	60478	60964	298676	56255	57828	61216	61491	61886

Table 13: The simultaneous trading venue participation rate (quarterly) in the EBBO

This table shows the joint venue participation rate (%) in the European Best Bid and Offer (EBBO), a hypothetical aggregate measure of limit order books across LSE, CHIX, BATS and Turquoise, builded on 500 milliseconds snapshots. The single, double, triple and quadruple refer the number of venue(s) which each time contributes in the EBBO. The EBBO is measured on a subsample of 45 stocks which were fragmented across four main exchanges immediately after the event of MiFID, and on which TRTH provides the maximum data support for the period 2008–2016.

		% EBBO (The highest bid price)					% EBBO (The lowest ask price)				
year	qtr	single	Double	triple	quadruple	total	single	Double	triple	quadruple	total
2008	1	100.00	-	-	-	100	100.00	-	-	-	100
2008	2	83.83	16.17	-	-	100	83.48	16.52	-	-	100
2008	3	73.56	25.78	0.66	-	100	73.34	25.88	0.78	-	100
2008	4	69.58	24.27	5.49	0.67	100	68.13	24.75	6.29	0.83	100
2009	1	59.43	25.11	12.53	2.93	100	57.37	25.47	13.63	3.53	100
2009	2	50.22	27.49	16.50	5.79	100	49.30	26.97	17.34	6.40	100
2009	3	56.77	23.18	13.36	6.70	100	56.39	23.18	13.58	6.85	100
2009	4	55.96	23.53	13.44	7.07	100	55.79	23.53	13.48	7.19	100
2010	1	50.19	26.46	16.12	7.24	100	50.02	26.41	16.14	7.44	100
2010	2	47.54	26.07	16.92	9.47	100	47.24	26.10	16.96	9.70	100
2010	3	48.13	24.26	15.95	11.66	100	48.13	24.25	15.93	11.69	100
2010	4	50.80	23.26	15.32	10.62	100	50.65	23.22	15.35	10.78	100
2011	1	51.63	22.83	14.69	10.86	100	51.52	22.84	14.68	10.96	100
2011	2	56.56	22.10	11.79	9.56	100	56.66	22.08	11.71	9.56	100
2011	3	58.02	22.22	10.61	9.16	100	58.01	22.21	10.59	9.19	100
2011	4	51.71	24.71	13.59	9.99	100	51.83	24.66	13.53	9.99	100
2012	1	42.60	26.72	18.90	11.79	100	42.45	26.71	18.94	11.90	100
2012	2	48.61	23.65	14.09	13.65	100	48.71	23.65	14.07	13.56	100
2012	3	49.92	22.90	15.14	12.04	100	49.89	22.84	15.12	12.15	100
2012	4	49.15	23.48	14.47	12.90	100	49.33	23.45	14.41	12.82	100
2013	1	53.95	22.74	12.44	10.87	100	54.00	22.78	12.37	10.85	100
2013	2	52.58	23.08	12.92	11.42	100	52.81	23.13	12.80	11.26	100
2013	3	54.21	22.26	12.76	10.76	100	54.38	22.27	12.73	10.61	100
2013	4	52.25	22.93	13.86	10.96	100	52.29	22.97	13.88	10.85	100
2014	1	54.65	22.15	12.89	10.30	100	54.85	22.20	12.82	10.13	100
2014	2	53.54	22.29	13.85	10.31	100	53.47	22.31	13.89	10.33	100
2014	3	54.45	23.47	13.82	8.26	100	54.43	23.44	13.80	8.33	100
2014	4	51.73	24.21	15.06	9.00	100	51.70	24.21	15.04	9.06	100
2015	1	48.22	22.80	15.24	13.74	100	48.31	22.79	15.21	13.69	100
2015	2	47.91	23.19	15.06	13.84	100	47.97	23.16	15.03	13.84	100
2015	3	46.82	23.66	15.47	14.05	100	46.68	23.71	15.52	14.09	100
2015	4	45.05	23.65	15.38	15.92	100	44.91	23.66	15.45	15.98	100
2016	1	46.00	24.26	15.70	14.04	100	45.85	24.18	15.75	14.22	100
2016	2	46.25	23.80	15.69	14.26	100	46.34	23.80	15.66	14.20	100
2016	3	48.78	22.33	15.00	13.88	100	48.64	22.31	15.06	14.00	100
2016	4	48.23	22.24	14.55	14.99	100	48.11	22.23	14.53	15.14	100
mean		54	23	13	10		54	23	13	10	

Table 14: The unique trading venue participation rate (quarterly) in the EBBO

This table shows the unique venue participation rate (%) in the European Best Bid and Offer (EBBO), a hypothetical aggregate measure of limit order books across LSE, CHIX, BATS and Turquoise, builded on 500 milliseconds snapshots. LSE, CHIX, BATS and TURQ refer the percentage of time each venue uniquely contributing in the consolidated best bid/offer (EBBO). The EBBO is measured on a subsample of 45 stocks which were fragmented across four main exchanges immediately after the event of MiFID, and on which TRTH provides the maximum data support for the period 2008–2016.

		% EBBO (The highest bid price)					% EBBO (The lowest ask price)				
year	qtr	LSE	CHIX	BATS	TURQ	total	LSE	CHIX	BATS	TURQ	total
2008	1	100.00	-	-	-	100	100	-	-	-	100
2008	2	68.88	31.12	-	-	100	67.94	32.06	-	-	100
2008	3	42.41	55.76	-	1.83	100	41.68	56.33	-	1.99	100
2008	4	34.66	53.39	1.85	10.10	100	34.08	53.58	1.92	10.42	100
2009	1	38.69	36.85	3.85	20.60	100	38.21	36.43	4.05	21.31	100
2009	2	48.15	36.79	11.05	4.01	100	47.05	37.18	11.54	4.23	100
2009	3	41.83	30.49	10.77	16.91	100	41.79	30.37	10.93	16.91	100
2009	4	32.44	37.33	9.86	20.37	100	32.39	37.32	9.87	20.43	100
2010	1	38.45	37.08	11.78	12.69	100	38.38	37.01	11.80	12.81	100
2010	2	36.98	41.19	10.65	11.18	100	36.59	41.33	10.72	11.35	100
2010	3	37.93	40.36	10.42	11.29	100	37.82	40.51	10.38	11.30	100
2010	4	34.27	39.79	16.72	9.22	100	34.27	39.95	16.60	9.17	100
2011	1	35.53	40.15	14.43	9.89	100	35.48	40.40	14.30	9.83	100
2011	2	15.00	71.67	7.14	6.18	100	14.98	71.73	7.12	6.17	100
2011	3	8.98	81.00	4.84	5.17	100	8.84	81.23	4.74	5.19	100
2011	4	13.71	61.93	13.54	10.82	100	13.54	62.12	13.54	10.79	100
2012	1	18.73	47.61	15.76	17.91	100	18.69	47.71	15.75	17.84	100
2012	2	32.88	40.89	11.57	14.67	100	32.87	40.91	11.54	14.69	100
2012	3	32.19	41.11	11.69	15.01	100	32.12	41.14	11.70	15.04	100
2012	4	37.11	32.85	13.19	16.85	100	37.25	32.79	13.15	16.81	100
2013	1	41.16	29.84	9.29	19.71	100	41.22	29.80	9.35	19.63	100
2013	2	47.44	27.07	8.15	17.35	100	47.47	27.13	8.18	17.21	100
2013	3	45.35	28.90	7.88	17.87	100	45.22	29.05	7.89	17.84	100
2013	4	43.85	27.65	9.08	19.41	100	43.83	27.72	9.05	19.39	100
2014	1	54.98	19.63	8.38	17.01	100	55.35	19.47	8.34	16.84	100
2014	2	57.89	18.15	9.12	14.84	100	58.13	17.98	9.12	14.77	100
2014	3	47.13	29.11	9.15	14.60	100	47.23	29.07	9.15	14.55	100
2014	4	48.22	25.80	8.60	17.39	100	48.25	25.72	8.60	17.43	100
2015	1	47.77	24.89	10.60	16.73	100	47.90	24.69	10.59	16.82	100
2015	2	50.70	22.98	10.78	15.54	100	51.06	22.74	10.77	15.44	100
2015	3	48.63	25.64	9.82	15.91	100	48.96	25.40	9.79	15.84	100
2015	4	47.14	28.25	7.93	16.69	100	46.98	28.36	7.99	16.67	100
2016	1	38.94	27.20	12.77	21.09	100	38.62	27.13	12.90	21.35	100
2016	2	41.42	23.34	13.91	21.33	100	41.45	23.30	13.93	21.33	100
2016	3	53.50	20.69	8.49	17.33	100	53.35	20.62	8.50	17.53	100
2016	4	57.91	17.93	7.49	16.66	100	57.92	17.89	7.51	16.69	100
mean		42	35	10	13		42	35	10	13	

Table 15: The effects of HFT and market fragmentation on liquidity: a simultaneous equations model estimation

This table presents the simultaneous equations model estimation of the equations (1)–(3) using both GMM (H3SLS) and 3SLS estimations for time weighted quoted spreads ($spread\_bps$) and volume weighted effective half-spreads ($espread$). Indices i and t represent stocks and day respectively, MQ_{it} represents one of the two log normalized market quality (liquidity) measures ($spread\_bps$, $espread$), HFT_{it} represents the HFT proxy ($hft2$), $MFrag_{it}$ represents the market fragmentation proxy ($HHItrd$), $\overline{MQ}_{-it}$ represents the average market liquidity level over all stocks in the same size group excluding stock i, $\overline{MFrag}_{-it}$ represents the average market fragmentation level over all stocks in the same size group excluding stock i, $\overline{HFT}_{-it}$ represents the average HFT intensity over all stocks in the same size group excluding stock i, $Log(mktcap)$ is the log normalized value of market capitalization, $Log(voltintra)$ is the log normalized value of intraday mid price range volatility, $invprice$ is the inverse of daily average price, $Log(size)$ is the log normalized average value of trade size , $Log(value)$ is the log normalized value of trading volume, indices $(_{(mq)})$, $(_{(hft)})$, $(_{(frg)})$ refer the respective coefficient of the equations MQ_{it}/(1), HFT_{it}/(2) and $MFrag_{it}$/(3) respectively. The regression is based on a balanced panel of 132 stocks and 2240 days (January 2008–December 2016), have both time (monthly time dummy for each of the 108 months) and stock fixed effects. Coefficient estimates are GMM (H3SLS) and 3SLS, t-statistics shown in the parentheses below the coefficient . ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	spread_bps						*espread*					
	H3SLS (GMM)			3SLS			H3SLS (GMM)			3SLS		
	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
$Log(HFT)_{it}$	-0.317***			-0.376***			-0.311***			-0.384***		
	(-87.92)			(-249.1)			(-80.6)			(-242.44)		
$MFrag_{it}$	0.189***			0.231***			0.073***			0.063***		
	-22.9			-56.24			-8.35			-14.54		
$log(\overline{MQ})_{-it}$	0.45***			0.372***			0.311***			0.239***		
	-54.94			-100.48			-31.2			-51.98		
$Log(mktcap)_{it}$	-0.187***			-0.182***			-0.143***			-0.118***		
	(-44.18)			(-104.03)			(-30.2)			(-63.84)		
$Log(volintra)_{it}$	0.183***			0.185***			0.219***			0.208***		
	-64.82			-170.98			-65.67			-182.68		
$inv(price)_{it}$	14.086***			14.979***			16.373***			18.568***		
	-17.36			-67.92			-17.13			-80.84		
$Log(MQ)_{it}$		0.726***			0.685***			1.253***			1.378***	
		-21.87			-47.3			-15.69			-39.02	
$MFrag_{it}$		0.149***			0.106***			0.138***			0.113***	
		-8.14			-10.61			-6.13			-9.45	
$Log(\overline{HFT})_{-it}$		0.429***			0.463***			0.371***			0.51***	
		-48.19			-113.05			-26.12			-82.05	
$Log(mktcap)_{it}$		0.296***			0.317***			0.405***			0.458***	
		-26.43			-69.65			-20.03			-53.06	
rtk_{it}		-462.761***			-386.573***			-712.829***			-582.874***	
		(-29.26)			(-115.61)			(-23.14)			(-55.95)	
$Log(size)_{it}$		-0.762***			-0.774***			-0.949***			-0.954***	
		(-44.64)			(-120.39)			(-27.92)			(-67.74)	
$Log(volume)_{it}$		0.702***			0.691***			0.769***			0.797***	
		-58.18			-136.6			-37.48			-90.91	
$Log(volintra)_{it}$		-0.049***			-0.043***			-0.142***			-0.172***	
		(-6.85)			(-14.19)			(-9.01)			(-26.01)	
$Log(MQ)_{it}$			0.01			0.248***			0.11***			0.241***
			-1.04			-51.29			-12.03			-53.1
$Log(HFT)_{it}$			0.209***			0.26***			0.246***			0.284***
			-41.53			-85.6			-46.27			-85.4
$\overline{MFrag}_{-it}$			0.629***			0.613***			0.627***			0.624***
			-71.1			-124.25			-70.69			-123.35
$Log(mktcap)_{it}$			0.216***			0.262***			0.238***			0.261***
			-50.01			-126.24			-55.27			-126.12
$Log(volume)_{it}$			-0.242***			-0.218***			-0.249***			-0.242***
			(-81.98)			(-146.77)			(-86.01)			(-156.93)
$Log(volintra)_{it}$			-0.005*			-0.049***			-0.024***			-0.051***
			(-1.83)			(-31.54)			(-8.65)			(-32.45)
observations	295680	295680	295680	295680	295680	295680	295680	295680	295680	295680	295680	295680
adjrsq	0.87			0.86			0.83			0.83		
adjrsq		0.91			0.91			0.85			0.83	
adjrsq			0.78			0.77			0.78			0.78

Table 16: The effects of HFT and market fragmentation on liquidity (large and small stocks): a simultaneous equations model estimation

This table presents the simultaneous equations model estimation of the equations (1)–(3) for large and small stocks using GMM(H3SLS)estimation for log normalized time weighted quoted spreads ($spread\_bps$) and volume weighted effective half-spreads ($espread$). Indices i and t represent stocks and day respectively, MQ_{it} represents one of the two market quality (liquidity) measures ($spread\_bps$, $espread$), HFT_{it} represents HFT proxy ($hft2$), $MFrag_{it}$ represents market fragmentation proxy ($HHItrd$), $\overline{MQ}_{-it}$ represents average market liquidity level over all stocks in the same size group excluding stock i, $\overline{MFrag}_{-it}$ represents average market fragmentation level over all stocks in the same size group excluding stock i, $\overline{HFT}_{-it}$ represents average HFT intensity over all stocks in the same size group excluding stock i, $Log(mktcap)$ is the log normalized value of market capitalization, $Log(voltintra)$ is the log normalized value of intraday mid price range volatility, $invprice$ is the inverse of daily average price, $Log(size)$ is the log normalized average value of trade size , $Log(value)$ is the log normalized value of trading volume , indices (mq), $((hft))$, (frg) refer the respective estimates of the equations MQ_{it}/(1), HFT_{it}/(2) and $MFrag_{it}$/(3) respectively. The regression is based on a balanced panel of 6 stocks and 2240 days (January 2008–December 2016) for each group of stock, have both time (monthly time dummy for each of 108 months) and stock fixed effects. Coefficient estimates are GMM (H3SLS), t-statistics shown in the parentheses below the coefficient . ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	spread_bps						*espread*					
	LARGE			SMALL			LARGE			SMALL		
	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
$Log(HFT)_{it}$	-0.277***			-0.379***			-0.266***			-0.382***		
	(-60.69)			(-71.68)			(-51.04)			(-68.43)		
$MFrag_{it}$	0.081***			0.268***			-0.074***			0.101***		
	-7.31			-22.35			(-5.92)			-8.19		
$Log(\overline{MQ})_{-it}$	0.585***			0.365***			0.333***			0.316***		
	-41.71			-31.72			-16.35			-25.97		
$Log(mktcap)_{it}$	-0.189***			-0.176***			-0.141***			-0.119***		
	(-35.43)			(-27.3)			(-23.25)			(-16.9)		
$Log(volintra)_{it}$	0.13***			0.239***			0.161***			0.284***		
	-35.56			-73.69			-35.27			-79.64		
$inv(price)_{it}$	13.963***			10.738***			12.239***			20.848***		
	-13.42			-10.32			-10.98			-15.82		
$Log(MQ)_{it}$		0.355***			0.535***			0.563***			0.689***	
		-12.33			-10.64			-8.27			-9.17	
$MFrag_{it}$		0.094***			0.325***			0.097***			0.36***	
		-5.29			-9.08			-4.78			-10.41	
$Log(\overline{HFT})_{-it}$		0.532***			0.325***			0.523***			0.281***	
		-64.65			-22.82			-48.58			-14.94	
$Log(mktcap)_{it}$		0.335***			0.202***			0.406***			0.219***	
		-28.89			-12.52			-17.8			-12.4	
rtk_{it}		-292.35***			-484.626***			-409.578***			-597.873***	
		(-13.84)			(-32.05)			(-10.88)			(-25.72)	
$Log(size)_{it}$		-0.89***			-0.525***			-1.009***			-0.541***	
		(-44.52)			(-26.5)			(-25.1)			(-23.59)	
$Log(volume)_{it}$		0.577***			0.661***			0.585***			0.666***	
		-56.94			-38.08			-40.42			-33.15	
$Log(volintra)_{it}$		-0.01			0.018			-0.029***			-0.022	
		(-1.54)			-1.64			(-2.81)			(-1.28)	
$Log(MQ)_{it}$			0.113***			0.063***			0.141***			0.158***
			-12.3			-3.78			-15.77			-10.75
$Log(HFT)_{it}$			0.186***			0.272***			0.214***			0.306***
			-33.78			-32.31			-36.38			-35.43
$\overline{MFrag_{-it}}$			0.661***			0.373***			0.653***			0.372***
			-57.33			-29.69			-56.71			-29.33
$Log(mktcap)_{it}$			0.219***			0.194***			0.23***			0.216***
			-43.02			-30.62			-44.74			-33.55
$Log(volume)_{it}$			-0.228***			-0.255***			-0.249***			-0.259***
			(-62.03)			(-60.57)			(-65.82)			(-66.41)
$Log(volintra)_{it}$			-0.016***			-0.025***			-0.015***			-0.051***
			(-4.49)			(-5.06)			(-4.37)			(-10.74)
observations	147840	147840	147840	147840	147840	147840	147840	147840	147840	147840	147840	147840
adjrsq	0.82			0.77			0.78			0.74		
adjrsq		0.9			0.82			0.88			0.8	
adjrsq			0.81			0.76			0.81			0.76

Table 17: The time-varying effects of HFT and market fragmentation on liquidity: a simultaneous equations model estimation

This table presents the simultaneous equations model estimation of the equations (1)–(3) using GMM (H3SLS) estimation for the sub periods (2008-2010), (2011-2013) and (2014-2016) for log normalized time weighted quoted spreads ($spread\_bps$) and volume weighted effective half-spreads ($espread$). Indices i and t represent stocks and days respectively, MQ_{it} represents one of the two market quality (liquidity) measures ($spread\_bps$, $espread$), HFT_{it} represents HFT proxy ($hft2$) , $MFrag_{it}$ represents market fragmentation proxy ($HHItrd$), $\overline{MQ}_{-it}$ represents average market liquidity level over all stocks in the same size group excluding stock i, $\overline{MFrag}_{-it}$ represents average market fragmentation level over all stocks in the same size group excluding stock i, $\overline{HFT}_{-it}$ represents average HFT intensity over all stocks in the same size group excluding stock i, $Log(mktcap)$ is the log normalized value of market capitalization, $Log(voltintra)$ is the log normalized value of intraday mid price range volatility, $invprice$ is the inverse of daily average price, $Log(size)$ is the log normalized average value of trade size , $Log(value)$ is the log normalized value of trading volume , indices ($_{mq}$), ($_{hft}$), ($_{frg}$) refer the respective estimates of the equations MQ_{it}/(1), HFT_{it}/(2) and $MFrag_{it}$/(3) respectively. The regression is based on a balanced panel of 132 stocks and 2240 days (January 2008–December 2016), have both time (monthly time dummy for each of the 36 months in each sub period) and stock fixed effects. Coefficient estimates are GMM (H3SLS), t-statistics shown in the parentheses below the coefficient . ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

$effective \quad half-spread$

	2008-2010			2011-2013			2014-2016		
	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$	$Log(MQ)_{it}$	$Log(HFT)_{it}$	$Mfrag_{it}$
	I	II	III	IV	V	VI	VII	VIII	IX
$Log(HFT)_{it}$	-0.251***			-0.253***			-0.221***		
	(-47.54)			(-45.09)			(-31.81)		
$MFrag_{it}$	0.239***			0.095***			0.01		
	-18.62			-9.94			-0.95		
$Log(\overline{MQ})_{-it}$	0.391***			0.477***			0.486***		
	-30.13			-31.7			-28.47		
$Log(mktcap)_{it}$	-0.222***			-0.25***			-0.231***		
	(-25.81)			(-28.15)			(-22.63)		
$Log(volintra)_{it}$	0.204***			0.175***			0.151***		
	-41.98			-56.27			-44.7		
$inv(price)_{it}$	19.067***			6.573***			46.527***		
	-16.63			-9			-16.81		
$Log(MQ)_{it}$		0.297***			0.297***			0.39***	
		-6.36			-6.46			-10.47	
$MFrag_{it}$		0.206***			0.304***			0.249***	
		-9.85			-10.57			-11.34	
$Log(\overline{HFT})_{-it}$		0.514***			0.587***			0.457***	
		-46.12			-55.7			-52.42	
$Log(mktcap)_{it}$		0.237***			0.175***			0.18***	
		-14.22			-10.42			-10.48	
rtk_{it}		-221.216***			-1006.162***			-875.426***	
		(-17.64)			(-30.09)			(-24.12)	
$Log(size)_{it}$		-0.618***			-0.314***			-0.517***	
		(-33.04)			(-24.33)			(-37.47)	
$Log(volume)_{it}$		0.527***			0.452***			0.552***	
		-42.38			-45.08			-66.02	
$Log(volintra)_{it}$		0.053***			0.041***			0.001	
		-5.87			-5.09			-0.15	
$Log(MQ)_{it}$			0.199***			0.105***			0.17***
			-15.88			-6.89			-13.73
$Log(HFT)_{it}$			0.212***			0.273***			0.382***
			-29.38			-35.21			-40.26
$\overline{MFrag}_{-it}$			0.685***			0.544***			0.557***
			-59.75			-36.63			-36.51
$Log(mktcap)_{it}$			0.2***			0.219***			0.357***
			-23.71			-19.94			-33.92
$Log(volume)_{it}$			-0.185***			-0.3***			-0.376***
			(-47.39)			(-75.46)			(-74.72)
$Log(volintra)_{it}$			-0.054***			0.01**			-0.011***
			(-12.48)			-2.53			(-3.28)
observations	97284	97284	97284	99528	99528	99528	98868	98868	98868
adjrsq	0.85			0.84			0.83		
adjrsq		0.92			0.93			0.95	
adjrsq			0.83			0.44			0.46

Table 18: The cross-market impact of high frequency trading and market fragmentation on liquidity: a simultaneous equations model estimation

This table presents the simultaneous equations model estimation for the system of equations (4)–(11) using the three-stage least squares methods for two liquidity measures: log normalized time weighted quoted spreads and log normalized volume weighted effective half-spreads. Indices i and t represent stocks and time (days) respectively, v represents one of the four venues: LSE, CHIX, BATS and Turquoise, HFT_{vit} represents the HFT proxy ($hft2$) developed on quotes update upto the fifth depth level, $HHItrd_{it}$ represents the market fragmentation proxy, $\overline{MQ}_{-vit}$ represents the average liquidity level over all stocks in the same size group excluding stock i at venue v, $\overline{HFT}_{-vit}$ represents the average HFT intensity at venue v over all stocks in the same size group excluding stock i, $ln(mktcap)$ is the log normalized market capitalization, $ln(voltintra)_{vit}$ is the log normalized intraday mid price range volatility, $invprice$ is the inverse of daily average price, $ln(size)_{vit}$ is the log normalized trade size, $ln(value)_{vit}$ is the log normalized trading volume, rtk_{vit} is the relative tick size. The estimation is based on a panel dataset of 149 stocks and 2060 days (October 2008–December 2016) and includes both time (the monthly time dummy for each of 99 months included in the panel) and stock fixed effects. Coefficient estimates are 3SLS , t-statistics shown in the parentheses below the coefficient. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Panel A presents the estimates for market quality equations (4–7) and Panel B presents those for HFT equations (8–11).

	I	II	III	IV	V	VI	VII	VIII
	$MQ_{vit} = Log(quoted \quad spreads)_{vit}$				$MQ_{(vit} = Log(effective \quad half-spreads)_{vit}$			
	Panel A							
	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$
$const$	4.134***	4.662***	3.876***	4.146***	3.241***	3.656***	3.198***	3.168***
	(198.68)	(211.7)	(150.98)	(165.36)	(159.75)	(168.25)	(128.16)	(128.45)
HFT_{vit}	-0.375***	-0.432***	-0.344***	-0.343***	-0.309***	-0.344***	-0.261***	-0.266***
	(-283.7)	(-320.37)	(-230.15)	(-231.81)	(-235.37)	(-255.86)	(-173.56)	(-177.83)
$HHItrd_{it}$	0.05***	-0.032***	-0.098***	-0.11***	0.056***	-0.036***	-0.1***	-0.103***
	(34.16)	(-18.69)	(-50.1)	(-57.85)	(36.05)	(-20.66)	(-50.53)	(-52.97)
$\overline{MQ}_{-vit}$	0.162***	0.186***	0.298***	0.274***	0.065***	0.125***	0.245***	0.233***
	(67.44)	(100.59)	(142.32)	(130.59)	(22.81)	(56.47)	(104.72)	(94.31)
$inv(price)_{it}$	13.148***	12.775***	15.018***	15.219***	15.8***	16.006***	17.75***	19.071***
	(61.9)	(52.1)	(52.66)	(54.88)	(70.04)	(61.86)	(60.31)	(66.32)
$ln(mktcap)_{it}$	-0.149***	-0.162***	-0.134***	-0.159***	-0.169***	-0.178***	-0.167***	-0.162***
	(-79.21)	(-76.77)	(-54.94)	(-67.11)	(-85.68)	(-81.85)	(-67.52)	(-66.14)
$ln(voltintra)_{vit}$	0.066***	0.028***	0.034***	0.026***	0.052***	0.02***	0.031***	0.02***
	(80.9)	(79.53)	(92.51)	(77.03)	(67.14)	(60.88)	(84.33)	(57.42)
	Panel B							
	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$
$const$	6.604***	6.242***	7.687***	7.957***	6.079***	5.684***	5.97***	6.213***
	(191.96)	(152.71)	(164.69)	(178.3)	(167.18)	(142.15)	(124.56)	(129.78)
$MQ_{(lse)it}$	0.077***	-0.477***	-0.634***	-0.726***	0.359***	-1.281***	-1.246***	-1.843***
	(6.08)	(-40.99)	(-47.13)	(-56.45)	(15.53)	(-67.39)	(-62.92)	(-93.2)
$MQ_{(chix)it}$	-0.561***	0.071***	-0.662***	-0.36***	-0.782***	0.608***	-0.636***	0.031**
	(-78.77)	(6.13)	(-62.59)	(-36.39)	(-64.93)	(37.05)	(-41.72)	(2.07)
$MQ_{(bats)it}$	0.199***	0.156***	0.328***	0.3***	0.308***	0.268***	0.944***	0.494***
	(47.63)	(31.4)	(38.4)	(52.52)	(52.37)	(41.17)	(81.08)	(62.73)
$MQ_{(turq)it}$	0.179***	0.302***	0.332***	0.181***	0.259***	0.518***	0.458***	0.831***
	(38.55)	(53.87)	(49.1)	(21.02)	(39.46)	(67.19)	(48.95)	(67.26)
$\overline{HFT}_{-vit}$	0.36***	0.434***	0.428***	0.413***	0.372***	0.445***	0.506***	0.488***
	(183.93)	(199.33)	(183.41)	(186.26)	(161.51)	(196.87)	(203.51)	(199.9)
$HHItrd_{it}$	0.145***	0.114***	0.152***	0.086***	0.151***	0.244***	0.274***	0.29***
	(51.67)	(35.75)	(38.93)	(23.18)	(41.19)	(60.71)	(56.82)	(61.17)
$ln(mktcap)_{it}$	-0.074***	-0.106***	-0.275***	-0.321***	0	-0.083***	-0.228***	-0.268***
	(-19.17)	(-24.99)	(-60.39)	(-75.61)	(-0.09)	(-19.23)	(-46.76)	(-57.15)
$ln(volume)_{vit}$	0.506***	0.492***	0.349***	0.393***	0.552***	0.531***	0.412***	0.458***
	(172.27)	(198.29)	(160.08)	(172.89)	(162.7)	(226.49)	(186.08)	(192.92)
$ln(size)_{vit}$	-0.536***	-0.51***	-0.349***	-0.332***	-0.6***	-0.522***	-0.374***	-0.377***
	(-125.84)	(-120.14)	(-102.07)	(-89.74)	(-98.16)	(-127)	(-108.02)	(-93.64)
$rtick_{vit}$	-203.879***	-199.162***	-2.578***	-1.168***	-296.621***	-193.904***	-2.476***	-1.018***
	(-62.46)	(-60.71)	(-7.63)	(-12.38)	(-46.92)	(-49.98)	(-6.94)	(-9.88)
$ln(voltintra)_{vit}$	0.011***	-0.015***	-0.006***	-0.007***	-0.005	-0.023***	-0.022***	-0.025***
	(5.28)	(-19.85)	(-9.92)	(-11.83)	(-1.53)	(-29.69)	(-31.38)	(-37.24)
observations	277563	277563	277563	277563	277563	277563	277563	277563
second-stage adj_Rsqr (MQ_{vit})	0.84	0.86	0.84	0.83	0.79	0.81	0.80	0.79
second-stage adj_Rsqr (HFT_{vit})	0.90	0.88	0.82	0.83	0.89	0.87	0.80	0.80
system weighted Rsqr	0.80				0.76			

Table 19: The cross-market impact of high frequency trading and market fragmentation on liquidity: a simultaneous equations model estimation for large stocks

This table presents the simultaneous equations model estimation for the system of equations (4)–(11) using the three-stage least squares methods for two liquidity measures: log normalized time weighted quoted spreads and log normalized volume weighted effective half-spreads. Indices i and t represent stocks and time (days) respectively, v represents one of the four venues: LSE, CHIX, BATS and Turquoise, HFT_{vit} represents the HFT proxy ($hft2$) developed on quotes update upto the fifth depth level, $HHItrd_{it}$ represents the market fragmentation proxy, $\overline{MQ}_{-vit}$ represents the average liquidity level over all stocks in the same size group excluding stock i at venue v, $\overline{HFT}_{-vit}$ represents the average HFT intensity at venue v over all stocks in the same size group excluding stock i, $ln(mktcap)$ is the log normalized market capitalization, $ln(voltintra)_{vit}$ is the log normalized intraday mid price range volatility, $invprice$ is the inverse of daily average price, $ln(size)_{vit}$ is the log normalized trade size, $ln(value)_{vit}$ is the log normalized trading volume, rtk_{vit} is the relative tick size. The estimation is based on a panel dataset of 74 large-cap stocks (above the median market capitalization stocks group) and 2058 days (October 2008–December 2016) and includes both time (the monthly time dummy for each of 99 months included in the panel dataset) and stock fixed effects. Coefficient estimates are 3SLS , t-statistics shown in the parentheses below the coefficient. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Panel A presents the estimates for market quality equations (6–7) and Panel B presents those for HFT equations (8–11).

	I	II	III	IV	V	VI	VII	VIII
	$MQ_{vit} = Log(quoted \quad spreads)_{vit}$				$MQ_{(vit} = Log(effective \quad half-spreads)_{vit}$			
Panel A								
	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$
$const$	4.221***	4.54***	4.203***	4.087***	3.617***	3.765***	3.527***	3.093***
	(163.13)	(181.53)	(150.67)	(150.65)	(144.1)	(148.97)	(131.66)	(111.24)
HFT_{vit}	-0.369***	-0.381***	-0.314***	-0.326***	-0.301***	-0.309***	-0.238***	-0.247***
	(-227.36)	(-263.81)	(-193.47)	(-215.16)	(-195.45)	(-216.11)	(-151.72)	(-160.68)
$HHItrd_{it}$	0.02***	-0.014***	-0.099***	-0.109***	0.018***	-0.014***	-0.091***	-0.097***
	(9.31)	(-6.33)	(-40.41)	(-44.86)	(7.83)	(-5.91)	(-36.15)	(-37.68)
$\overline{MQ}_{-vit}$	0.174***	0.143***	0.24***	0.232***	-0.059***	-0.01***	0.149***	0.16***
	(51.33)	(48.51)	(82.97)	(83.41)	(-13.56)	(-2.7)	(43.66)	(43.37)
$inv(price)_{it}$	14.125***	13.192***	15.231***	16.904***	16.078***	16.317***	16.835***	21.897***
	(53.81)	(48.39)	(49.3)	(57.79)	(57.03)	(55.27)	(53.46)	(66.47)
$ln(mktcap)_{it}$	-0.136***	-0.163***	-0.157***	-0.139***	-0.173***	-0.186***	-0.189***	-0.142***
	(-59.59)	(-70.89)	(-60.61)	(-55.03)	(-72.39)	(-75.48)	(-72)	(-52.14)
$ln(voltintra)_{vit}$	0.035***	0.024***	0.033***	0.019***	0.031***	0.012***	0.027***	0.013***
	(37)	(45.86)	(72.63)	(50.51)	(36.92)	(25.23)	(62.5)	(35.08)
Panel B								
	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$
$const$	7.711***	7.683***	6.998***	8.94***	7.323***	7.266***	5.594***	6.753***
	(199.54)	(169.58)	(106.49)	(165.22)	(176.9)	(170.08)	(88.76)	(106.82)
$MQ_{(lse)it}$	-0.078***	-0.184***	-0.336***	-0.639***	0.188***	-1.366***	-1.329***	-2.598***
	(-5.05)	(-11.65)	(-14.16)	(-31.7)	(4.57)	(-39.7)	(-26.33)	(-52.69)
$MQ_{(chix)it}$	-0.673***	-0.47***	-1.252***	-0.476***	-0.909***	0.272***	-0.918***	0.598***
	(-54.48)	(-28.07)	(-57.02)	(-24.91)	(-32.07)	(8.78)	(-21.55)	(13.98)
$MQ_{(bats)it}$	0.204***	0.07***	0.758***	0.447***	0.214***	0.079***	1.243***	0.478***
	(30.81)	(9.26)	(48.52)	(45.78)	(24.38)	(8.55)	(63.94)	(33.06)
$MQ_{(turq)it}$	0.118***	0.291***	0.37***	-0.214***	0.136***	0.541***	0.648***	0.886***
	(17.57)	(37.82)	(32.12)	(-16.36)	(13.15)	(47.71)	(36.96)	(37.51)
$\overline{HFT}_{-vit}$	0.318***	0.321***	0.393***	0.305***	0.316***	0.321***	0.408***	0.377***
	(145.44)	(128.84)	(125.62)	(113.83)	(127.62)	(136.3)	(128.72)	(121.32)
$HHItrd_{it}$	0.108***	0.045***	0.132***	0.009*	0.102***	0.14***	0.233***	0.224***
	(31.76)	(12.08)	(23.53)	(1.74)	(23.59)	(31.3)	(33.61)	(32.06)
$ln(mktcap)_{it}$	-0.118***	-0.139***	-0.169***	-0.311***	-0.087***	-0.16***	-0.106***	-0.236***
	(-27.21)	(-28.31)	(-25.32)	(-60.82)	(-14.63)	(-34.47)	(-15.11)	(-39.66)
$ln(volume)_{vit}$	0.457***	0.481***	0.43***	0.403***	0.492***	0.502***	0.49***	0.516***
	(160.28)	(169.02)	(128.73)	(139.82)	(165.8)	(209.32)	(160.74)	(153.96)
$ln(size)_{vit}$	-0.511***	-0.488***	-0.393***	-0.322***	-0.563***	-0.479***	-0.414***	-0.398***
	(-103.73)	(-93.43)	(-70.99)	(-62.56)	(-78.29)	(-98.48)	(-76.34)	(-66.04)
$rtick_{vit}$	-148.319***	-152.959***	-124.478***	-1.398***	-163.34***	-49.812***	-59.925***	-1.037***
	(-24.89)	(-23.38)	(-15.06)	(-4.87)	(-14.1)	(-6.87)	(-5.67)	(-3.22)
$ln(voltintra)_{vit}$	0.022***	-0.003**	-0.02***	0.001	0.02***	0	-0.033***	-0.02***
	(10.91)	(-2.38)	(-16.9)	(1.57)	(7.54)	(-0.1)	(-26.66)	(-21.78)
observations	147501	147501	147501	147501	147501	147501	147501	147501
second-stage adj_Rsqr (MQ_{vit})	0.80	0.82	0.79	0.82	0.78	0.78	0.75	0.78
second-stage adj_Rsqr (HFT_{vit})	0.90	0.88	0.79	0.82	0.89	0.88	0.79	0.78

Table 20: The cross-market impact of high frequency trading and market fragmentation on liquidity: a simultaneous equations model estimation for small stocks

This table presents the simultaneous equations model estimation for the system of equations (4)–(11) using the three-stage least squares methods for two liquidity measures: log normalized time weighted quoted spreads and log normalized volume weighted effective half-spreads. Indices i and t represent stocks and time (days) respectively, v represents one of the four venues: LSE, CHIX, BATS and Turquoise, HFT_{vit} represents the HFT proxy ($hft2$) developed on quotes update upto the fifth depth level, $HHItrd_{it}$ represents the market fragmentation proxy, $\overline{MQ}_{-vit}$ represents the average liquidity level over all stocks in the same size group excluding stock i at venue v, $\overline{HFT}_{-vit}$ represents the average HFT intensity at venue v over all stocks in the same size group excluding stock i, $ln(mktcap)$ is the log normalized market capitalization, $ln(voltintra)_{vit}$ is the log normalized intraday mid price range volatility, $invprice$ is the inverse of daily average price, $ln(size)_{vit}$ is the log normalized trade size, $ln(value)_{vit}$ is the log normalized trading volume, rtk_{vit} is the relative tick size. The estimation is based on a panel dataset of 75 small-cap stocks (below the median market capitalization stocks group) and 2048 days (October 2008–December 2016) and includes both time (the monthly time dummy for each of 98 months included in the panel dataset) and stock fixed effects. Coefficient estimates are 3SLS , t-statistics shown in the parentheses below the coefficient. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Panel A presents the estimates for market quality equations (4–7) and Panel B presents those for HFT equations (8–11).

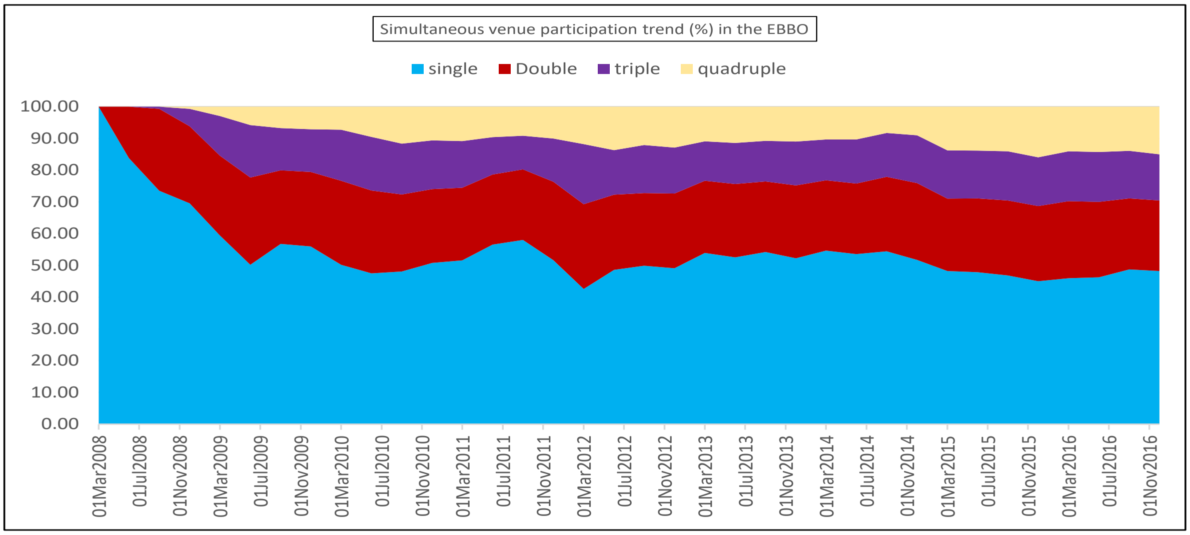
	I	II	III	IV	V	VI	VII	VIII
	$MQ_{vit} = Log(quoted\quad spreads)_{vit}$				$MQ_{(vit} = Log(effective\quad half-spreads)_{vit}$			
	Panel A							
	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$
$const$	4.333***	5.486***	4.398***	5.289***	3.311***	4.315***	3.771***	4.234***
	(124.24)	(134.9)	(91.27)	(115.87)	(97.39)	(111.59)	(80.82)	(97.37)
HFT_{vit}	-0.453***	-0.557***	-0.459***	-0.422***	-0.364***	-0.431***	-0.351***	-0.32***
	(-205.2)	(-227.73)	(-166.63)	(-152.8)	(-163.03)	(-178.48)	(-124.2)	(-114.83)
$HHItrd_{it}$	0.068***	-0.049***	-0.1***	-0.105***	0.071***	-0.063***	-0.12***	-0.111***
	(31.69)	(-18.14)	(-32.15)	(-35.5)	(31.8)	(-23.36)	(-37.87)	(-36.96)
$\overline{MQ}_{-vit}$	0.075***	0.119***	0.212***	0.166***	0.016***	0.069***	0.158***	0.121***
	(20.56)	(41.79)	(61.83)	(48.86)	(3.83)	(21.26)	(42.87)	(32.28)
$inv(price)_{it}$	10.013***	9.285***	13.389***	9.465***	13.21***	11.921***	15.391***	12.68***
	(29.04)	(20.96)	(25.5)	(18.8)	(35.38)	(26.41)	(28.64)	(25.19)
$ln(mktcap)_{it}$	-0.171***	-0.212***	-0.162***	-0.27***	-0.202***	-0.242***	-0.22***	-0.288***
	(-49.04)	(-49.97)	(-33.12)	(-57.68)	(-55.52)	(-57.28)	(-44.07)	(-61.44)
$ln(voltintra)_{vit}$	0.097***	0.028***	0.034***	0.028***	0.078***	0.021***	0.034***	0.02***
	(70.88)	(53.87)	(59.09)	(47.76)	(58.07)	(42.89)	(56.18)	(34.67)
	Panel B							
	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$
$const$	6.245***	5.603***	6.025***	5.471***	5.633***	5.151***	4.566***	4.121***
	(114.4)	(85.62)	(76.31)	(71.03)	(102.54)	(83.47)	(57.29)	(52.82)
$MQ_{(lse)it}$	-0.114***	-0.377***	-0.68***	-0.735***	0.325***	-0.811***	-1.232***	-1.593***
	(-5.61)	(-22.62)	(-34.61)	(-38.59)	(9.79)	(-34.23)	(-47.37)	(-61.43)
$MQ_{(chix)it}$	-0.41***	0.112***	-0.563***	-0.343***	-0.669***	0.361***	-0.645***	-0.202***
	(-49.55)	(7.19)	(-42.12)	(-27.1)	(-49.46)	(18.91)	(-35.27)	(-11.77)
$MQ_{(bats)it}$	0.151***	0.079***	0.326***	0.223***	0.255***	0.138***	0.853***	0.427***
	(28.59)	(11.43)	(24.83)	(27.27)	(35.07)	(16.41)	(52.23)	(41.78)
$MQ_{(turq)it}$	0.197***	0.318***	0.54***	0.649***	0.269***	0.517***	0.778***	1.242***
	(30.24)	(37.19)	(51.32)	(43.38)	(29.12)	(47.31)	(55.84)	(65.32)
$\overline{HFT}_{-vit}$	0.253***	0.378***	0.414***	0.406***	0.286***	0.401***	0.507***	0.471***
	(75.77)	(100.3)	(93.86)	(94.98)	(67.89)	(104.61)	(107.11)	(102.93)
$HHItrd_{it}$	0.171***	0.105***	0.181***	0.152***	0.159***	0.2***	0.325***	0.348***
	(41.7)	(21.25)	(29.48)	(25.79)	(29.5)	(33.61)	(43.67)	(47.75)
$ln(mktcap)_{it}$	-0.058***	-0.072***	-0.194***	-0.143***	0.032***	-0.054***	-0.154***	-0.087***
	(-8.89)	(-10.44)	(-23.86)	(-17.53)	(3.57)	(-7.86)	(-17.71)	(-10.13)
$ln(volume)_{vit}$	0.486***	0.484***	0.34***	0.422***	0.56***	0.502***	0.386***	0.455***
	(96.66)	(119.98)	(92.23)	(101.81)	(97.4)	(146.9)	(107.23)	(114.38)
$ln(size)_{vit}$	-0.476***	-0.463***	-0.326***	-0.385***	-0.557***	-0.459***	-0.349***	-0.415***
	(-78.2)	(-73.8)	(-63.54)	(-65.05)	(-69.74)	(-80.65)	(-68.8)	(-70.17)
$rtick_{vit}$	-171.337***	-175.994***	-2.463***	-1.273***	-270.638***	-182.192***	-2.613***	-1.162***
	(-45.1)	(-45.87)	(-6.52)	(-11.77)	(-37.32)	(-40.91)	(-6.57)	(-10.13)
$ln(voltintra)_{vit}$	0.028***	-0.018***	-0.012***	-0.023***	-0.016***	-0.022***	-0.026***	-0.035***
	(7.36)	(-18.69)	(-12.91)	(-23.87)	(-2.74)	(-23.17)	(-25.35)	(-33.5)
observations	127864	127864	127864	127864	127864	127864	127864	127864
second-stage adj_Rsqr (MQ_{vit})	0.70	0.76	0.70	0.72	0.66	0.71	0.6	0.68
second-stage adj_Rsqr (HFT_{vit})	0.80	0.74	0.58	0.60	0.78	0.74	0.53	0.55
system weighted Rsqr	0.7				0.63			

Table 21: The cross-market time-varying impact of high frequency trading and market fragmentation on liquidity: a simultaneous equations model estimation

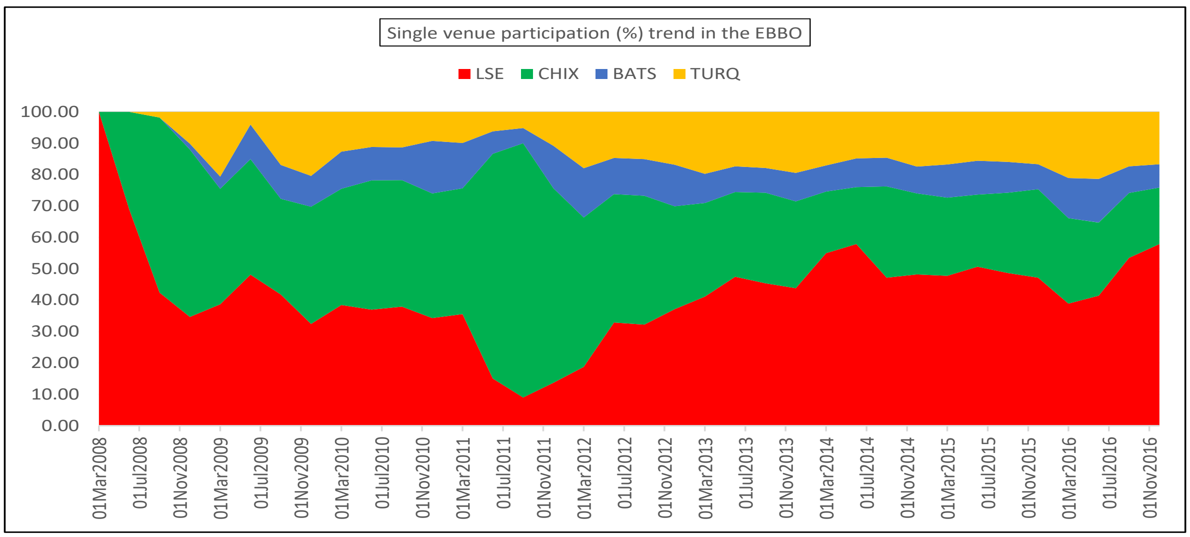
This table presents the simultaneous equations model estimation for the system of equations (3.1)–(3.8) using the three-stage least squares methods for two liquidity measures: log normalized time weighted quoted spreads and log normalized volume weighted effective half-spreads. Indices i and t represent stocks and time (days) respectively, v represents one of the four venues: LSE, CHIX, BATS and Turquoise, HFT_{vit} represents the HFT proxy ($hft2$) developed on quotes update upto the fifth depth level, $HHItrd_{it}$ represents the market fragmentation proxy. To conserve space, coefficients for $\overline{MQ}_{-vit}$, $\overline{HFT}_{-vit}$, $ln(mktcap)$, $ln(voltintra)_{vit}$, $ln(size)_{vit}$, $ln(value)_{vit}$, and rtk_{vit} are not presented. Estimations are based on three subsamples (2008–2010, 2011–2013 and 2014–2016) divided over the sample period with 149 stock each and include both time (the monthly time dummy for each months) and stock fixed effects. Coefficient estimates are 3SLS , t-statistics shown in the parentheses below the coefficient. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Panel A presents the estimates for market quality equations (3.1–3.4) and Panel B presents those for HFT equations (3.5–3.8).

	I	II	III	IV	V	VI	VII	VIII
	$MQ_{vit} = Log(quoted\ \ spreads)_{vit}$				$MQ_{(vit} = Log(effective\ \ half-spreads)_{vit}$			
Panel A								
	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$	$MQ_{(lse)it}$	$MQ_{(chix)it}$	$MQ_{(bats)it}$	$MQ_{(turq)it}$
2008-2010								
HFT_{vit}	-0.318***	-0.371***	-0.34***	-0.238***	-0.254***	-0.288***	-0.261***	-0.152***
	(-117.89)	(-146.07)	(-120.38)	(-80.5)	(-88.02)	(-110.07)	(-90.27)	(-50.96)
$HHItrd_{it}$	0.102***	0.034***	-0.047***	-0.096***	0.101***	0.008**	-0.056***	-0.098***
	(32.1)	(9.88)	(-11.07)	(-22.58)	(29.13)	(2.14)	(-12.74)	(-22.29)
2011-2013								
HFT_{vit}	-0.288***	-0.366***	-0.322***	-0.295***	-0.234***	-0.265***	-0.235***	-0.227***
	(-147.18)	(-155.96)	(-115.06)	(-103.92)	(-108.78)	(-112.89)	(-80.68)	(-77.5)
$HHItrd_{it}$	0.064***	-0.062***	-0.097***	-0.114***	0.065***	-0.066***	-0.115***	-0.107***
	(30.97)	(-24.35)	(-30.05)	(-35.07)	(28.83)	(-25.68)	(-34.77)	(-32.35)
2014-2016								
HFT_{vit}	-0.405***	-0.418***	-0.347***	-0.394***	-0.306***	-0.326***	-0.26***	-0.312***
	(-176.55)	(-207.51)	(-152.09)	(-202.31)	(-155.86)	(-164.86)	(-115.52)	(-161.38)
$HHItrd_{it}$	0.027***	-0.046***	-0.11***	-0.083***	0.016***	-0.058***	-0.117***	-0.09***
	(11.95)	(-18.79)	(-39.99)	(-34.44)	(7.27)	(-22.58)	(-41.65)	(-35.99)
Panel B								
	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$	$HFT_{(lse)it}$	$HFT_{(chix)it}$	$HFT_{(bats)it}$	$HFT_{(turq)it}$
2008-2010								
$MQ_{(lse)it}$	0.152***	0.125***	0.387***	-0.732***	0.858***	-0.204***	0.202***	-1.498***
	(4.57)	(4.13)	(9.23)	(-17.99)	(11.67)	(-4.44)	(3.17)	(-22.55)
$MQ_{(chix)it}$	-1.075***	-0.848***	-1.617***	-0.86***	-1.953***	-0.886***	-2.415***	-1.08***
	(-39.52)	(-23.7)	(-37.47)	(-20.91)	(-37.96)	(-16.68)	(-36.2)	(-16.1)
$MQ_{(bats)it}$	0.39***	-0.002	-0.002	0.546***	0.715***	0.036*	0.654***	0.921***
	(29.3)	(-0.1)	(-0.06)	(27.1)	(32.53)	(1.67)	(16.14)	(28.56)
$MQ_{(turq)it}$	0.235***	0.46***	0.576***	-0.041**	0.209***	0.773***	0.977***	0.865***
	(23.12)	(40.03)	(36.66)	(-2.05)	(12.4)	(45.59)	(39.21)	(26.1)
2011-2013								
$MQ_{(lse)it}$	0.611***	-0.225***	-0.927***	-0.495***	0.696***	-0.797***	-1.442***	-0.876***
	(23.67)	(-10.63)	(-35.84)	(-19.6)	(19.67)	(-23.91)	(-40.5)	(-23.6)
$MQ_{(chix)it}$	-0.474***	-0.059***	-0.065***	-0.015	-0.756***	0.366***	0.045	0.099***
	(-32.49)	(-2.77)	(-3.35)	(-0.79)	(-35.45)	(12.47)	(1.59)	(3.62)
$MQ_{(bats)it}$	0.067***	0.097***	0.688***	0.053***	0.138***	0.151***	1.035***	0.13***
	(8.93)	(12.5)	(47.26)	(5.52)	(15.48)	(15.6)	(63.52)	(11.13)
$MQ_{(turq)it}$	0.203***	0.23***	0.203***	0.416***	0.316***	0.379***	0.325***	0.689***
	(25.47)	(27.75)	(19.15)	(33.38)	(31.03)	(34.35)	(24.83)	(44.98)
2014-2016								
$MQ_{(lse)it}$	-0.058***	-0.105***	-0.375***	-0.161***	0.967***	-1.167***	-1.705***	-1.133***
	(-4.73)	(-7.09)	(-22.07)	(-10.27)	(25.1)	(-36.46)	(-54.34)	(-34.95)
$MQ_{(chix)it}$	-0.284***	0.4***	-0.421***	-0.312***	-0.584***	1.139***	0.092***	-0.04**
	(-37.09)	(26.65)	(-31.46)	(-26.52)	(-35.8)	(48.66)	(4.35)	(-2.24)
$MQ_{(bats)it}$	0.154***	0.07***	0.021*	0.153***	0.328***	0.218***	0.728***	0.349***

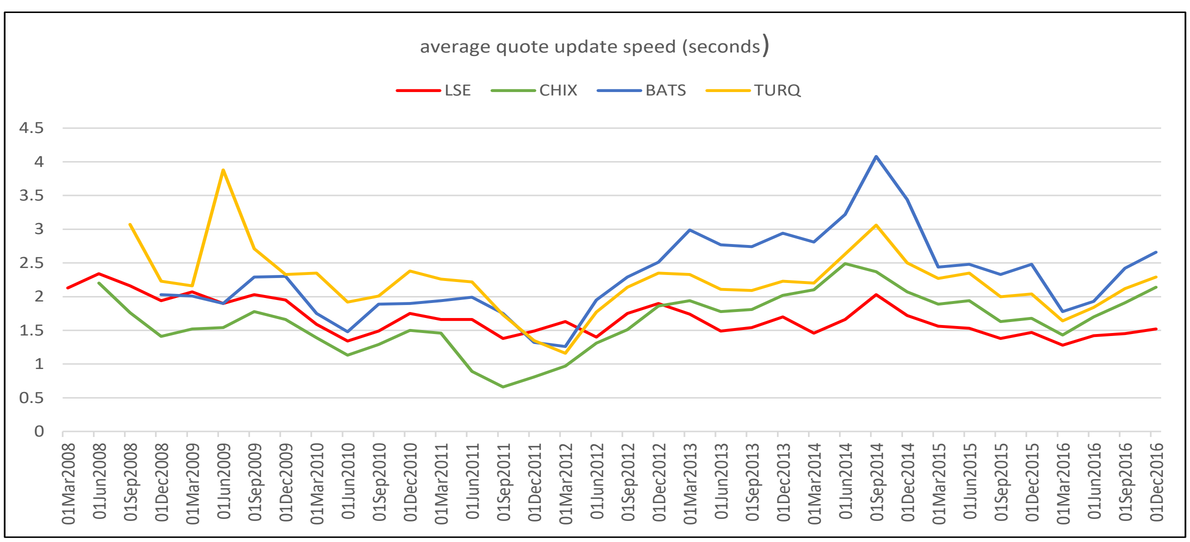
Figures



(a) The joint venue participation rate (% EBBO)



(b) The unique venue participation rate (% EBBO)



(c) The quotes update speed

Fig. 1: Cross-market trends of quotes update speed and venue participation rate in the EBBO

Figure 5: *After one partial order of the investor hits Chi-X and leads to a transaction, the co-located HFT then reacts by cancelling duplicate orders on other trading venues. Because HFT have invested in ultrafast connections to trading venues, these cancellations arrive at these trading venues before the remaining partial orders of the investor do.*

(a) Cross-market quote updating

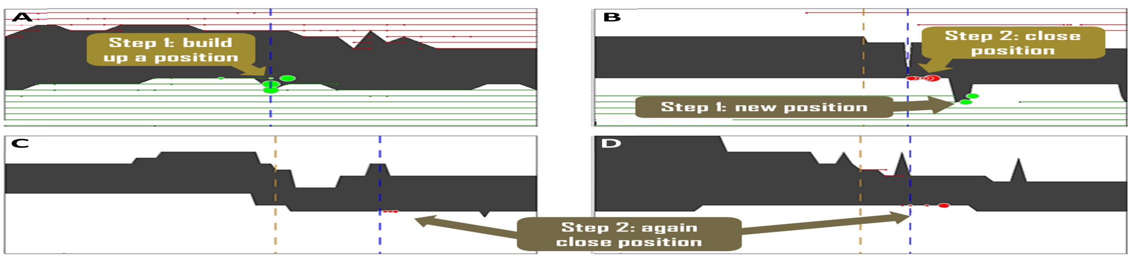


Figure 7a to 7d: *Cross-market trading visualization of one HFT firm. Each box shows the trading conduct of this HFT on one trading venue. The horizontal axis denotes time and the vertical axis the price (axis values not shown). The green/red bars represent buy/sell orders from start (left-hand side) to end (right-hand side), whereas the green/red dots represent buy/sell transactions. Larger dots represent larger sized transactions. We only show orders and transactions for the one HFT. The grey area represents the spread for the entire market. The blue, vertical lines in each box represent the time at which the HFT performs its first transaction on that specific trading venue. The orange vertical lines, on the other hand, represent the time of the first transaction over all trading venues (i.e., the first signal it can react to).*

(b) Cross-market trading visualization

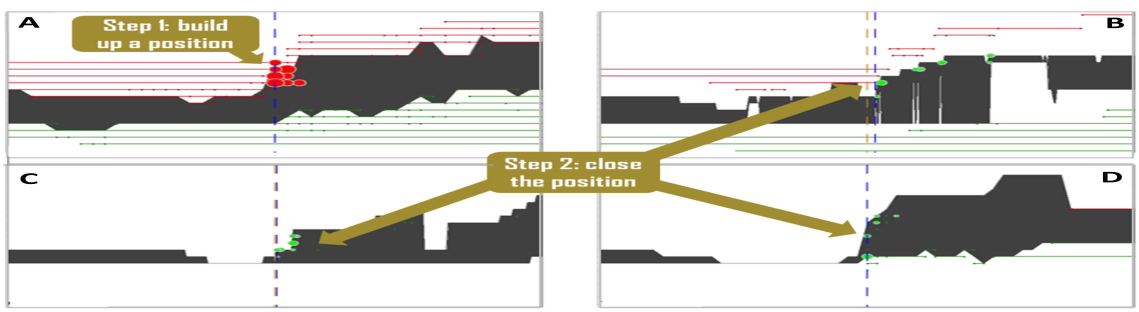


Figure 8a to 8d: *A more typical example (compared to the a-typical one in 7a to 7d) of HFT trading conduct. In Figure 8a the HFT passively builds up a position with the large investor being the counterparty. It then closes the position aggressively on other trading venues (Figures 8b to 8d), typically earning a few cents profit per share. There were no additional trades with the incoming (partial) orders of the investor.*

(c) Cross-market positioning

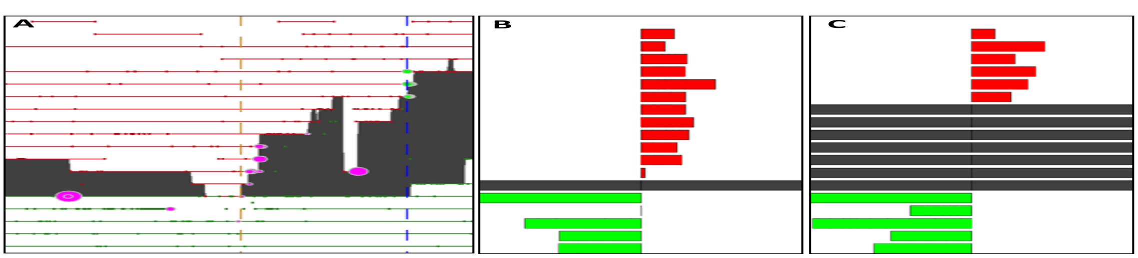
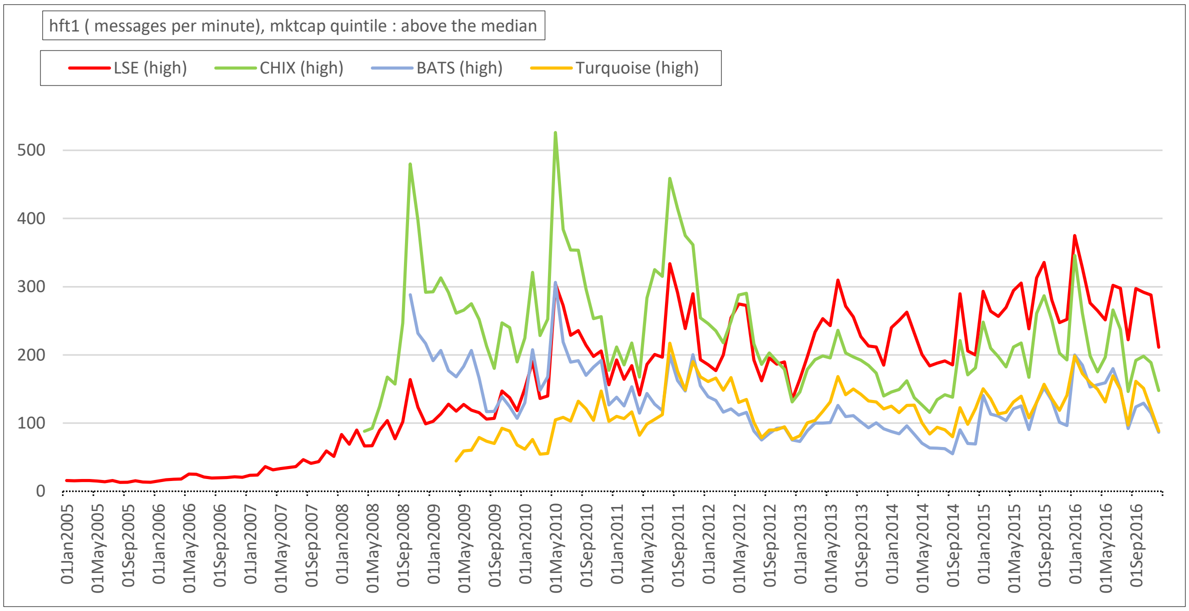


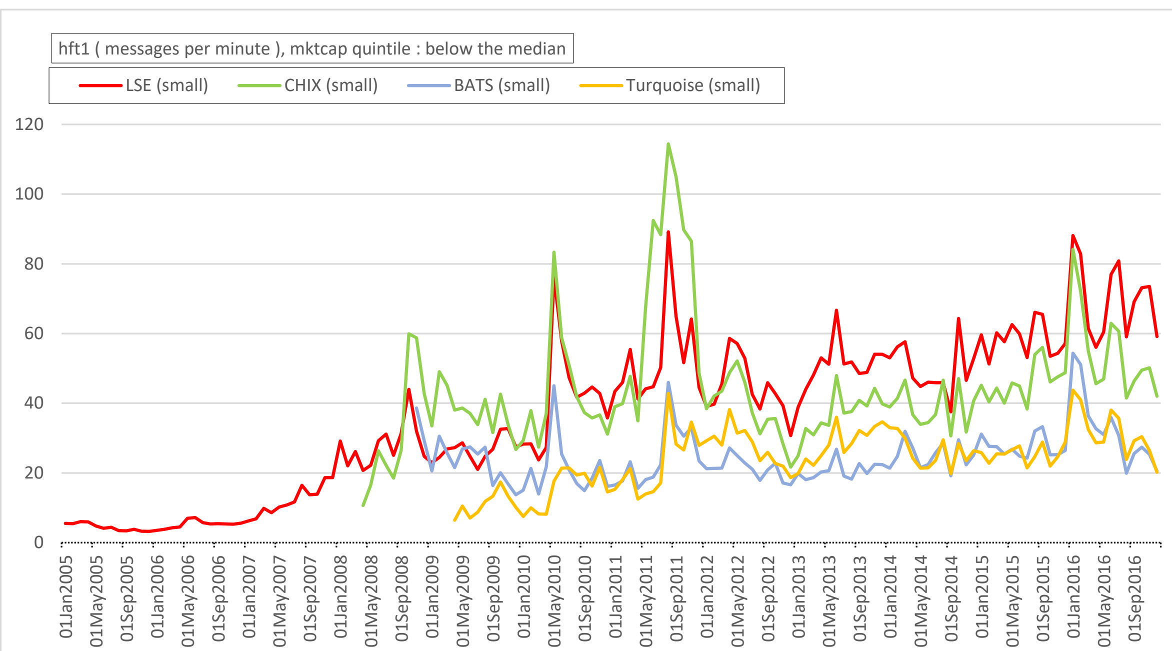
Figure 9a to 9c: *Figure 9a illustrates all orders and trades on one trading venue. The orange dotted line represents the time at which the first partial order of the investor is matched on another trading venue. The blue dotted line represents the exact time when the partial order of the investor hits this specific trading venue. The red/green bars represent sell/buy orders, from begin (left-hand side) to end (right-hand side). The purple dots represent trades by firms other than the investor, whereas the green dots represent the buy trades of the investor. Figure 9b and 9c respectively represent the order book during the orange dotted line and blue dotted line. Each bar represents the volume on a particular price level. The vertical axis denotes the price and the horizontal axis the volume. Red/green bars represent sell/buy liquidity, whereas the grey area represents the spread (which is similar to the grey area in Figure 9a).*

(d) Cross-market order matching time

Fig. 2: A typical HFT firm's market making across markets (source: The Netherlands Authority for the Financial Markets (2016))

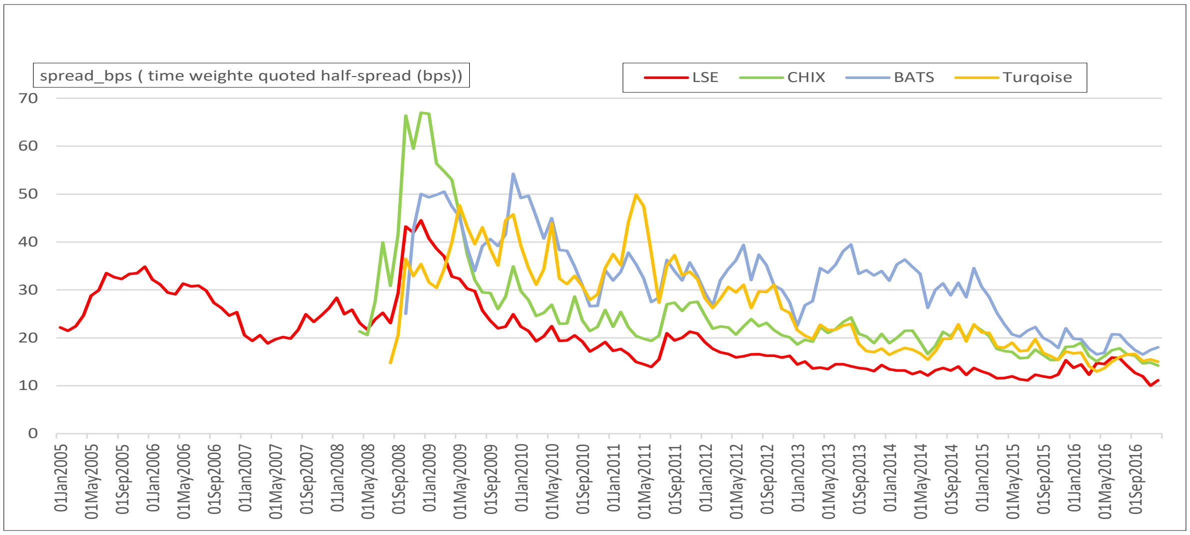


(a) Large stocks

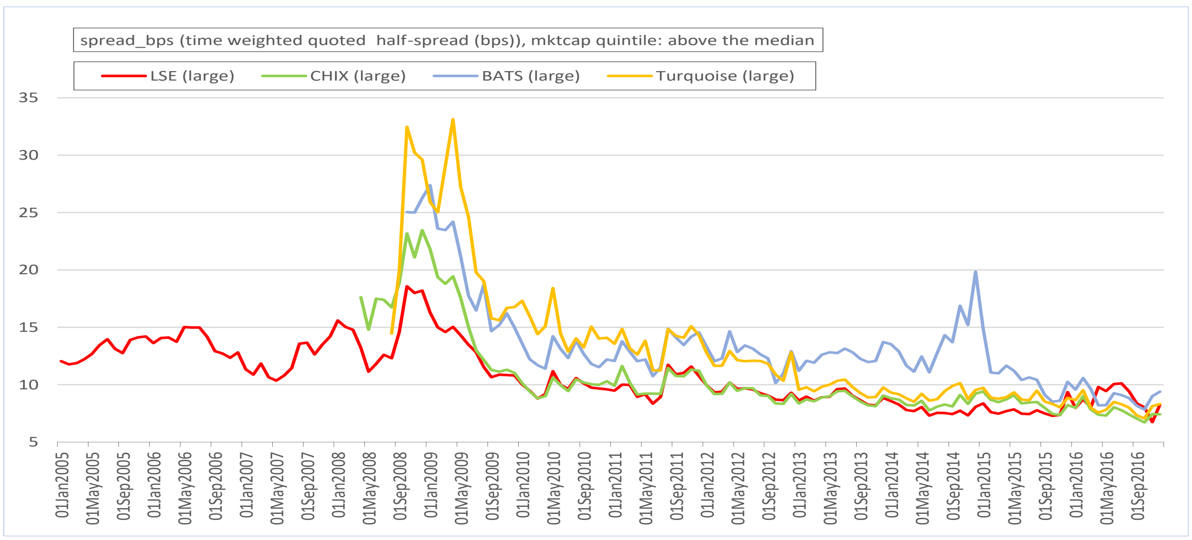


(b) Small stocks

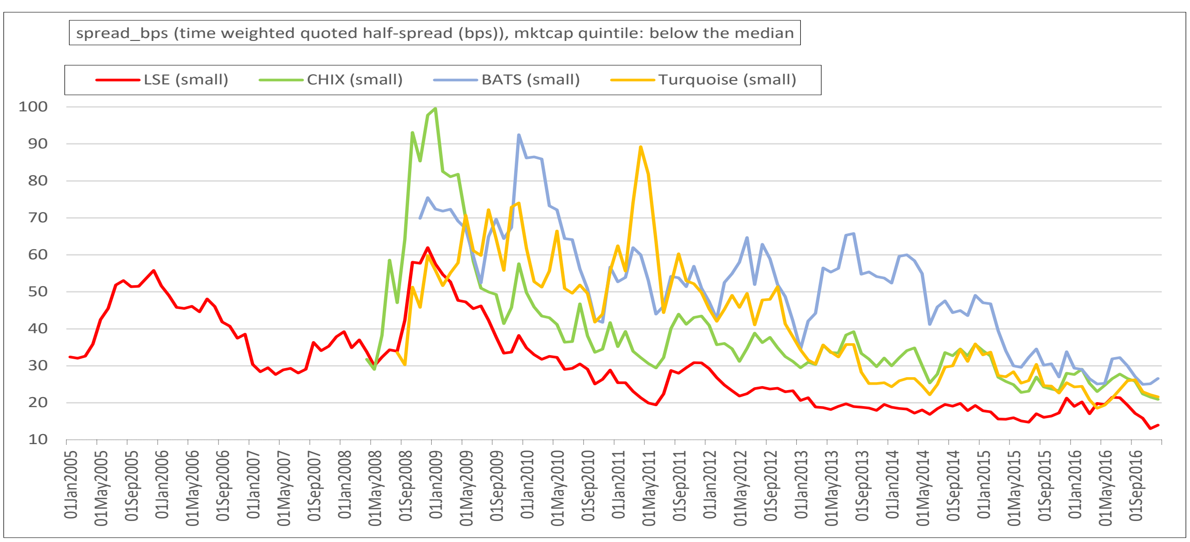
Fig. 3: Cross market trends in average electronic message rate per-minute (for the best 10 depth levels)



(a) All stocks

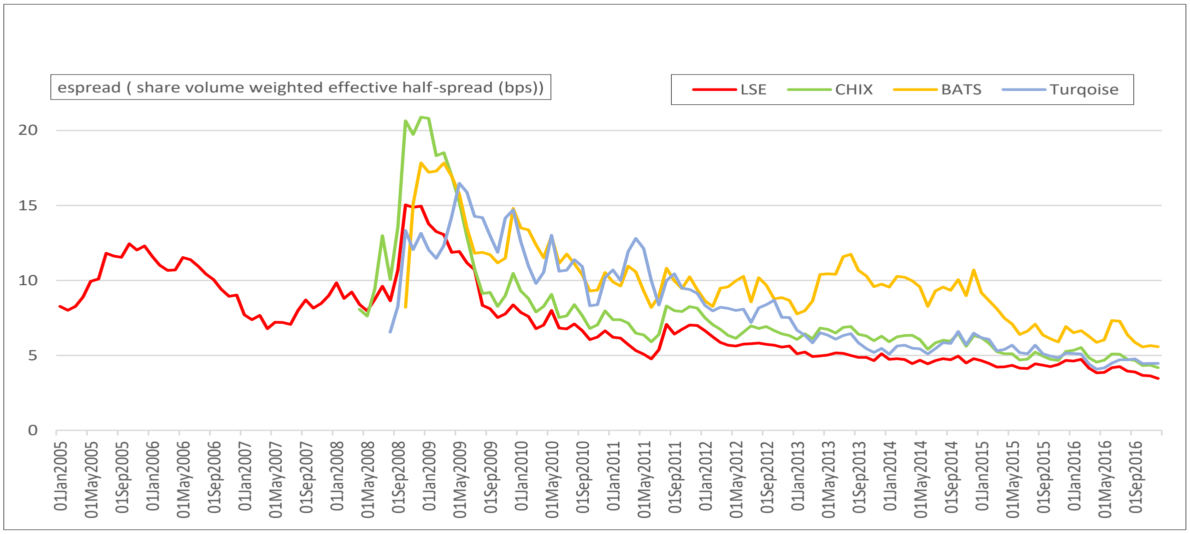


(b) Large stocks

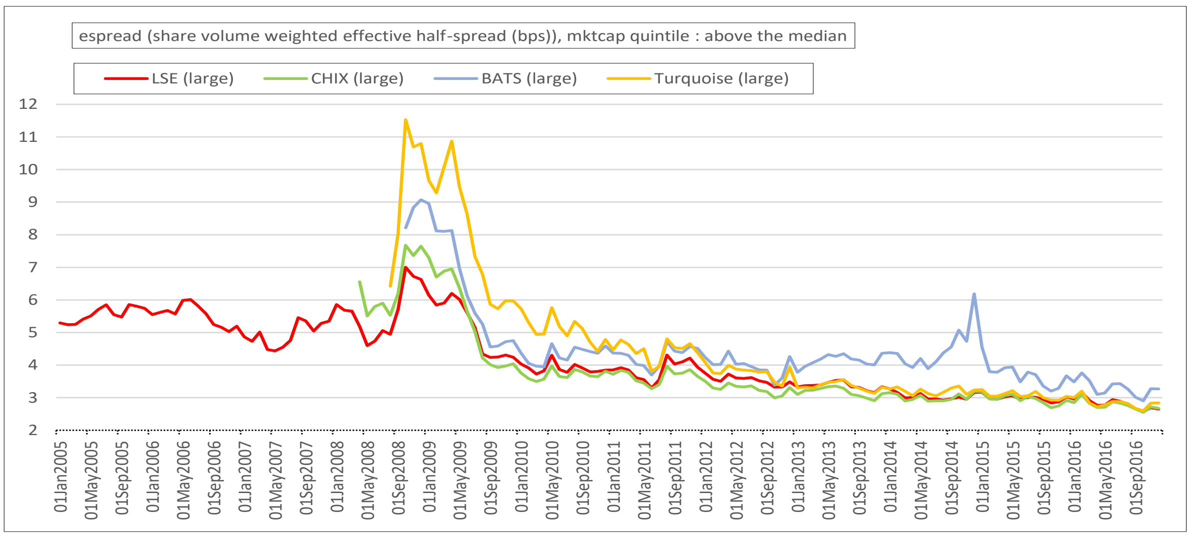


(c) Small stocks

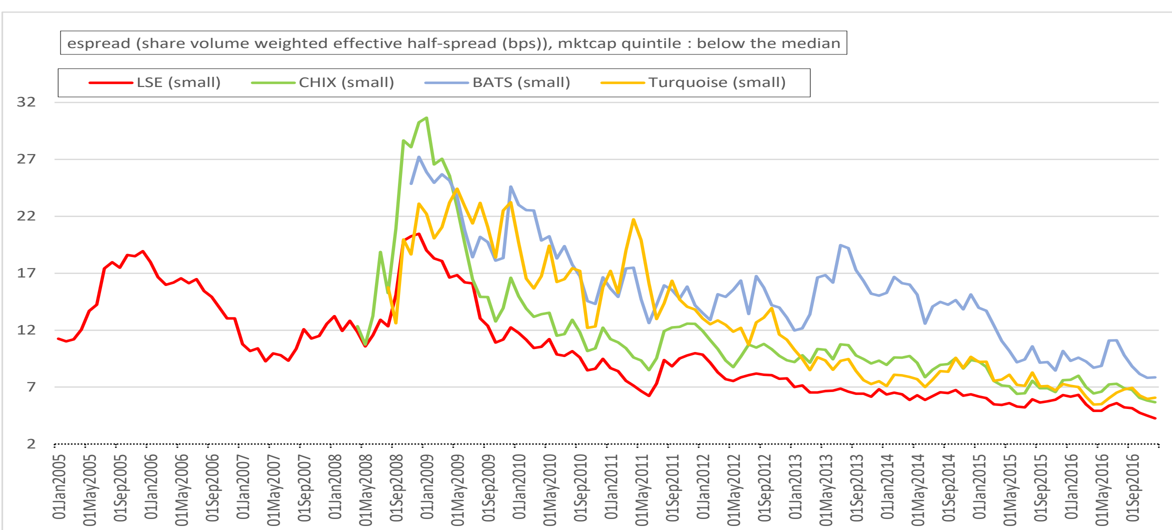
Fig. 4: Trends in time weighted quoted spreads across markets



(a) All stocks

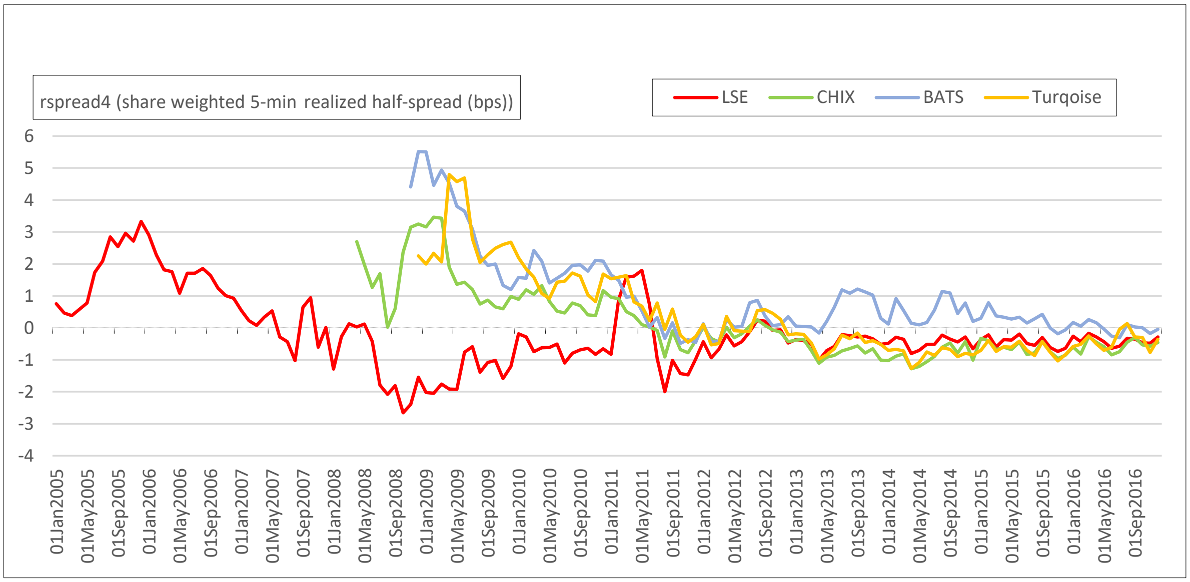


(b) Large stocks



(c) Small stocks

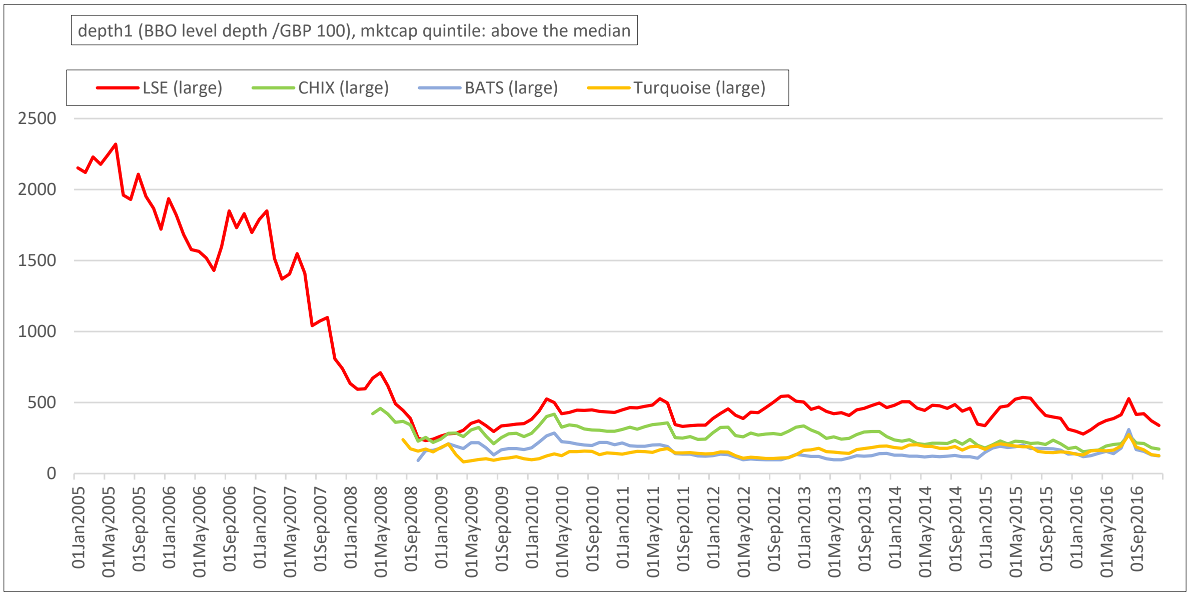
Fig. 5: Trends in volume weighted effective-half spreads across markets



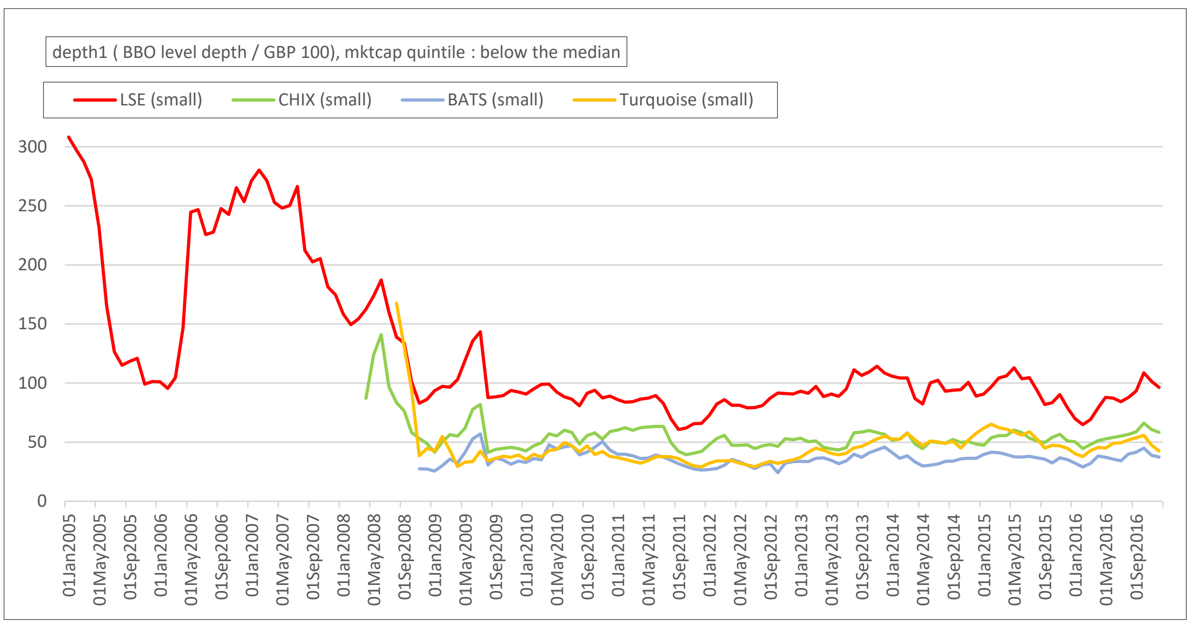
(a) realized half-spreads

(b) price impacts

Fig. 6: Trends in 5-minute realized half-spreads and price impacts across markets

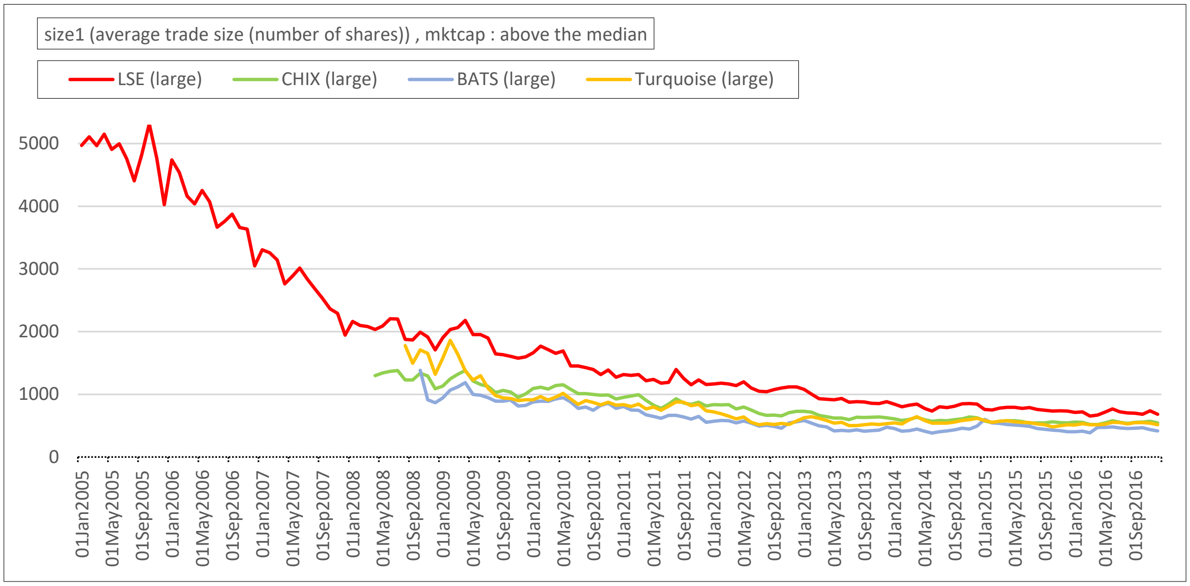


(a) Large stocks

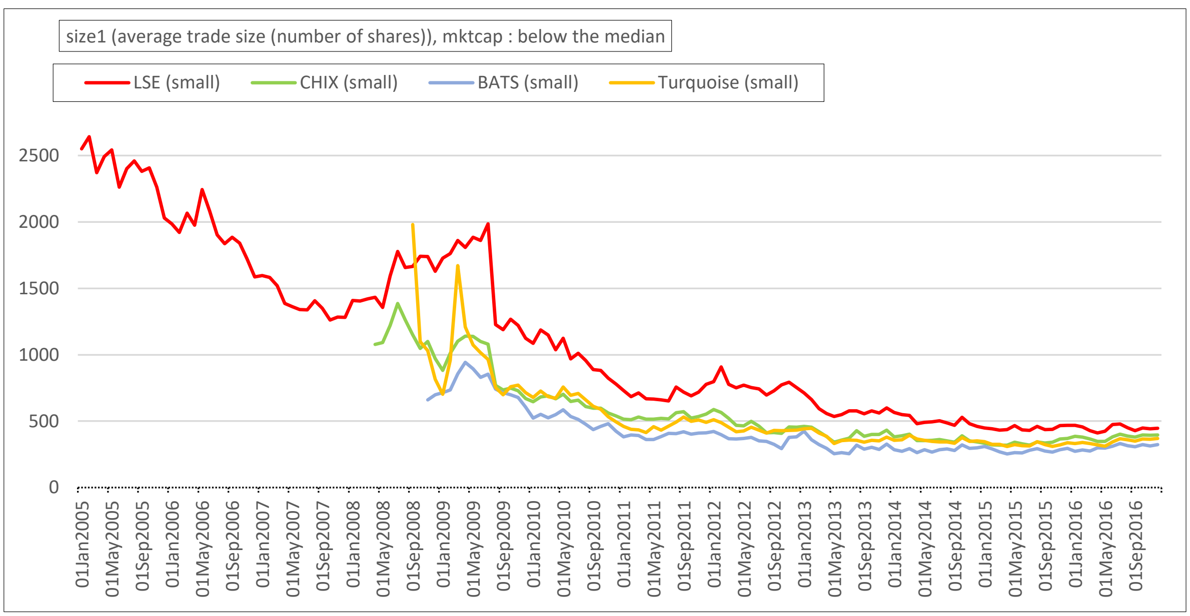


(b) Small stocks

Fig. 7: Trends in average quoted depths (GBP100) at best limit price across markets

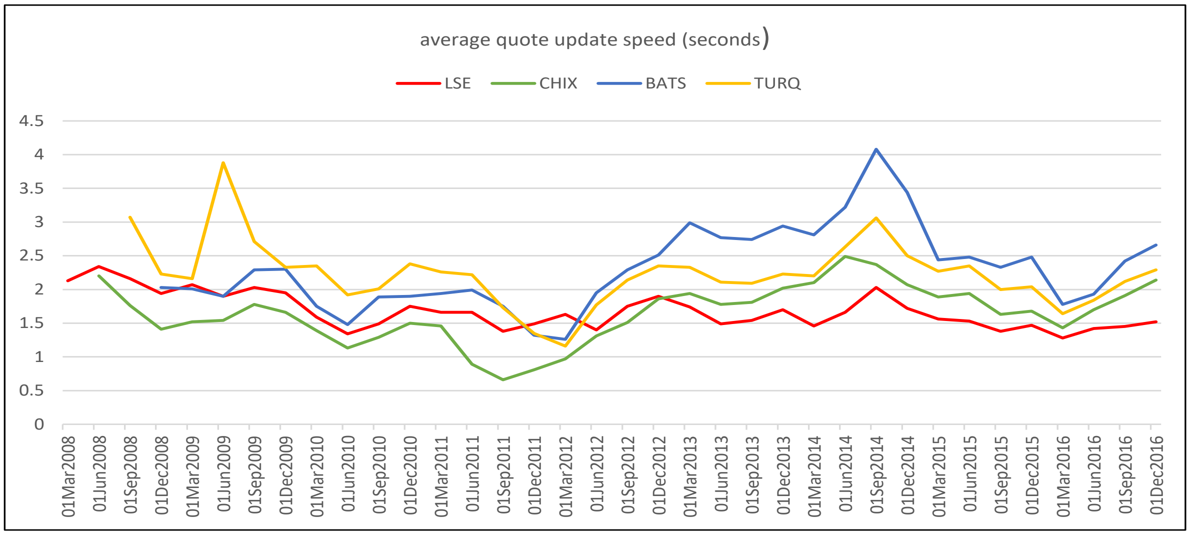


(a) Large stocks

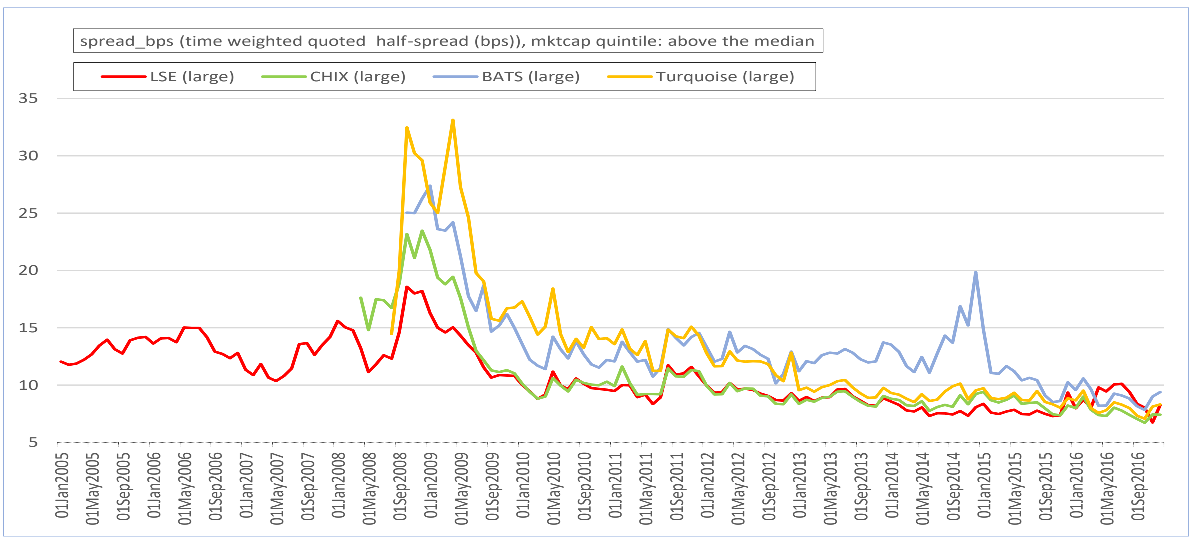


(b) Small stocks

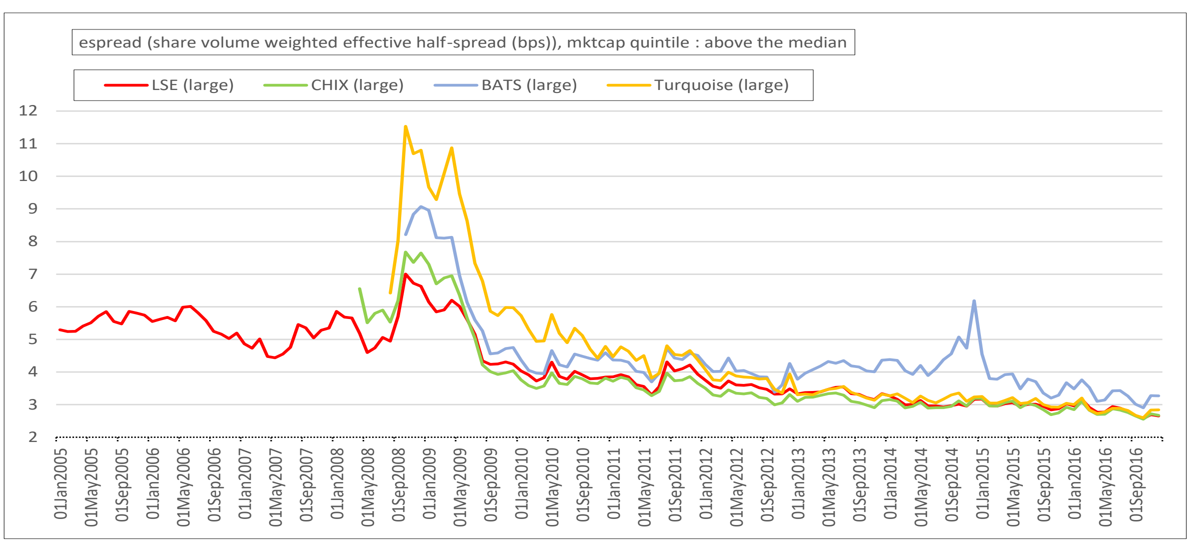
Fig. 8: Trends in average trade sizes (number of shares)



(a) Trends in quotes update speed



(b) The average quoted spread (large stocks)



(c) The average effective half-spreads (large stocks)

Fig. 9: Cross-market trends in speed competition and quoted spreads