SSE Riga Student Research Papers
2013 : 6 (154)

THE IMPACT OF HIGH FREQUENCY TRADING: SYSTEMATIC RISK IN EUROPEAN EQUITY MARKETS

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ISSN 1691-4643
ISBN 978-9984-842-73-8

November 2013
Riga

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May 2013
Riga

Abstract

High frequency trading (HFT) has grown considerably over the past few years and has become a controversial issue with many unanswered questions about its effects on financial markets. We are the first to provide evidence on HFT's impact on systematic risk. In this paper we use daily data on 12 European countries in the methodological framework based on Hendershott, Jones, and Menkveld (2011) and Karolyi, Lee, and Dijk (2012). We use the entry of Chi-X trading facility in Europe in 2007 as an exogenous market structure change that instruments for HFT activity. The main findings suggest that HFT increases systematic risk (both in returns and liquidity) in European equity markets. This causal relationship is more pronounced for less liquid and more volatile stocks, where HFT growth is relatively higher. In addition, we find that the effect on systematic risk is transmitted through market liquidity and price delay for returns and through market liquidity and market volatility for liquidity.

Keywords: High frequency trading, algorithmic trading, systematic risk, liquidity.

Acknowledgements

We are very grateful to our thesis supervisor Dr. Tālis Putniņš for his invaluable input in all stages of our thesis development; his guidance, advice and support kept us motivated. He also provided the extensive dataset that was a crucial component of the thesis.

We also want to thank our coursemates in the Stockholm School of Economics in Riga Kristaps Vasiļjevs and Dominykas Gruodis for their feedback and advice that helped us improve our paper.

We are thankful to our families for their support during our studies, and also the Stockholm School of Economics in Riga for the knowledge and skills that it has given us.

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1. Introduction

In recent years the nature of financial securities' trading has evolved due to technological development. Human traders face implications of emergence of a new trader type – computer algorithms, which are able to process and react to information much faster than humans. Computerized trading has been rapidly growing all around the world, and plays an increasingly important role in financial markets. The estimated share of algorithmic trading (AT) is around 40% of total European and 50% of total U.S. equities' trade orders (The New York Times Company, 2012; Stothard, 2012). This has substantial consequences on the financial system and market participants; therefore, investigation of effects and risks created is crucial to understand the modern world of financial securities' trading. This paper looks for new evidence on the impact of computerized trading.

The concept of algorithmic trading can be defined as trading done by a computer that is programmed with an algorithm, which places and manages orders for a trade of financial instruments. The algorithm automatically analyzes price, volume and holding period of the possible trade. A subset of AT is high frequency trading (HFT), which is conceptually similar, i.e., done by programmed algorithms, but has considerably higher trading speed generating a large amount of electronic messages, and HF traders hold a very limited amount of asset inventories for extremely short time periods (Cartea & Penalva, 2011). In general, HF traders engage in either liquidity provision or proprietary trading. Algorithms search for trading opportunities and earn from small security price movements that provide profits from large amounts of daily orders. HFT is a more controversial issue than AT, and concerns about a possible increase in risks have emerged; therefore, we examine the impact of HFT on systematic risk, which constitutes the non-diversifiable part of every stock's total risk and thus is a crucial concept in financial markets and relevant to every investor.

Not only market participants are interested in AT/HFT, but also serious academic interest has been attracted. However, current literature is not unanimous. Several scholars have found empirical evidence that AT activity is beneficial to markets. Hendershott, Jones, and Menkveld (2011), and Angel, Harris, and Spatt (2010) conclude that AT improves market liquidity. Hasbrouck and Saar (2012) and Brogaard (2011a) document that AT lowers spreads and volatility. AT can also improve price discovery (Brogaard, Hendershott, & Riordan, 2012; Riordan & Storkenmaier, 2011; Hendershott & Moulton, 2011). Meanwhile, another part of literature has examined the potential negative effects, which have alarmed regulatory bodies, e.g., liquidity evaporation, risk of adverse selection, and asset mispricing.

However, the majority of current studies on AT/HFT are limited to investigation of market quality measures, like liquidity, price discovery, and volatility. Existing literature contains scarce evidence on HFT's direct effect on systematic risks; there are even less studies on European markets, which are very interconnected and fragmented; in other words, a gap exists in the academic literature. Attention to HFT and systematic risk relationship is drawn due to several reasons, for example, HFT is associated with extreme systemic market events. Moreover, HFT strategies involve trading on asset mispricing across and within markets. This implies excessive cross and intra-market correlation of returns or liquidity, which could translate into higher systematic risk.

Evidently, the importance of HFT is growing and there are still many unanswered questions about the effects on financial markets, and especially systematic risk. The aim of this paper is to answer the research question: "What is the impact of high frequency trading on systematic risk in European equity markets?" We investigate whether during the time period of 2007-2009 European equity markets have experienced a change in systematic risk due to HFT activity, which we measure by looking at the change in commonality in stock returns (systematic return risk) and commonality in liquidity (systematic liquidity risk). We are among the first to perform an empirical analysis of this relationship and hence fill the gap in current literature.

To answer the research question, we use daily consolidated order books for 12 European equity markets. Our dataset is unique as it consolidates almost all trading platforms and off-market trades in each of the 12 countries chosen for analysis. It is more comprehensive than datasets used by other scholars, including papers on fragmentation in Europe, for example, Degryse, Jong, and Kervel (2011) and Gresse (2012). To examine the effect of HFT on systematic risk, we look at both risk related to returns and liquidity, and perform a quasi-experimental analysis based on the methodological framework of Hendershott et al. (2011), which apply instrumental variables regressions. Since data distinguishing trades initiated by humans or algorithms are very limited and not accessible for the selected sample, it is important to be able to identify HFT activity and find a robust proxy to measure it. The entry of Chi-X multilateral trading facility in European stock markets starting in 2007 is an exogenous market structure change that we use as an instrument to identify HFT activity, because the Chi-X trading platform is particularly designed to fit the needs of HF traders (Jovanovic & Menkveld, 2012). Given that the main indicator of HFT activity is increased electronic message flow, our main HFT proxy is the ratio of dollar trading volume to the number of electronic messages (Hendershott et al., 2011). Our systematic risk measures are commonality in returns and commonality in liquidity, which capture individual stock return and liquidity comovement with the market (Karolyi, Lee, & Dijk, 2012). We look at systematic risk within countries, different specification terciles and over time, and investigate what is the impact of HFT development.

We find that increased HFT activity leads to greater systematic risk both in returns and liquidity. The quotes of HF traders are more informed and timely, which leads to higher price adjustment speeds and common price factors, thus influencing systematic return risk. The effects are more significant for small and mid-trading volume stocks, in which HFT activity in our sample period grows most substantially. The effect on systematic risk in liquidity, similarly to returns, is also more significant for smaller volume terciles. We find that the effect on systematic liquidity risk is stronger for less liquid stocks with lower competition, which might be the result of HF traders acting as market makers and causing liquidity to co-move across stocks. Another explanation relates to market volatility, which transmits the effect of HFT to systematic liquidity risk. In state of high volatility, HF traders face inventory risk and trading behaviour becomes more correlated, facing the need to adjust their holdings.

This paper has several contributions. Firstly, it adds new empirical evidence to HFT literature about the relationship with systematic risk, which has not been directly studied yet, and also supplements the literature of computerized trading in general. Secondly, our paper is relevant for regulatory bodies, which are responsible for developing stable financial markets. Policy makers are questioning the nature of HFT and it has become a topic of intense discussions among regulators and professionals; hence, additional evidence would help settle this debate and propose appropriate regulations. Next, market participants also might be interested in our results, since they are directly affected by this new trader type; moreover, systematic risk cannot be diversified away and must be considered by every investor. Last but not least, our unique dataset with almost complete information on all chosen stocks together with the developed methodology gives an insight in European markets, which are relatively less covered in HFT literature.

The paper is organized in the following sequence. Section 2 presents the relevant literature and theoretical background. Information on data sample is provided in Section 3. Section 4 introduces the methodological framework. Section 5 describes the results. Additional analysis on the results is showed in Section 6. Section 7 is discussion of results. Section 8 presents conclusions of the paper. Appendices include relevant tables and figures.

2. Literature Review

This section presents the theoretical framework and evidence on systematic risk, and reviews the relevant literature on high frequency trading. We start with presenting the controversial nature of this topic, and then continue with explaining systematic risk and its measures. Further we present studies that report evidence on possible underlying mechanisms how HFT could increase systematic risk, approving the conceptual relationship that we investigate in this paper. Additionally, the viewpoint of industry and regulatory bodies is presented illustrating the importance of this issue and surrounding discussions.

2.1. *Controversies of HFT*

Attention to HFT has been drawn for a while now. Scholars have found diverse evidence about HFT, and the debate about whether it should be encouraged or restricted is not settled. It must be noted that extensive research has found that HFT is beneficial to financial markets. Academics that document positive effects look at various market measures. One of the most examined ones is liquidity. For example, Hendershott et al. (2011), Angel et al. (2010), Chaboud, Chiquoine, Hjalmarsson, and Vega (2011), Hasbrouck and Saar (2012), Menkveld (2012) suggest that AT/HFT increases liquidity. Furthermore, studies that look at price discovery and efficiency suggest that it is improved due to computerized trading (Brogaard et al., 2012; Riordan & Storkenmaier, 2011; Hendershott & Moulton, 2011). Malinova, Park, and Riordan (2012) find that HFT creates positive externalities and costs for traditional traders are decreased. Meanwhile, Hasbrouck and Saar (2012), Brogaard (2011a), Brogaard (2012) document a decrease in volatility.

Next to these studies that document positive effects from AT and HFT, several scholars have found evidence that HFT may be damaging to financial markets. Examples are worsened liquidity, higher volatility, information asymmetries, adverse selection, etc. An increasing number of scholars raise questions particularly about HFT effect on systematic risk in financial markets and suggest that it should be examined. For example, Foucault (2012) concludes his survey of AT stating that the effect on systematic risk is unclear and more work is needed.

2.2. *Systematic risks in financial markets*

To investigate what are the effects of HFT on systematic risk in European equity markets we look at two types of systematic risk; one is related to stock returns and the other to stock liquidity. We introduce terms systematic return risk and systematic liquidity risk and use this denotation further in our paper, which both in our research are treated as composing the overall systematic risk that we study.

Systematic return risk, commonly known as market risk, is the part of a securities return variance that is related to market variance. Systematic risk cannot be diversified away and investors are rewarded for bearing it; therefore, it is important to understand and investigate this concept (Dodds, Puxty, & Wilson, 1988; Martin & Senchack, 1990; Megginson, Smart, & Lucey, 2008; Taylor, 2007). Systematic risk in returns is treated also as commonality, i.e., individual stock's return comovement with the market return. There are several studies that examine commonality in returns. To mention a few, Bali, Brown, and Caglayan (2011) try to explain differences in hedge fund returns and find that their systematic risk measure is significantly correlated with variation in fund returns. Hasbrouck and Seppi (2001) analyze 30 stocks from the Dow Jones Industrial Average index and conclude that order flows and returns of these stocks have common influencing factors. Fama and French (1993), Haugen and Baker (1996) analyze U.S. stocks and document commonality in stock returns, observing cross-sectional variation in returns due to common risk factors. Moreover, a steady rise in stock return comovement during the last decade has been observed, indicating that systematic return risk has increased substantially in the U.S. financial market (Schutte & DeLisle, 2012). We attempt to discover whether HFT could have contributed to this increase.

Systematic liquidity risk is a similar concept and measures the covariance of stock's liquidity with market liquidity (Acharya & Pedersen, 2005). Such systematic liquidity is often referred to as commonality in liquidity, meaning that individual stock's liquidity is correlated and co-moves with market liquidity (Martínez, Nieto, Rubio, & Tapia, 2002; Hasbrouck & Seppi, 2001; Chordia, Roll, & Subrahmanyam, 2000; Huberman & Halka, 2001). Empirical literature proves the relevance of this concept. According to Acharya and Pedersen (2005), asset prices are affected by liquidity risk, and required returns of a security depend on commonality in liquidity. Pastor and Stambaugh (2003) document commonality in liquidity across stocks in the U.S. and conclude that market-wide liquidity is a source of risk and thus is priced. As described by Bai and Qin (2010), systematic liquidity risk is driven by correlated trading behaviour of investors. This applies to algorithmic trades, which are perceived to be more correlated than human trades (Chaboud et al., 2011). In particular, Boehmer, Fong, and Wu (2012) report that algorithmic trades influence systematic liquidity. Roll and Subrahmanyam (2010) document a substantial increase in liquidity skewness in recent years due to more competition in liquidity provision. Skewness can be used as a liquidity risk measure, and Ernst, Stange, and Kaserer (2012) find that asset total risk is undervalued if liquidity risk is disregarded. Since HF traders participate in liquidity supply, then an increase in risk due to HFT activity is plausible.

To draw conclusions about causal inference of HFT on systematic risk, we measure both commonality in liquidity and returns. From this follow:

Hypothesis 1: High frequency trading increases systematic return risk

Hypothesis 2: High frequency trading increases systematic liquidity risk

2.3. *How can HFT increase systematic risk?*

Existing literature has very limited evidence on HFT's impact on systematic risk directly. However, several factors inherent to HFT ground the logic behind this relationship. We present the three most relevant.

Firstly, a source of fragility is that HF traders rely on pre-programmed algorithms in trading decisions. Algorithms use public information in decision making process. It includes hard quantitative information on historical or real time market data and different types of news and announcements (Johnson, 2010). Zhang (2012) documents that algorithms are better at interpreting quantitative than qualitative information, because, first, it is harder for algorithms to comprehend soft information, and second, they are not able to detect possible mistakes or errors in the news. Therefore, instead of wrongfully reacting to soft information, they might withdraw from trading. Hence, fragility may increase, leading to more risk in the market. In addition, when HF traders operate in high volumes, non-high frequency (NHF) traders may misinterpret these signals, and this can cause speculative trading. In addition, Zhang (2010) reports that there is a positive correlation between stock price volatility and HFT, being more distinctive when markets are under stress, for example, when there are rapid volatility swings or unexpected price fluctuations. This leads to market overreaction to news when HFTs are actively participating. He concludes that overall HFT may be harmful to the U.S. equity market. Another study by Jarrow and Protter (2011) proves that HF traders increase volatility and earn profits by disadvantaging NHF traders.

Trading algorithms also have a possibility to contain small errors, which can lead to chaos in the market (Donefer, 2011). Such errors, which can create false trading activity, are hard to identify timely due to market fragmentation. This is because traders are able to place orders in several venues across different markets, making various HFT trading strategies difficult to capture. Donefer (2011) suggests that regulators should take actions to prevent systemic events caused by computerized trades.

Secondly, there are several mechanisms how HFT can create risks by negatively affecting liquidity in the market. One is that HF traders often use predatory trading strategies (Foucault, 2012; Hasbrouck & Saar, 2012). According to Brunnermeier and Pedersen (2005), predatory trading has a considerable impact on financial markets. It can cause price overshooting and decrease liquidation value for other market participants. Traders using this strategy often take away liquidity from the market, especially in turbulent times, and hence generate risk the market, because algorithmic trades are more correlated. This is justified by Chaboud et al. (2011) who study trading with algorithms in the foreign exchange market. They report that the amount of automated trading strategies is limited, because the underlying algorithms are pre-programmed and follow predetermined rules; thus, HF traders' behaviour might be similar. They exploit trading opportunities in microseconds while having a balanced position and low level of inventories. These are crucial factors for trading decisions of underlying algorithms. Furthermore, market fragmentation contributes to HFT expansion across markets, which creates cross-sectional correlations. This makes markets co-move together and become more interdependent (Forbes & Rigobon, 2002), which implies higher systematic risk.

Furthermore, HFT strategies are designed to duplicate trading activities of traditional market makers, which by definition are firms that "buy and sell a particular security on a regular and continuous basis (..), ensure that an investor can always trade a particular security" (Johnson, 2010; European Commission, 2011). This is consistent with Menkveld (2012) who characterizes HF traders as "modern market makers". The duplication effect is stimulated by HFT advantages of reduced latency due to co-location and direct data feeds, and also weak regulations for order disclosure, which indirectly promotes HFT by keeping their algorithm strategies unrevealed. The role of market makers might increase risk, because traditional market makers are obligated to maintain a buy/sell balance in the market, while HF traders are not. This allows them to suspend liquidity provision during unfavourable times and cause liquidity evaporation. Liquidity suppliers that exit the market worsen conditions for NHF traders (Arnuk & Saluzzi, 2009). Barnes (2010) approves this and states that the phenomenon of HF traders duplicating market makers can significantly damage market stability. This has been observed in the U.S. equity markets. Moreover, Arnuk and Saluzzi (2009) suggest that liquidity provided by HF traders is low quality, since there are no minimum share and quote time requirements.

The third factor of HFT relation with systematic risk is that HF traders can create systemic events that weaken the financial system and increase comovements, thus contributing to larger systematic risk. Financial markets have experienced several systemic events amplified by HFT. The most well-known is the so called Flash Crash in the U.S. on May 6, 2010, when financial markets experienced extreme volatility. Largest stock indices and other financial instruments dropped in price by approximately five percent within 30 minutes and bounced back quickly (Kirilenko, Kyle, Samadi, & Tuzun, 2011). For the Dow Jones Industrial Average this was historically the largest point drop in one day (Easley, Prado, & O'Hara, 2011). Kirilenko et al. (2011) examine the behaviour and activities of HF traders during May 6 and find that there was no change in behaviour; nevertheless, HF traders accounted for about one third of overall trading volume, which is a significant share for one trader type. In addition, to meet the close-to-zero inventory targets, HF traders executed trades aggressively and decreased liquidity in the market (Easley et al., 2011). Consequently, although HF traders did not cause the Flash Crash, they did magnify the downward price pressures, which boosted volatility even more and contributed to market turmoil.

2.4. *Regulatory and industry view*

Also regulators and financial industry participants are concerned. Regulatory bodies both in Europe and the U.S. engage in discussions about the potential effects of automated trading growth on financial markets and risk. In this review, we maintain our focus on Europe.

European Systemic Risk Board (2011), a central financial system supervisor, has stated that innovation and structural changes in the market should be treated with caution as it can create risks and affect stability of equity markets and the real economy. Concerns are expressed about HFT ability to transmit shocks across markets and cause systemic events. They state that this is done through two mechanisms, also emphasized in empirical literature; first, HF traders might stop liquidity supply and illiquidity could spread across markets. Second, HF traders employ cross-market arbitrage strategies and this might accelerate interdependence and correlations that make markets more fragile. The Board also advises further investigation of AT/HFT effects on risks in financial markets. In addition, in early 2010, The Committee of European Securities Regulators (CESR) released a report stressing that more evidence is needed on possible manipulations using AT/HFT (The Committee of European Securities Regulators, 2010a).

Industry members have different views on how HFT affects markets. After more than two years of the Markets in Financial Instruments Directive (MiFID) being in place, which is one of the main financial market regulations among European countries, CESR surveyed market participants on the recent technology developments, including HFT (The Committee of European Securities Regulators, 2010b). For instance, SIX Swiss Exchange points out that in the environment of fragmented markets, HFT is left without common supervision across markets (SIX Swiss Exchange, 2010). The Chartered Financial Analysts (CFA) Institute suggests enforcing broker-dealer risk management procedures to monitor HFT orders, and also internal risk mitigation procedures, which would help to avoid systemic risk (CFA Institute, 2010). Meanwhile, Chi-X Europe is more optimistic about HFT, stating that HFT strategies do not create systemic risk if effective controls and sufficient technological capacity of trading platforms are present (Chi-X Europe Ltd, 2010). Also Nasdaq OMX and NYSE Euronext have a positive outlook and state that HFT improves market quality and does not pose any risks (Nasdaq OMX, 2010; NYSE Euronext, 2010). Similarly, London Stock Exchange emphasizes that HFT brings net benefits (London Stock Exchange Group, 2010). Obviously, the opinions differ.

But looking at the future perspective, new evidence on HFT is still necessary and appreciated by regulators. Only four years since the enforcement of MiFID, the EU Commission has proposed, but not yet accepted, amendments that will revoke the current edition and give place for the so called MiFID II. Introduction of proper regulations for automated trading is among the main short-term and long-term goals of the new proposal. The suggested operational regulation would introduce a legal requirement for all HF traders to register as investment firms, which would make them subject to the rules of MiFID II. Furthermore, the proposal includes regulations that demand HF traders to have appropriate risk controls, and market operators to prevent system errors. The proposal offers a rule that obligates HF traders to provide liquidity on a continuous basis. If accepted, this obligation would counter one of the main concerns about HFT – liquidity evaporation.

Before these amendments in Europe-wide regulations have been accepted. New empirical evidence on several European markets can both suggest reducing or strengthening future regulation of equity markets. This proves why our research would be important for regulatory bodies.

Overall, academic literature has reviewed various issues regarding HFT and its potential damaging effects on markets, but the direct impact on systematic risk is still unknown. To our knowledge, this paper is the first to investigate this relationship directly and therefore add unique evidence to the existing body of literature about HFT and systematic risk.

3. Data

The data sample consists of daily trade and quote data for stocks that is constructed from hourly snap-shots of consolidated order books and hourly aggregates of trade and quote activity. The consolidated order book contains separate orders books merged for each hour and stock of every individual exchange. We aggregate the hourly data to stock-day observations. Order books are consolidated for 12 European countries separately: Austria, Belgium, Denmark, France, Finland, Germany, Italy, the Netherlands, Norway, Spain, Sweden and the UK[1]. The panel consolidates trading activity from each country's primary exchange or regulated market, further called home exchange, and also MTFs, systematic internalizers and off-market trades (complete list in Table 1, Appendix A).

We apply quasi-experimental research design and use instrumental variables regression. To do this, we need an exogenous instrument. Expansion of new trading venues in Europe caused an exogenous market structure change. Following Hendershott et al. (2011), we use this change to construct an instrumental variable (IV) to be able make causal inference on the relationship between HFT and systematic risk in European equity markets. In our analysis, the entry of Chi-X trading facility is the market structure change that is used as the IV. The sample period is from February 1, 2007, to February 28, 2009, which covers two months prior the first Chi-X entry in Europe, starting with the Dutch and German markets, and two months after Chi-X started to operate in Spain. The data are obtained from the Thomson Reuter Tick History (TRTH) database (Thomson Reuters, 2012).

The panel includes 1311 stocks and has 674,308 stock-day observations. Individual stock selection bases on several considerations. To be able to execute the intended methodology, the sample includes stocks that are traded on the Chi-X platform, and those that are not and will be used as a control group. Firstly, all stocks that have been traded on the Chi-X platform during the sample period are selected. Secondly, stocks sorted by country are ranked according to their aggregate trading volume during the sample period. Top 75 stocks in each country are selected and added to the stocks traded on Chi-X. Following Hendershott et al. (2011), outlier stocks with price above 1000 EUR are sorted away. It should be noted that the highest volume stocks mostly coincide with the stocks traded on Chi-X; however, that does not eliminate the control group of stocks in any of the countries.

[1] The decision for choosing the above listed countries is related to Chi-X trading platform's expansion, which is shown in Figure 4. The stock market of Switzerland is excluded from the initial sample because of data gathering problems; whereas, Ireland and Portugal were dismissed because in these two countries Chi-X entered considerably later, which would unnecessarily extend the sample period.

We exclude weekends and national holidays in each country. Additionally, if the trade or quote activity occurs before the official starting date of the Chi-X platform[2], all values are set to zero for the Chi-X data.

Observation for an individual stock contains hourly data on the number of electronic messages (defined as the sum of best bid and ask updates during the day, where an update is a change to the price of the best quote or the number of shares offered to buy or sell at the best quote), trading volume, midquote at end of interval, the number of executed trades.

Trading activity between 8:00am and 4:30pm GMT is recorded in the panel[3]. Moreover, quotes or trades that are more than 20% away from the price on the home exchange are excluded to avoid currency conversion flaws when performing consolidation and computation of variables. All variables are 99% winsorized within country, meaning that values smaller than 0.5% and larger than 99.5% of a particular country are set equal to the threshold level value.

4. Methodology

4.1. *High frequency trading measure*

One of the main obstacles for HFT analysis is that for most of historical market data there is no indicator distinguishing between trades and quotes initiated by algorithms (HF traders) or humans, the only available information is about the trade or quote itself (size, quantity, price etc.), but not about whether it was done by a human trader or a computer programmed with an algorithm. Only a few academics have conducted research on datasets which have flags identifying HF trades (Brogaard et al., 2012; Brogaard, 2012). It is not possible yet to gather a European-wide dataset with such properties.

We introduce proxies that use electronic message traffic to capture HFT. In a similar manner to Hendershott et al. (2011) and Boehmer et al. (2012) the first proxy $HFTvolume_{i,t}$ is constructed as the negative trading volume in 100 EUR over the number of messages. In other words, it is the negative euro volume per quote update:

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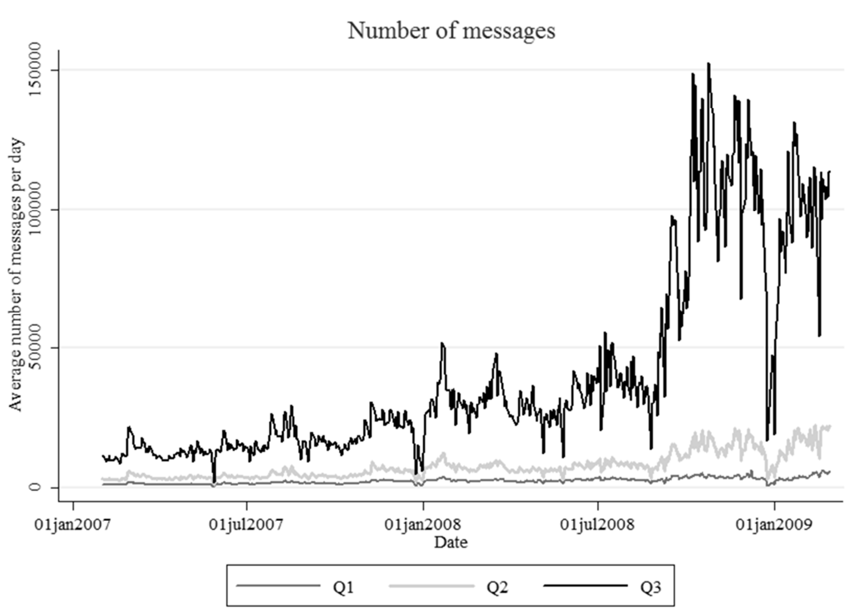
[2] In almost all countries some stocks started to trade on a test regime prior the official Chi-X opening date and therefore non-zero values of traded volume are observed.

[3] These trading hours capture most exchanges, except those having substantially different time zone, e.g., Tokyo. Although such exchanges do trade our sample stocks, consolidation is done in the European market and, when it is closed, trades are not included. Thus a rule is imposed to exclude exchanges that are +/- 3 hours beyond GMT.

$$HFTvolume_{i,t} = -\frac{dvol_{i,t}}{100*messages_{i,t}} \quad (1)$$

where i is a stock index, t is the trading day index, $dvol_{i,t}$ is the stock i day t consolidated trading volume, $messages_{i,t}$ denotes the stock i day t number of electronic messages. The intuition behind this measure is that the main indicator of HFT activity is increased message traffic, because computers are able to place orders at a very high speed and algorithms constantly search and exploit small trading opportunities; therefore, they submit huge amount of messages each day (see Figure 1).

Figure 1. Number of daily messages. The graph shows the average number of messages in all countries. Terciles are constructed by collecting stocks in each country that are divided according to total daily trading volume for the whole sample period. Tercile 1 (T1) consists of stocks with the smallest total daily trading volume.



Source: created by the authors using data from the TRTH database (Thomson Reuters, 2012).

Messages include order submissions, modifications, cancelations and trades. We normalize the message variable by trading volume in order to control for overall growth in trading in the market, and also focus our proxy particularly on the increase in order submissions, modifications and cancellations (because if a trade happened, it will be normalized by increase in trading volume and the overall ratio will not change), which comes only from HF traders.

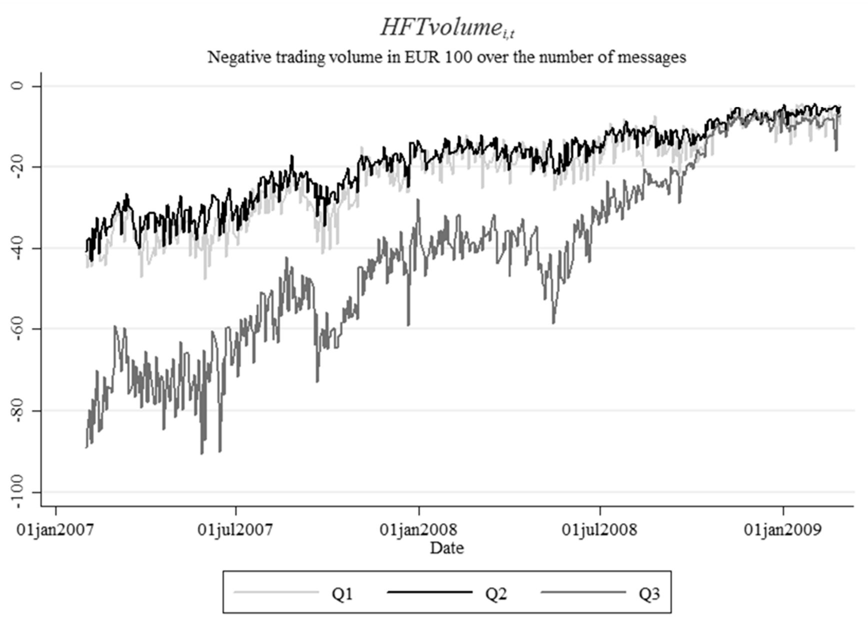
The second proxy for HFT is the number of messages divided by number of trades in each day:

$$HFTtrades_{i,t} = \frac{messages_{i,t}}{trades_{i,t}} \quad (2)$$

where $trades_{i,t}$ is the number of trades for stock i on day t. Since HF trades are electronically sent to trading venues and HFT computers have much higher capacity to submit messages, the observed change in message per trade ratio in recent years could not be driven by human initiated trading but is a result of HFT expansion.

Both proxies are calculated for home exchange and Chi-X separately, and also for the consolidated market. An increase in both of these ratios shows growth in the use of HFT (see Figure 2).

Figure 2. High frequency trading measure. This graph shows tercile specific values of our proxy for HFT – negative trading volume in 100 EUR over the number of messages, i.e., the negative euro volume per quote update.



Source: created by the authors using data from the TRTH database (Thomson Reuters, 2012).

These proxies capture the growth in HFT activity, which might be due to the change in the total proportion of investment firms using HFT, and any trend in strategy modification that leads to more intensified use of HFT, e.g., practice to split large orders into smaller to reduce market impact (Hendershott et al., 2011)

4.2. *Liquidity measures*

We have chosen the liquidity measure $LIQ_{i,t}$ developed by Amihud (2002) and applied by Karolyi et al. (2012) as the main liquidity proxy. It measures the stock price reaction to a 1 EUR change in trading volume. Amihud (2002) proves that the measure is strongly positively related to other commonly used microstructure liquidity estimates like bid-ask spread and price impact. Goyenko, Holden, and Trzcinka (2009) and Hasbrouck

(2009) report that Amihud's measure is a good liquidity estimator. Besides, by comparing higher frequency measures with monthly and annual measures, Goyenko et al. (2009) report that in the post decimalization period[4] correlation between effective spread and Amihud's measure, in contrast to other liquidity measures, has increased.

The measure is widely applied to capture systematic liquidity risk. Acharya and Pedersen (2005) document that stocks with higher average illiquidity have greater commonality with the market liquidity. Kamara, Lou, and Sadka (2008) investigate commonality in liquidity in U.S. stocks and use Amihud's measure, because it does not require intraday data and allows sample construction for a longer period.

To obtain our main liquidity proxy, first, the stock-day 1-hour bps consolidated midquote returns are calculated:

$$R_{i,t} = 10000 * log(\frac{MQ_{i,t}}{MQ_{i,t-1}}) \quad (3)$$

where $R_{i,t}$ denotes the stock i day t midquote return, $MQ_{i,t}$ is the stock's i midquote on day t, where midquote is defined as the average of bid and ask prices for stock i on day t, and $MQ_{i,t-1}$ is its lagged value.

Second, the Amihud's liquidity measure is computed as the consolidated midquote return per 1000 EUR traded consolidated volume:

$$LIQ_{i,t} = -log(1 + 1000 * \frac{|R_{i,t}|}{dvol_{i,t}}) \quad (4)$$

where $LIQ_{i,t}$ is the Amihud's liquidity measure for stock i on day t, $|R_{i,t}|$ is the absolute midquote return, $dvol_{i,t}$ represents daily consolidated trading volume. A constant is added to avoid problems on days with zero returns (Karolyi et al., 2012). It should be noted that we take the logarithm to make $LIQ_{i,t}$ more normally distributed. Then it is multiplied with -1 to reverse the formula and have a variable that is increasing in liquidity.

For robustness test trading volume is also used as a liquidity proxy. In addition, we compute another liquidity measure – relative quoted spread $SPREAD_{i,t}$ in bps, which is calculated for the consolidated order book:

$$SPREAD_{i,t} = 10000 * \frac{Ask_{i,t} - Bid_{i,t}}{MQ_{i,t}} \quad (5)$$

where $Ask_{i,t}$ and $Bid_{i,t}$ are the ask and bid prices for stock i on day t, respectively.

[4] In 2001 stock price quotations in dollar fractions were substituted with prices in decimals - dollars and cents.

4.3. *Market fragmentation measures*

An increase in the number of venues, where a stock is traded, makes liquidity more dispersed (Bennett & Wei, 2006). Amihud, Lauterbach, and Mendelson (2003) show that fragmentation might impose costs due to increased illiquidity. Therefore, to control for possible liquidity changes from increased market fragmentation, the dataset includes four market fragmentation proxies. $FR1_{i,t}$ represents the number of trading venues that have executed trades in stock i on day t. Its use is motivated by the intuition that the larger the number of venues, the more fragmented is the order flow. $FR2_{i,t}$ is the Herfindahl-Hirschman index (HHI) and is applied by Degryse et al. (2011) and Gresse (2012), who investigate market fragmentation effects on market liquidity in European markets:

$$FR2_{i,t} = 1 - \sum \left(\frac{dvol_{i,t}}{dvol_{m,t}}\right)^2 \quad (6)$$

where $dvol_{m,t}$ stands for the consolidated market daily trading volume. $FR3_{i,t}$ is similar to the second measure, except it is calculated using the number of trades instead of trading volume $dvol_{m,t}$. The last fragmentation variable $FR4_{i,t}$ is the euro volume market share of all venues other than home exchange; thus, it ranges in interval 0 to 1.

4.4. *Systematic risk measures*

Commonality measures are used to decompose systematic and firm-specific factors affecting returns and liquidity. Following Morck, Yeung, and Yu (2000), Hameed, Kang, and Viswanathan (2010), and Karolyi et al. (2012), we use commonality in returns and commonality in liquidity to draw conclusions about systematic risk. The former is observed by collecting monthly R^2 values from regressions of individual stock returns on market returns. Large R^2 value indicates a high degree of stock price comovement. This means that systematic risk is a large proportion of the total risk of the asset. The latter, commonality in liquidity, is captured by the R^2 of regression of individual stock's liquidity measure on country-wide liquidity. High R^2 value indicates large systematic liquidity risk. Acharya and Pedersen (2005) find that higher commonality in liquidity of a stock translates in greater stock's return sensitivity to market liquidity. Therefore, in our analysis we use both measures to evaluate the impact of HFT on systematic risk. Both measures are able to capture co-variation in returns and liquidity.

4.4.1. Commonality in returns

We collect R_r^2 values for stock i in month p, which represent the monthly measure of commonality in returns, from the following regression:

$$r_{i,t} = \alpha_i^r + \sum_{j=-1}^{1} \beta_{i,j}^r r_{m,t+j} + u_{i,t}^r \qquad (7)$$

where $r_{i,t}$ is the daily midquote return of stock i on day t from equation (1), $r_{m,t+j}$ represents the aggregate return in the country of stock i calculated as the equally weighted average of stock returns for all stocks in the country (except for stock i)[5], and $u_{i,t}^r$ is the error term. This regression is performed for each stock-calendar-month and collects up to 25 monthly observations for each stock.

4.5. *Commonality in liquidity*

Similar procedure applies for commonality in liquidity. In line with the methodology of Karolyi et al. (2012), we run regression (8):

$$LIQ_{i,t} = \alpha_i + \beta_i LIQ_{i,t-1} + \sum_{j=1}^{5} \gamma_{i,j} D_j + \omega_{i,d}^{LIQ} \qquad (8)$$

where D_j is a dummy for all working days of the week (differently from Karolyi et al. (2012), a control variable for turnover is not included because we do not study commonality in turnover). We include lagged liquidity of each stock in regression (8) to observe innovation in liquidity when measuring commonality; thus, these effects are filtered from stock's liquidity (Acharya & Pedersen, 2005). As a robustness test, we use alternative liquidity measures $SPREAD_{i,t}$ and $dvol_{i,t}$, and use them in regression (8). Regression (8) is used to predict residuals for the following regression to establish R_{LIQ}^2 as the measure for commonality in liquidity:

$$\widehat{\omega}_{i,t}^{LIQ} = \alpha_i^{LIQ} + \sum_{j=-1}^{1} \beta_{i,j} \widehat{\omega}_{m,t+j}^{LIQ} + \varepsilon_{i,t}^{LIQ} \qquad (9)$$

where $\widehat{\omega}_{m,t+j}^{LIQ}$ stands for aggregate residuals from regression (8) which is the equally weighted average of all individual stocks' residuals (excluding stock i) in each country. For robustness check, market measures are also calculated using trading volume weighting.

We include lag and lead value of respective market-wide measures in regressions (7) and (9) as per Karolyi et al. (2012) and Chordia et al. (2000). This is intended to capture any lagged adjustments in commonalities.

[5] It is done to avoid spurious relationship in case the stock has a large proportion in the index and correlation between dependent and explanatory variables.

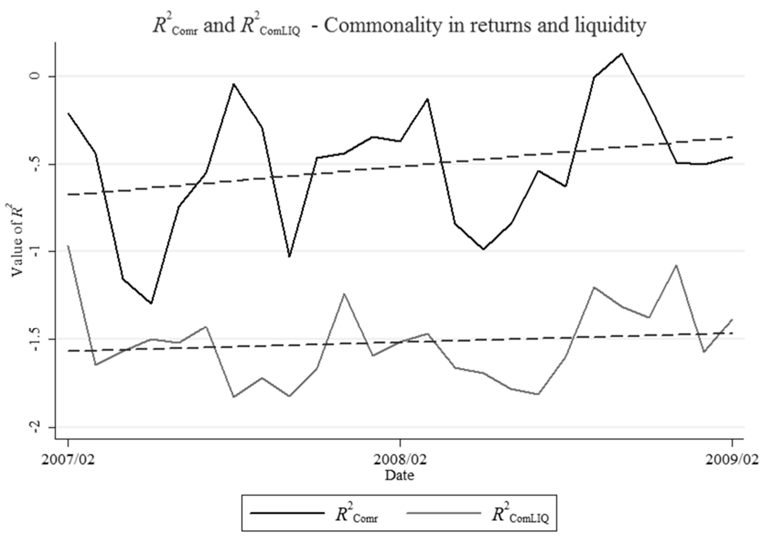
When constructing monthly R^2, the minimum number of daily observations used for estimation is 15. We use daily observations of non-overlapping months to control for serial correlation. Following Hameed et al. (2010), a robustness check is performed by repeating all our estimations of monthly R^2_{LIQ} for each stock using the change in liquidity instead of levels.

Since our commonality measure is the R^2 with value bounded in the interval [0,1], it has to be transformed before applied as a dependent variable in further regressions. Following Morck et al. (2000), Hameed et al. (2010) and Karolyi et al. (2012) we do logistic transformation of R^2 measures and depict them in Figure 3:

$$R^2_{ComLIQ} = ln(\frac{R^2_{LIQ}}{1- R^2_{LIQ}}) \qquad (10)$$

$$R^2_{Comr} = ln(\frac{R^2_{r}}{1- R^2_{r}}) \qquad (11)$$

Figure 3. Commonality measures. This graph depicts $\boldsymbol{R^2_{Comr}}$, which is our commonality in returns measure, and $\boldsymbol{R^2_{ComLIQ}}$, which is commonality in liquidity measure. These are equally weighted averages of monthly commonality measures of all sample stocks. Dashed lines show fitted values of each commonality measure.



Source: created by the authors using data from the TRTH database (Thomson Reuters, 2012).

As the figure shows, both commonality measures are fluctuating during the whole sample period, but the trend is upward sloping, indicating that commonality, or systematic risk, has increased. To measure commonality in returns and liquidity we use another metric, i.e., the beta coefficients from regressions (7) and (9), respectively (Hameed et al., 2010). The betas on lead, lag and contemporaneous market measures are summed for each stock-month to obtain the Dimson betas (Dimson, 1979) that are alternative commonality measures for returns and liquidity - β_{Comr} and β_{ComLIQ} .We use the summed betas further on in a similar manner to the R^2 measures.

4.6. *Systematic risk analysis*

To be able to analyze the causal relationship of HFT on systematic risk, we use quasi-experimental research design, which allows to estimate the treatment effect on stocks. A stock is treated if it is traded on the Chi-X trading platform. We use the differences-in-differences approach to make causal inference on the HFT impact on systematic risk by comparing the effect of increase in HFT between non-treated stocks, which do not trade on Chi-X in the sample period, and the treatment group – stocks that are traded on Chi-X.

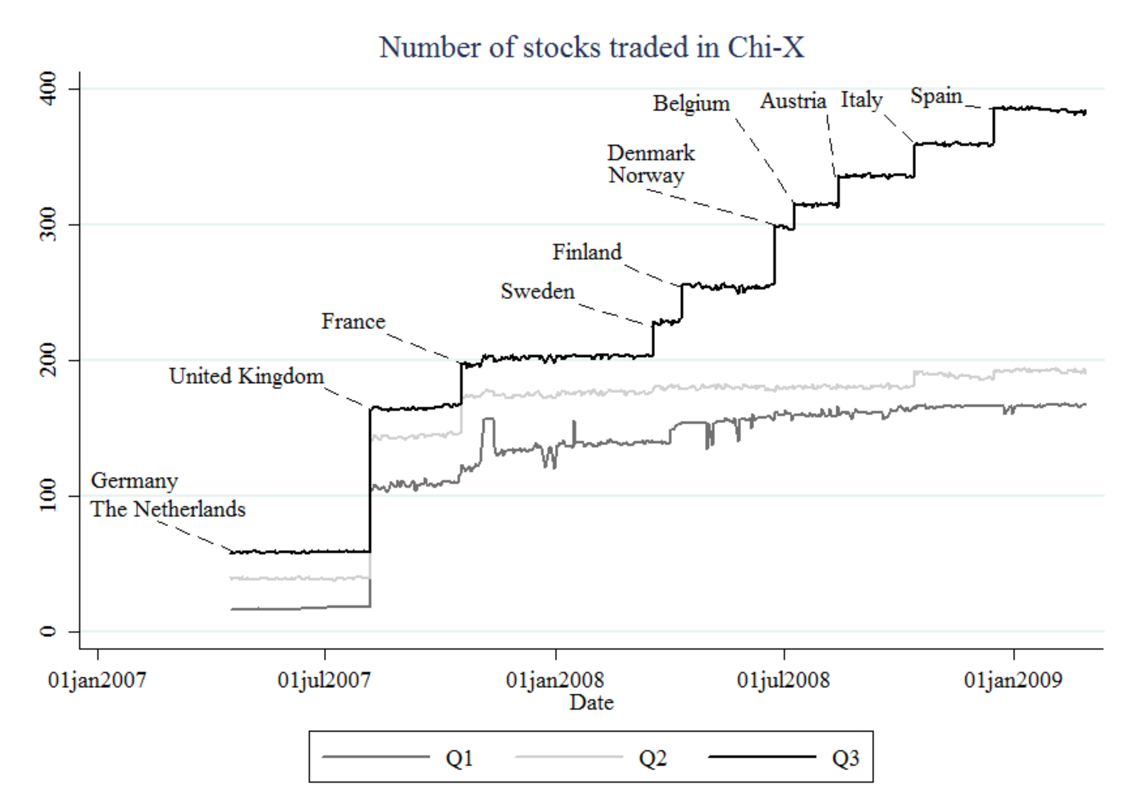
4.6.1. Chi-X trading platform – our instrument

The entry of Chi-X trading platform in European equity markets is a change in market structure, and is used as the source for an exogenous increase in HFT. Hence, we perform instrumental variables regression, where the Chi-X entry is used as the instrument that allows to identify HFT activity and prevents having a spurious relationship.

For the Chi-X entry to be a valid instrument it has to be exogenous and relevant, i.e., it cannot be correlated with error terms of regressions (7) or (9), and it has to be related to an increase in HFT. We test for instrumental relevance using first-stage F-statistic, which tests the null hypothesis of the coefficient on our instrument being zero, i.e., not entering the first stage regression. Logically, the Chi-X platform's infrastructure allows both HF and NHF traders to benefit from using it; however, HF traders have relatively higher value of using Chi-X instead of home exchange, if compared with NHF traders. Therefore, Chi-X should conform to the relevance condition, because the new platform will attract HF traders more than NHF traders; hence, Chi-X is directly related to an increase in HFT.

The staggered inclusions of stocks in Chi-X are essential for the differences-in-differences approach. Figure 4 shows the sequence by country how Chi-X entered in Europe and the total number of stocks traded on the platform.

Figure 4. Stock inclusion in the Chi-X platform. The graph provides an overview of staggered Chi-X introduction to European markets. It shows the number of stocks traded on Chi-X on each day during the sample period divided according to terciles (T1 – smallest trading volume by country).



Source: created by the authors using data from the TRTH database (Thomson Reuters, 2012).

Meanwhile, the requirement of exogeneity is more of an expert judgement. Similarly to our study, when applying the autoquote as an instrument, Hendershott et al. (2011) argue that this market structure improvement cannot directly affect liquidity through NHFT, because NHF traders do not exploit the benefits of the millisecond-level improvements. For the exogeneity condition to be satisfied, the Chi-X entry must not directly determine our systematic risk measures. In the context of our research, we see it as a plausible argument that there should not be any mechanism how introduction of Chi-X could directly contribute to systematic risk, as only through the expansion of HFT. Even if the decision of including some stocks in Chi-X earlier than others or not including at all is based on the stock's commonality with the market or other stock-specific properties, this will be captured by stock fixed effects and other control variables.

To execute the established methodology and draw conclusions about the impact on systematic risk, the Two Stage Least Squares (TSLS) model is applied. In the first stage we do the differences-in-differences analysis of the treatment and control groups, and obtain our

HFT proxy using the entry of Chi-X as an instrumental variable that identifies HFT activity. Then we use our HFT proxy in the second stage of the TSLS model and test what is the impact of HFT on our commonality measures, in other words, obtain evidence on the causal relationship between HFT and systematic risk. All variables used in the analysis are listed and explained in Table 2 (Appendix A).

4.6.2. First stage

The first stage regression in the TSLS model is as follows:

$$HFT_{i,t} = \alpha_i + \gamma_t + \beta CX_{i,t} + \varphi CV_{i,t} + \theta FR_{i,t} + \varepsilon_{i,t} \qquad (12)$$

where $HFT_{i,t}$ is the daily proxy of HFT for stock i on day t, either $HFTvolume_{i,t}$ or $HFTtrades_{i,t}$, α_i is stock i fixed effects (dummy), γ_t– time t fixed effects (dummy), $FR_{i,t}$ – one of 4 possible fragmentation proxies used as a control variable, $CV_{i,p}$ is a vector of control variables. It includes such measures as the daily trading volume, volatility and 1/midquote. $CX_{i,t}$ is a dummy variable for stock i on day t. $CX_{i,t}$ is equal to zero on days without message activity on Chi-X for the particular stock, and equal to one on days with message activity, $\varepsilon_{i,t}$– is the error term. We include exogenous control variables to pick up systematic differences between treatment and control groups (Stock & Watson, 2003).

4.6.3. Second stage

The second stage regression is as follows:

$$SR_{i,p} = \alpha_i + \gamma_p + \beta \widehat{HFT_{i,p}} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p} \quad (13)$$

where SR_{ip} denotes the systematic risk measure for stock i in month p, i.e., commonality in returns - R^2_{Comr} or β_{Comr}, and commonality in liquidity - R^2_{ComLIQ} or β_{ComLIQ}, $\widehat{HFT_{i,p}}$ is the predicted value of HFT for stock i in month p from the first stage regression (12) (aggregated monthly average from daily predicted values), $CV_{i,p}$ is a vector of the same control variables. We include stock and time fixed effects to eliminate any stock-specific or time effects influencing our commonality measures.

The β coefficient in regression (13) will show whether there is any causal relationship between our systematic risk measures and HFT during our sample period. A positive beta coefficient on $\widehat{HFT}_{i,p}$would indicate that systematic risk is higher due to increase in HFT. We will investigate the relationship across markets and in time, and also across different terciles. For robustness check, the regressions are done also using variables in first differences to see whether the results change and stationarity should be addressed.

5. Results

5.1. *Summary statistics*

Summary statistics of the main variables for all 12 countries and daily trading volume size terciles are presented in Table 3 (Appendix B). It contains monthly values of market returns, volatility, daily trading volume, liquidity and our measures of systematic risk, i.e., commonality in returns (R^2_{Comr}) and liquidity (R^2_{ComLIQ}), and alternative liquidity commonality measures based on relative quoted spread and trading volume, which are used for robustness checks. Countries are listed in descending order according to commonality in returns measure.

The level of R^2_{Comr} differs from country to country and ranges from 25% to 51% (see Figure 5 and 6 in Appendix B). The highest levels of systematic return risk can be observed in Sweden and France, followed by Germany and the UK. The lowest commonality in returns is in Belgium and Austria. Meanwhile, systematic liquidity risk R^2_{ComLIQ} is the highest in the UK with 28% and Italy 26%. Lowest commonality in liquidity levels are in Austria and the Netherlands. The within standard deviations are mostly similar, but Italy and the UK have relatively higher time series volatility than others. Similar patterns are observable for commonality in spread and commonality in trading volume measures.

Figures 5 and 6 (Appendix B) show that countries that display the highest commonality in returns are also among those with the greatest commonality in liquidity (Sweden, the UK, Germany, Spain, and France). This is consistent with the findings of Yafeng (2007) who presents evidence on commonality in liquidity having positive relationship with stock price comovement. Also Brockman, Chung, and Pérignon (2009) find that London Stock Exchange and Frankfurt Stock Exchange exhibit higher commonality in liquidity as compared to neighbour exchanges. We also looked at commonality in high frequency trading volume – our HFT proxy. Again, the UK and France have the highest levels (23% commonality), while Belgium and the Netherlands have the lowest (16% commonality). The results show a pattern of some countries, including the UK, Sweden, and Germany, having higher levels of all commonality measures. Commonalty level in different countries in our sample varies substantially despite the relatively homogenous development of financial markets. For instance, the range of the time series average commonality in liquidity in countries of our sample is wider than found by, e.g., Karolyi et al. (2012) who analyzed a panel of 14 years across 40 countries. The highly volatile time period that our panel captures and the relatively short sample are potential explanations both for higher absolute commonality in liquidity and greater differences among countries.

Tercile analysis shows that the third tercile, which includes stocks with highest trading volume by country, has the highest commonality levels across all measures, confirming that most active markets have higher systematic return and liquidity risk.

5.2. *The impact of Chi-X entry*

Since our main objective is to investigate the relationship of HFT and systematic risk, we examine the impact of Chi-X trading platform's entry, which is our instrument and allows identifying HFT activity, on other variables that are included in the TSLS model.

Table 4 (Appendix B) reports the relationship of our Chi-X dummy with other variables. Dependent variables in regressions (1) – (3) are possible HFT proxies. The coefficients on tercile-specific regressions show that the effect is stronger for the largest tercile, i.e., most active stocks. $HFTvolume_{i,t}$ is our preferred measure and has a statistically significant positive relationship with the Chi-X trading platform's entry in the whole sample and all terciles, which is in line with our intuition that the entry of Chi-X has increased HFT. The same is proven by other two measures - $HFTtrades_{i,t}$ and $messages_{i,t}$. The coefficient 31,346 on Chi-X dummy in regression (3) for the whole sample can be interpreted as an increase in the daily number of messages by an average of 31 thousand messages per day due to Chi-X introduction, all else equal.

To understand the significance of this increase, the mean of $messages_{i,t}$ in the period before the first Chi-X entry (on 16 April 2007) should be compared with the coefficient. The average number of daily messages before 16 April 2007 for stocks that are later traded on Chi-X was 9,597, and 5,883 for all stocks in the panel. This means that Chi-X entry increases average daily message traffic at least threefold, which indicates that Chi-X introduction in European equity markets has a strong and positive economic impact on message traffic. The effect is more distinct for larger volume stocks. Since increased message activity is the main indicator of HFT, these results confirm our expectations that Chi-X entry can serve as a valid instrument for identifying HFT activity.

Chi-X dummy also has a consistent relationship with trading volume and fragmentation proxies. The effect on other dependent variables is not so consistent, but still mostly significant. These are used further in the analysis as control variables. Results show that $FR2_{i,t}$ is the most appropriate and reliable fragmentation proxy and should be used further.

5.3. *Analysis of high frequency trading impact on systematic risk*

We investigate the possible relationship between stock return and liquidity commonality and the growing HFT activity in Europe. This section presents the results of statistical analysis; more comprehensive interpretation and explanations are presented later in the discussion part. The analysis is based on a panel of 674,308 stock-day observations for a period of February 1, 2007, to February 28, 2009. The panel contains observations for 1311 stocks which are sorted in 3 terciles by country according to total trading volume in the whole sample period, where Tercile 1 refers to the smallest and Tercile 3 to the largest volume stocks. It means that each of the three terciles - top, middle and lowest – contains stocks of all 12 countries. To have a more diverse analysis, in a similar manner we divide the panel stocks also in terciles according to their mean volatility and liquidity.

In the first stage regression we obtain fitted values of our HFT proxy which is then further used to find the effects on systematic risk. Each first stage regression is run separately for each tercile and country. From this we construct a panel of 32,233 stock-month observations containing R^2 values, obtained from regressions (7) and (9), and monthly averages $\widehat{HFT}_{i,p}$ of fitted values for our HFT proxy from first stage regressions (from regression (12)).

The second stage regression (13) results are presented in Tables 5 and 6 (Appendix C). Instrument relevance is not a concern in neither of regressions, e.g., for the whole sample period F-statistic is 174.29 (should be above 1). The beta coefficients in the table are multiplied by 1,000 to have reportable values with 3 decimal digits. All regressions include control variables, and results for commonality in returns and liquidity are reported. To account for the change in market structure we control for market fragmentation effect. In the main analysis the second fragmentation proxy $FR2_{i,t}$ is used. This measure is good at capturing trading volume dispersion among all trading venues. It is chosen as the most reliable because it is better to use a trading volume based measure, since our primary proxy for HFT is also calculated using trading volume. Additionally, pairwise correlations between the four fragmentation proxies are above 35% (only the correlation between $FR1_{i,t}$ and $FR4_{i,t}$ is 18%) and inclusion of any of the four proxies does not change our main results.

Results from the regression for the whole sample suggest that increase in HFT leads to rise in both commonality in stock returns and liquidity, in other words, HFT increases systematic risk. Table 5 reports statistically significant positive coefficients on both commonality in returns and liquidity, our measures of systematic risk. In economic sense, the coefficient 7.197 on R^2_{Comr} means that one standard deviation increase in our proxy for HFT, $HFTvolume_{i,p}$, leads to increase in systematic return risk by 7.13%[6] (see Table 7, Appendix C). Comparison can also be made with the mean value (time series average), i.e., if HFT proxy changes from its mean of 2700 EUR per message to 2600 EUR per message (growth in HFT), then systematic return risk rises by 0.17%. The effect for systematic liquidity risk is even more significant. The coefficient 13.481 on R^2_{ComLIQ} in the full sample regression means that one standard deviation increase in HFT proxy results in 9.52% growth in systematic liquidity risk. Moreover, if HFT activity increases and changes mean value of $HFTvolume_{i,p}$ by 100 EUR, then systematic liquidity risk grows by 0.20%. The results are in line with our initial intuition that HFT increases systematic risk in European equity markets.

Tercile results are also interesting. For the top daily volume stocks (T3) the results are less significant than for smallest terciles (T1 and T2), which is rather surprising. Table 7 (Appendix C) shows that economic significance is the largest for T2, and the impact of one standard deviation is very remarkable, i.e., around 30% increase in systematic risk. We also divided stocks in daily trading volume terciles where they are not sorted by countries (thus the largest tercile has a high number of LSE stocks, because they have the highest volumes), but results for the largest tercile remain insignificant (not reported). The tendency of more significant effects in smaller terciles can be substantiated by comparing relative change of HFT activity in each of terciles, and it turns out that smaller terciles have higher mean for $HFTvolume_{i,p}$; hence, it is in line with our main results that more HFT activity increases systematic risk. Regarding liquidity terciles, it appears that the effect on both systematic return and liquidity risk is stronger for less liquid stocks. Again, the relative change of HFT activity is the largest in T2, where the effect on systematic risk is most pronounced, and smaller in T3, where the effect lacks significance, or in simple words, more HFT results in

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[6] Since all R^2 values have been transformed, we have to perform a reverse transformation to be able to interpret the obtained coefficients. To calculate the effect of one standard deviation (σ) (or any value of interest) change in $HFTvolume_{i,p}$ on the value of our systematic risk measures (R^2_{LIQ} and R^2_r), the following equation is used (Karolyi et al., 2012):

$$\Delta R^2 = \frac{e^{\alpha+\beta(\mu+\sigma)+\theta*Cv}}{1+\ e^{\alpha+\beta(\mu+\sigma)+\theta*Cv}} - \frac{e^{\alpha+\beta*\mu+\theta*Cv}}{1+\ e^{\alpha+\beta*\mu+\theta*Cv}}$$

where α denotes intercept, β is coefficient on our high frequency trading measure, both from our second stage regression. θ is a vector of coefficients on time and stock fixed effects and other control variables, and Cv is a vector of means of the same variables.

higher systematic risk. Economic significance is also highest for less liquid stocks. Furthermore, while in all volatility terciles HFT have significant effects on systematic liquidity risk, for return risk the effect is stronger for more volatile stocks. When looking at the time period tercile, both systematic risk measures show that the relationship was significant before the breakpoint date[7], and lack evidence after it. This seems logical as the period before this date was a time of increased activity in the financial markets and thus more opportunities existed for HF traders that they could exploit.

Table 6 (Appendix C) shows country-specific second stage results. The majority of results lack statistical power, and this might be due to lower number of observations. Therefore, these results are hard to interpret, but in most countries the sign on systematic risk measures is positive, which is in line with our main results from Table 5. Also the first stage F-statistic indicates that the Chi-X instrument is weak only in Germany and the UK.

For robustness check the analysis is performed using alternative liquidity measures – spread and trading volume. Using R^2_{SPREAD} and R^2_{DVOL} as commonality in liquidity, the second stage regression results have exactly the same signs for all coefficients as when our main liquidity proxy is used (not reported). Furthermore, the regressions are done using variables in first differences to test whether our findings are robust to taking changes instead of levels for the analysis. The results are very similar (not reported), meaning that data should not be transformed for the main regressions.

As mentioned before, we also look at beta coefficients of regressions (7) and (9) as alternative measures of systematic risk. Most of results lack statistical significance due to no time series variation in market beta coefficients (not reported), so we focus on the R^2 results.

5.4. *Additional analysis of results - mediation tests*

After investigating what is the impact of HFT on systematic risk, we apply multiple mediation models to explain how HFT can affect systematic risk, i.e., what are the possible channels through which this relationship is realized. This implies assessing and comparing the significance of indirect effects in formal mediation tests (Preacher & Hayes, 2008; Preacher & Hayes, 2004).

[7] The statistical "Chow test" is used to find a structural break point in our panel data. 13 October 2008 is the breakpoint date. This date coincides with the time when a number of governments and central banks announced their intentions to ease the credit crisis by making large funds available to the banking sector (Grynbaum, 2008). In this day major stock indices and equities experienced excess volatility and high activity.

5.5. *Tests for possible channels of HFT impact on systematic return risk*

To examine the possible channels through which the impact of HFT on systematic return risk is realized, we test two possible mediators, i.e., market liquidity and price delay measure, illustrated in Figure 7 (Appendix D). Price delay measure is calculated as shown in the equation (Hou & Moskowitz, 2005):

$$PD_{i,p} = 1 - \frac{R^2_{current}}{R^2} \qquad (14)$$

where $PD_{i,p}$ is price delay for stock i in month p, R^2 is the R^2 from the unrestricted regression of stock returns on current and 4 lags of market returns (regression 15), and $R^2_{current}$ is the R^2 from the restricted model where lagged values are excluded and stock returns are regressed only on market return (regression 16):

$$r_{i,t} = \alpha_i^r + \Sigma_{j=1}^{4} \beta_{i,j}^r r_{m,t-j} + u_{i,t}^r \quad (15)$$

$$r_{i,t} = \alpha_i^r + \beta_{i,j}^r r_{m,t} + u_{i,t}^r \quad (16)$$

The motivation for choosing particularly these two mediators is based on theory and existing empirical evidence. Firstly, HFT activity affects market liquidity because a large part of HF traders act as market makers and submit limit orders, and hence increase liquidity in the market. The next link is from liquidity to price delay, which is conceptually the opposite of speed of adjustment (how fast market news are incorporated in stock prices). Schutte and DeLisle (2012) posit that speed of adjustment (price delay) is positively (negatively) correlated to stock liquidity, and it is consistent with findings of Hou and Moskowitz (2005), which state that price adjustment is faster because liquid stocks adjust to news more rapidly and are more visible to investors (Frieder & Subrahmanyam, 2005). Our empirical results are in line with findings of others (Hendershott et al., 2011; Hasbrouck & Saar, 2012) and suggest that HFT improves liquidity (see Table 8 in Appendix C).

Next, the link from price delay to systematic return risk can be based on evidence that return correlation among stocks is found to be higher due to faster and more homogenous market participants' responses to market and industry news, i.e., due to more efficient information diffusion (Schutte & DeLisle, 2012). Specifically, higher price adjustment speed (lower price delay) is associated with stronger stock price comovement, also known as "information diffusion view" formulated by Barberis, Shleifer, and Wurgler (2005). This could be a result of faster and more efficient information arrival to traders facilitated by the introduction of new information and communication technologies. HF traders are able to process information and execute orders in shorter time periods than human traders.

According to “information diffusion view”, market frictions cause information to be reflected in stocks’ prices at different rates. For instance, stocks held by traders with faster access to the market (like HF traders) are able to react faster. Common return factors are produced for stocks with similar information incorporation speeds. This applies directly to HF traders that are distinguishable from other traders due to their speed; hence, the “information diffusion view” supports the link from HFT to comovement in returns, or in our paper, systematic return risk.

In short, HF traders supply liquidity in the market and increase speed of adjustment (decrease price delay) due to higher trading speed and greater capacity for information processing, and this link substantiates our choice of these two mediators in the mediation tests. Therefore, we hypothesize that HFT transmits its effect on stock price comovement through market liquidity and price delay and test these two variables as mediators for this relationship.

Formal tests are performed using the serial multiple mediator model (Hayes, 2012; Preacher & Hayes, 2008). The underlying idea is to test whether the effect of HFT on systematic risk measure (the beta coefficient on the HFT measure in a regression including both mediators – direct effect) is lower than in the basic second stage regression (13) in systematic risk analysis without mediators (total effect). If the direct effect of HFT measure on systematic risk measure is smaller when mediators are included, then it means that the mediators are relevant and transmit the effect of HFT on systematic risk, i.e., they are mediating this relationship and can be classified as channels for the impact. A three-step procedure is applied to examine the mediational path (Hayes, 2012):

HFT (X) → market liquidity ($M1$) → price delay ($M2$) → systematic return risk (Y)

In the first step the mediator $M1$ is regressed on X, our HFT measure; in the second step the mediator $M2$ is regressed on X and mediator $M1$; and lastly in the third step the systematic risk measure Y is regressed on X, $M1$ and $M2$ (detailed regression equations in Figure 7 in Appendix D). As mentioned before, the beta coefficient on X from the third step regression is our indicator for the existence of mediation. If the mediators turn out to have a significant influence, we also calculate to what extent $M1$ and $M2$ individually transmit the $X \rightarrow Y$ effect, conditional on inclusion of the other mediator.

Results for the serial mediation model, showing the mechanics how HFT transmits effect on systematic return risk, are displayed in Figure 7 (Appendix D). The regression estimates of beta coefficients are as we expected, except for market liquidity relationship with price delay, which suggest that greater liquidity induces prices to be more delayed. It means that one of the three specific indirect effects of this model – HFT affecting systematic return risk through both mediators in serial ($\beta_1 * \beta_2 * \beta_4$) – has an opposite sign as the total effect. However, this specific indirect effect is significant only at 10% significance level. The second and third specific indirect effects are through market liquidity individually ($\beta_1 * \beta_5$) and price delay individually ($\beta_3 * \beta_4$). Both specific indirect effects are estimated conditional on the presence of other single and serial mediator. The results show that market liquidity mediates 9.0% and price delay mediates 35.1% of the total effect HFT has on systematic return risk, and these results are in line with the theoretical framework explained above and our expectations. The remaining 55.9% of the total effect is a direct effect that is mediated by other (from our model omitted) mediators.

5.6. *Tests for possible channels of HFT impact on systematic liquidity risk*

A similar approach is applied to examine the impact of HFT on systematic liquidity risk, testing two possible channels. The two mediators tested are market liquidity and market volatility.

Similar to the scheme for systematic return risk, also for liquidity risk market liquidity is used as a mediator. The link from HFT to market liquidity and to systematic liquidity risk is based on the evidence that commonality in liquidity (our systematic risk measure) arises when stocks have common market makers (Coughenour & Saad, 2004). And it is known that HF traders often act as market makers and supply liquidity to others (Menkveld, 2012); hence, they are involved in increasing market liquidity and thus creating commonality in liquidity.

The other mediator is market volatility. Also this choice is based on literature, and our results, which show that HFT increases volatility (see Table 8 in Appendix C). Kamara et al. (2008) report that market wide volatility creates similar trading behavior among traders and hence affects liquidity commonality. Also Karolyi et al. (2012) state that there is more liquidity comovement when market volatility is higher. Changes in market volatility have an impact on inventory levels that HF traders hold (Chordia et al., 2000). This applies both to proprietary traders, which aim to hold close to zero inventories (Cartea & Penalva, 2011), and market makers, which are subject to inventory risk (Yafeng, 2007; Brogaard, 2011b). The majority of HF traders engage in proprietary trading (Biais, Foucault, & Moinas, 2011). Hasbrouck and Saar (2012) examine HFT strategies and state that they are likely to be correlated, and emphasize that dynamic proprietary strategies use the low latency advantages, have common message flows; and Cartea and Penalva (2011) propose that strategies, which combine high speed advantages and small inventories, influence market conditions. Meanwhile, market makers can also have common inventory control models (Menkveld, 2012). Chordia et al. (2000) suggest that if inventory levels are changing in a similar pattern among traders, then liquidity commonality can emerge. It is also directly reported that volatility influences inventory levels of liquidity suppliers (Yafeng, 2007). In short, market volatility can mediate the path from HFT to systematic liquidity risk by affecting inventory levels of HF traders, and hence create correlated behavior that leads to comovements in liquidity.

Here the parallel multiple mediator model is used and, in comparison to the serial multiple mediator model applied for systematic return risk, the three-step procedure differs in the second step, where mediator *M2* is regressed only on *X* (detailed regression equations in Figure 8 description in Appendix D). The mediational path is as follows:

$$\text{HFT } (X) \quad \rightarrow \quad \begin{array}{c} \text{market liquidity } (M1) \\ \text{market volatility } (M2) \end{array} \quad \rightarrow \quad \text{systematic liquidity risk } (Y)$$

The results for the parallel multiple mediator model are shown in Figure 8 (Appendix D). In a similar manner, we estimate how much of the total effect of HFT activity on systematic liquidity risk is mediated through market liquidity ($\beta_1 * \beta_3$) and market volatility ($\beta_2 * \beta_4$). All coefficients are consistent to our prior analysis (HFT has a positive relationship with market liquidity and volatility, see Table 8 in Appendix C). Market liquidity transmits 5.14% and market volatility 18.83% of the total effect HFT has on the risk. Both of these effects are significant at 5% level. The rest of total effect of 76.03% is mediated by unknown and therefore omitted variables. These results also suggest that HFT is affecting market conditions, i.e., improving market liquidity and making market prices more volatile that in turn increases systematic liquidity risk. This is also consistent with theory.

6. Discussion

Our main results suggest that high frequency trading increases systematic risk both in returns and liquidity in European equity markets in period 2007-2009, which supports Hypothesis 1 and Hypothesis 2. We find that HFT activity has grown in these years, and that the causal relationship between high frequency trading and systematic risk is statistically and economically significant. To our knowledge this particular relationship has not been empirically investigated yet; hence, we do not have other similar studies to compare our results to. Nevertheless, other papers provide evidence that might explain and substantiate our findings. Bai and Qin (2010) discover that systematic liquidity risk arises from correlated trading behaviour of investors, also Koch, Ruenzi, and Starks (2009) find that commonality in liquidity (our measure of systematic liquidity risk) is driven by traders with similar trading behaviour and inventories. Similarly for systematic return risk, according to Hasbrouck and Seppi (2001), comovement in returns is largely determined by commonality in order flows; also Schutte and DeLisle (2012) document higher return comovement due to more correlation in trading. Therefore, an intuitive explanation for the causal relationship of HFT and systematic risk might be correlated trades by HF traders, which is supported by other authors, including Foucault (2012) and Chaboud et al. (2011), who conclude that HF traders have similar trading strategies.

In addition, we find that HFT increases liquidity, which is in line with findings of Hendershott et al. (2011). Also volatility has risen, but this contradicts other academics' conclusions that HFT lowers volatility, for example, Brogaard (2012); however, evidence on this is not unanimous. Our tercile analysis shows that less liquid stocks have more significant positive effects on systematic risk from HFT. This is observed both in terciles divided according to liquidity and trading volume, which also proxies for liquidity. According to Hendershott and Riordan (2012), in times of wide spreads (low liquidity in the market), algorithmic traders that act as markets makers are more likely to submit limit orders and supply liquidity; hence, HFT activity is higher, which explains more pronounced effects on the risk. Meanwhile, in volatility terciles the strongest effects on systematic risk are observed for most volatile stocks, where HFT activity is relatively higher. Since HF traders often use predatory trading strategies and search for arbitrage opportunities, then it seems logical that they will trade stocks that are more volatile and more often might be mispriced due to rapid price swings. Another explanation might be that for more volatile stocks there is more information available and HF traders can employ their speed advantage in obtaining this information and hence participate proportionally more in trading by disadvantaging slower traders (Benos & Sagade, 2012).

The country-specific results are rather inconclusive. Cross-country variation in commonality changes from period to period. The lowest variation across countries is observed in mid-2008. Much larger differences emerge to the year-end, which coincides with the turmoil in the financial markets. Karolyi et al. (2012) report that in October 2008 the U.S. was among countries with the highest level of commonality in liquidity, which contrasts with empirical evidence on commonality levels being higher in less developed markets. Therefore, it is plausible that in our sample period countries with larger GDP per capita (proxy for financial development), e.g., the UK and Sweden, present greater liquidity comovement. We explain higher commonality in liquidity in a country with differences in market volatility and the level of correlated trading (see Table 3 in Appendix B). Indeed, countries with higher time series average market volatility and commonality in trading volume are those characterised by larger comovement.

We also find that France, Italy, Germany and the UK have the highest market volatility, liquidity and volume, i.e., the most developed capital markets; whereas, Belgium and Austria have relatively less developed. The results indicate that our systematic risk measures are positively related with capital market conditions, being higher in more developed countries. Nevertheless, we find statistically significant relationship between HFT activity and systematic return risk for only three countries, i.e., the UK, Norway and Austria. Signs of the point estimates indicate a positive impact (though for Norway and Austria it is significant only at 10% level). The relation between HFT and systematic liquidity risk is even more ambiguous. Only for the UK, Finland and Belgium the null hypothesis of HFT having no effect on the risk cannot be rejected. Regression results suggest that in Finland HFT has a negative effect on commonality in liquidity. Four countries show a negative relation between HFT and risk for both types of risks (although significant in one case), meaning that HFT reduces systematic risk. A plausible explanation of such inconsistency is that our country analysis results suffer from lack of statistical power. This might be due to lower number of observations[8] and/or shorter period of the Chi-X treatment. For instance, statistical and economic significance of results for the UK, which has more than twice as many stocks in our sample than other markets, supports this claim.

Our main results provide support to both hypotheses that we previously stated, i.e., that HFT increases systematic return risk and systematic liquidity risk. Findings of HFT changing market conditions, e.g., liquidity and volatility, are consistent to previously found empirical evidence. The linkage between market conditions and the change in systematic liquidity risk, which we prove to be present in Europe by applying mediation models, is consistent to supply- and demand-side explanation of commonality in liquidity. Rising market volatility (result of HFT activity) creates correlated behaviour of market participants, e.g., traders liquidate their positions to reduce risk and therefore lower liquidity (Garleanu &

[8] The number of stock-month observations range from 1948 to 2434, except for the UK which has 8850 observations.

Pedersen, 2007; Karolyi et al., 2012). This demand side effect in turn causes other liquidity suppliers (market makers) to hit capital constraints, and hence reduce liquidity supply concurrently. However, we must remember that our HFT measure is a proxy not direct data on HF trades. Hence, there is still place for research in this area and it would be interesting to investigate this relationship on a dataset with trade flags identifying HFT activity.

As mentioned previously, HFT currently is a controversial issue in the financial world, and our findings not only add new empirical evidence to the existing academic literature, but also have a broader significance. Policy makers in many countries, for example, Germany are discussing new regulations for HFT that would affect a great part of financial markets, since HFT is widely used among traders of equity, currency and other instruments (Busemann, 2013). Our results, which show that HFT increases systematic risk (investigated from two perspectives - returns and liquidity), indicate that HFT can have negative effects on financial markets. In other words, stricter regulations would be in order to create more stability. This is especially relevant to the MiFID II regulations that are still in progress and will be enacted in a few years. One of suggestions how to limit HFT activity or prevent the negative influence would be to set a minimum holding period for each quote, because HF traders often post and cancel trades and quotes in extremely high speed, resulting in excess activity that other traders might misinterpret, or create adverse selection.
Another solution might be to collect fees proportional to message activity. Furthermore, regulators could establish a certain minimum trade/quote ratio that every trader should fulfil. Then HF traders would have to limit their cancellations and submissions and follow the threshold by making proportionally more trades. Some policy makers also propose that HF traders should disclose their algorithms. This might limit the possible negative HFT effects like market manipulation, liquidity evaporation and excess volatility.

7. Conclusions

This paper studies the causal relationship of high frequency trading and systematic risk in European equity markets. We apply quasi-experimental research design with a differences-in-differences method on a unique dataset, where we exploit the staggered entry of Chi-X trading platform in Europe as an exogenous instrument to identify HFT activity. The main finding is that HFT increases systematic risk. Additional analysis also reveals channels through which this relationship is transmitted.

Investigation of 12 European stock markets in a period from 2007 to 2009 suggests that systematic return risk and systematic liquidity risk have increased due to growing HFT activity. The statistical and economic significance of the effect is more pronounced for stocks with medium trading volume, stocks that are less liquid and characterized by highest return volatility. We find that HFT has a positive relationship with both types of risk in the upward market before the culmination of financial crisis. Our results are robust to the choice of liquidity measure, proxy for HFT, and data transformation to differences. The data for individual countries do not provide clear evidence, and it is hard to draw specific conclusions about country-level impact. However, cross-country comparison could unveil important evidence and is open for research in the future.

By applying formal mediation tests, we find that HFT transmits the effect on systematic return risk by enhanced price adjustment speed to market news and improved liquidity. We explain this with the technological speed advantages that trading algorithms have over other traders. Changes in capital market conditions, which were partially due to growing HFT activity, contributed to the rise of systematic liquidity risk. The tests reveal that more than one fifth of HFT effect on systematic liquidity risk is mediated through market volatility and market liquidity. This is another proof that HFT leads to significant changes in equity markets. Therefore, answer to the research question "What is the impact of high frequency trading on systematic risk in European equity markets?" is that high frequency trading increases systematic risk in European equity markets both in returns and liquidity.

Besides filling the gap in academic literature, our results have implications on various parties. Market participants should take into account that more HFT activity leads to higher systematic risk, and since this risk cannot be diversified away, investors should be rewarded for bearing it. Hence, there are implications for asset pricing. In addition, the evidence of HFT increasing systematic risk might be useful for regulators and policy makers when drafting new legislation. To maintain financial market stability and strength, some restrictions should be imposed on HF traders to prevent the potentially damaging effects they have on the markets.

For future research it would be interesting to analyze a longer sample period and use more recent data. Moreover, the analysis could be done using data that identify HF traders, if such data were accessible. This would allow more in-depth investigation of various HF trader strategies and their individual impact on systematic risk. Further studies on inventory risk of HF traders could reveal important details about how correlated trading behaviour is created. Alternatively, intraday data could show how HF traders react in different situations and what impact does this leave on comovements in the market. Furthermore, channels found in this paper, through which the relationship is mediated, are only responsible for a part of the total effect; the remaining part is unknown yet worth examining.

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Appendix 1. Information about data

Table 1 List of exchanges used as the source for data consolidation

This table summarizes venues that are used to consolidate market data for our panel. Trading data are consolidated for each home exchange of the 12 countries, and also from all exchanges, where stocks are cross-listed, and trading venues, where stocks are traded.

Exchange name	Country
Buenos Aires SE	Argentina
Medzona Stock Exchange	Argentina
Vienna SE	Austria
Brussels Deriv Exchange	Belgium
Euronext Brussels	Belgium
Botswana SE	Botswana
CHI-X Canada	Canada
Pure Trading	Canada
OMEGA ATS	Canada
TMX Select	Canada
Toronto SE	Canada
Alpha Trading Systems	Canada
Prague SE	Czech
Copenhagen SE	Denmark
NYSE ARCA	Europe
Sigma X	EUROPE
Helsinki SE	Finland
MONEP	France
Euronext Paris	France
Berlin SE	Germany
RWB	Germany
Xetra	Germany
Frankfurt SE	Germany
Hamburg SE	Germany
Hanover SE	Germany
Munich SE	Germany
Stuttgart SE	Germany
Tradegate SE	Germany
Xetra International Market	Germany
Hong Kong SE	Hong Kong
Instinet HK	Hong Kong
Budapest SE	Hungary
Quote MTF Ltd	Hungary
Irish SE	Ireland
Tel Aviv SE	Israel
Milan SE	Italy
Euro TLX	Italy
Tokyo SE	Japan
Kazakhstan Stock Exchange	Kazakhstan
Luxembourg SE	Luxembourg
Mexico SE	Mexico
Namibian SE	Namibia
Euronext Amsterdam	Netherlands
New Zealand SE	New Zealand
Burgundy MTF	Nordic Region
Oslo SE	Norway
Warsaw SE	Poland
Euronext Lisbon	Portugal
Bucharest SE	Romania
Russian Trading System	Russia
Saudi SE	Saudi Arabia
SGX-ST	Singapore
Johannesburg SE/Safex	South Africa
Barcelona SE	Spain
Bilbao SE	Spain
Madrid SE	Spain
Mercado Continuo	Spain
Valencia SE	Spain
Nordic Growth Market	Sweden
Stockholm Options	Sweden
Berne SE	Switzerland
Scoach Switzerland	Switzerland
Swiss Blue Chip Segment	Switzerland
Taiwan Futures Exchange	Taiwan
Norwegian Fund Broker Asstn	Norway
Istanbul SE	Turkey
NASDAQ Dubai(ex-DIFX)	UAE
Equiduct	United Kingdom
BATS Europe	United Kingdom
Channel Islands SE	United Kingdom
CHI-X Europe	United Kingdom
London SE	United Kingdom
PLUS Markets Group Plc	United Kingdom
Turquoise	United Kingdom
Nyse Amex (Options)	USA
Cincinnati SE	USA
NASDAQ ADF	USA
New York SE	USA
NYSE Consolidated	USA
Direct Edge Holdings EDGA - Global Select Market	USA
Direct Edge Holdings EDGX EDGX - Global Select Market	USA
Nasdaq Consolidated	USA
OTC Bulletin Board	USA
NASDAQ Stock Market	USA
Other-OTC (Pinksheets)	USA
Third Market Stock	USA
Chicago Options	USA
BATS Trading For Nasdaq OMX Global Market(Large Cap)	USA
BATS Y Trading For Nasdaq OMX Global Market	USA
Intl Sec Exch - Equities	USA
Chicago SE	USA
Lusaka Stock Exchange	Zambia

Source: created by the authors using data from the TRTH database (Thomson Reuters, 2012).

Table 2 Descriptive statistics of main variables

This table reports descriptive statistics of the panel data for the period 1 Feb 2007 - 28 Feb 2009. The panel consists of 1311 stocks, and 674,308 stock-day observations. Means (time series averages) of variables are calculated for separate terciles and the whole panel. Terciles are constructed by collecting stocks in each country that are divided according to total daily trading volume for the whole sample period in every market. Tercile 1 (T1) consists of stocks with the smallest total daily trading volume. All variables are 99% winsorized. The standard deviation is calculated within time, $x_{it}^{*} = x_{it} - \bar{x}_{i}$.

Variable	Description	Mean Total	Mean T1	Mean T2	Mean T3	St.dev. within
$r_{i,t}$	stock-day consolidated hourly midquote returns (bps)	-20.83	-18.97	-22.41	-21.02	472.58
$LIQ_{i,t}$	consolidated midquote return per 1000 EUR traded consolidated volume, Amihud liquidity measure (bps/EUR)	-0.38	-0.83	-0.34	-0.03	0.63
$SPREAD_{i,t}$	time-weighted relative quoted spread for the consolidated order book (bps)	111.68	240.77	78.01	19.04	438.41
$SPREAD\_home_{i,t}$	time-weighted relative quoted spread for each home exchange (bps)	125.30	276.37	86.66	21.16	536.01
$SPREAD\_chix_{i,t}$	time-weighted relative quoted spread for Chi-X (bps)	79.30	138.27	101.46	50.48	83.57
$trades_{i,t}$	number of daily trades in the consolidated order book	1,468.67	194.01	701.65	3,510.31	1,401.25
$trades\_home_{i,t}$	number of daily trades in each home exchange	1,282.01	185.02	657.38	3,003.60	1,070.22
$trades\_chix_{i,t}$	number of daily trades in Chi-X	91.70	1.48	21.82	251.78	421.57
$messages_{i,t}$	number of daily electronic messages in the consolidated order book, a proxy for high frequency trading activity	17,145.36	2,380.58	7,825.14	41,229.87	37,564.75
$messages\_home_{i,t}$	number of daily electronic messages in each home exchange	6,298.07	1,154.20	3,441.85	14,298	7,505.50
$messages\_chix_{i,t}$	number of daily electronic messages in Chi-X	2,918.46	198.28	1,081.07	7,475.96	13,613.77
$HFTvolume_{i,t}$	negative trading volume in 100 EUR over the number of messages, a proxy for high frequency trading for the consolidated order book	-27.46	-21.26	-19.20	-41.72	52.49
$HFTvolume\_home_{i,t}$	negative trading volume in 100 EUR over the number of messages, a proxy for high frequency trading for each home exchange	-41.38	-26.61	-29.09	-67.65	170.14
$HFTvolume\_chix_{i,t}$	negative trading volume in 100 EUR over the number of messages, a proxy for high frequency trading for Chi-X	-1.52	-0.23	-0.93	-2.42	4.35
$HFTtrades_{i,t}$	number of daily electronic messages over the number of daily trades, a proxy for high frequency trading for the consolidated order book	27.86	55.10	18.99	12.53	299.94
$HFTtrades\_home_{i,t}$	number of daily electronic messages over the number of daily trades, a proxy for high frequency trading for each home exchange	17.26	30.23	12.34	10.94	151.77
$HFTtrades\_chix_{i,t}$	number of daily electronic messages over the number of daily trades, a proxy for high frequency trading for Chi-X	192.34	329.16	289.98	110.52	1,937.74

Table 2 - *Continued*

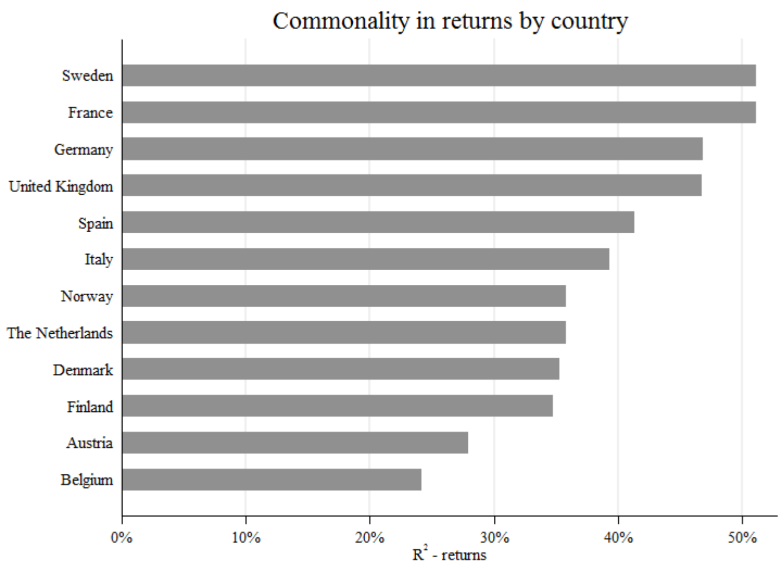
Variable	Description	Mean Total	Mean T1	Mean T2	Mean T3	St.dev. within
$dvol_{i,t}$	daily trading volume for the consolidated order book (EUR)	33,202,334	1,500,782	7,890,903	90,214,247	45,613,583
$dvol\_home_{i,t}$	daily trading volume for each home exchange (EUR)	28,239,624	1,380,962	7,184,429	76,152,575	38,523,727
$dvol\_chix_{i,t}$	daily trading volume for Chi-X (EUR)	667,499	3,528.55	95,680	1,903,265	3,766,404
$FR1_{i,t}$	number of venues that execute trades in the stock in the particular day, a proxy for fragmentation	3.57	1.98	2.95	5.77	1.77
$FR2_{i,t}$	Herfindahl-Hirschman index (using volume) in EUR, a proxy for fragmentation	0.07	0.05	0.06	0.11	0.10
$FR3_{i,t}$	Herfindahl-Hirschman index (using trades), a proxy for fragmentation	0.07	0.05	0.05	0.11	0.10
$FR4_{i,t}$	EUR volume market share of all venues other than the home market (0 to 1), a proxy for fragmentation	0.08	0.08	0.06	0.11	0.13
$invmidquote_{i,t}$	inverse of the closing midquote for the consolidated order book at 4:30pm GMT	0.26	0.37	0.27	0.14	0.41
$volatility_{i,t}$	standard deviation of hourly intraday midquote returns (bps)	79.65	79.74	70.19	80.13	169.13

Source: Created by the authors using data from the TRTH database (Thomson Reuters, 2012).

Appendix 2. Summary statistics

Figure 5. Commonality in returns by country.

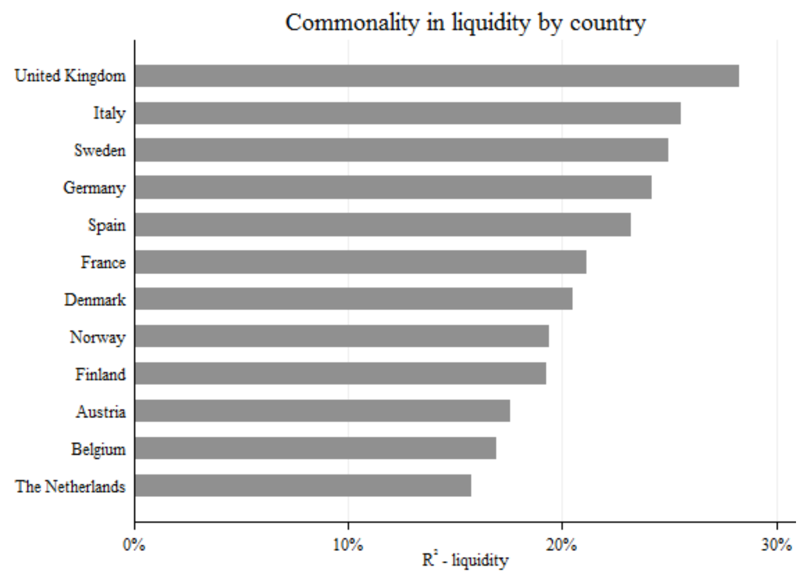
This graph depicts levels of systematic return risk measure – commonality in returns – for each of the 12 countries (in %). Monthly values of commonality in returns are equally weighted averages of monthly commonality measures of all sample stocks in each country.



Source: Created by the authors using output from data analysis in STATA.

Figure 6. Commonality in liquidity by country.

This graph depicts levels of systematic liquidity risk measure - commonality in liquidity (based on Amihud liquidity) – for each of the 12 countries (in %). Monthly values of commonality in liquidity are equally weighted averages of monthly commonality measures of all sample stocks in each country.



Source: Created by the authors using output from data analysis in STATA.

Table 3 Summary statistics of commonality and market measures for all countries and terciles

This table reports summary statistics for each of the 12 countries, whole panel and 3 terciles based on daily trading volume, where T1 contains stocks aggregated from each country with the lowest daily trading volume. Countries are listed in descending order according to commonality in returns measure R_r^2. The table presents mean (time series average) and standard deviation of main systematic risk measures, i.e., commonality in returns R_r^2 and commonality in liquidity R_{LIQ}^2 that is based on Amihud liquidity. Alternative commonality in liquidity measures based on relative quoted spread, R_{SPREAD}^2, and daily trading volume, R_{DVOL}^2, are also reported. $R_{HFT\ volume}^2$ is commonality in high frequency trading measure. All commonality measures have monthly values, calculated as equally weighted averages of respective variables for all stocks in each country and tercile. In last four columns table also reports monthly market measures for returns, liquidity, volatility and trading volume. Market return (in bps), liquidity (log form) and trading volume (in EUR) are calculated as equally weighted averages of the respective variable for all stocks in each country and tercile. Market liquidity is based on Amihud liquidity measure and the absolute value increases with higher liquidity. Market volatility (in bps) is the average of monthly standard deviations of daily market returns. Standard deviations are presented for each country and tercile, and are calculated within time, $x_{it}^* = x_{it} - \bar{x}_i$.

Country	R_r^2		R_{LIQ}^2		R_{SPREAD}^2		R_{DVOL}^2		$R_{HFT\ volume}^2$		Market return	Market liquidity	Market volatility	Market volume
	mean	st.dev	mean	st.dev	mean	st.dev	mean	st.dev	mean	st.dev	mean	mean	mean	mean
Sweden	0.51	0.19	0.25	0.16	0.26	0.21	0.24	0.15	0.21	0.15	-25.67	-0.20	190.77	21.76
France	0.51	0.19	0.21	0.14	0.21	0.18	0.27	0.17	0.23	0.16	-19.10	-0.04	162.09	79.53
Germany	0.47	0.19	0.23	0.15	0.17	0.13	0.28	0.18	0.20	0.16	-20.91	-0.05	178.92	80.92
United Kingdom	0.47	0.18	0.28	0.18	0.23	0.18	0.24	0.16	0.23	0.16	-19.76	-0.14	161.03	35.24
Spain	0.41	0.19	0.21	0.15	0.18	0.13	0.21	0.15	0.19	0.14	21.53	-0.27	127.85	43.13
Italy	0.39	0.21	0.26	0.17	0.21	0.16	0.22	0.14	0.20	0.14	-21.86	-0.09	175.07	45.24
Norway	0.36	0.18	0.19	0.13	0.18	0.13	0.19	0.14	0.18	0.13	-24.21	-1.01	162.34	10.81
The Netherlands	0.36	0.18	0.16	0.12	0.17	0.12	0.20	0.14	0.17	0.13	-19.24	-0.68	130.68	27.62
Denmark	0.35	0.18	0.20	0.14	0.20	0.14	0.19	0.13	0.18	0.13	-25.5	-0.66	119.22	5.69
Finland	0.35	0.18	0.18	0.13	0.18	0.13	0.19	0.14	0.17	0.13	-18.72	-0.73	116.36	13.51
Austria	0.28	0.17	0.17	0.13	0.18	0.14	0.21	0.16	0.18	0.13	-19.96	-0.71	125.59	3.49
Belgium	0.25	0.16	0.17	0.12	0.17	0.12	0.18	0.13	0.16	0.12	-13.05	-1.10	88.29	7.99
Tercile 1	0.35	0.17	0.22	0.15	0.19	0.14	0.19	0.14	0.19	0.14	-20.83	-0.35	150.66	32.91
Tercile 2	0.40	0.18	0.22	0.15	0.21	0.16	0.21	0.14	0.19	0.14	-20.31	-0.39	148.11	33.04
Tercile 3	0.47	0.19	0.24	0.16	0.21	0.16	0.27	0.17	0.22	0.16	-20.41	-0.40	148.11	33.01
Total	0.41	0.18	0.23	0.15	0.20	0.15	0.22	0.15	0.20	0.15	-20.51	-0.38	148.93	32.98

Source: Created by the authors using data from the TRTH database (Thomson Reuters, 2012).

Table 4 Impact of Chi-X instrument on other variables

This table reports the impact of Chi-X entry on various variables during the whole sample period. The model specification is:

$$H_{i,t} = \alpha_i + \gamma_t + \beta CX_{i,t} + \varepsilon_{i,t}$$

where $H_{i,t}$ is one of the dependent variables shown in the table, $CX_{i,t}$ is a dummy variable that is equal to zero on days without message activity on Chi-X for a particular stock, and equal to one on days with message activity, α_i and γ_t are stock and time fixed effects. The regressions are performed on the whole panel and also for terciles. Terciles are constructed from all stocks by country according to total trading volume in the whole sample period where Tercile 1 (T1) refers to the smallest and Tercile 3 (T3) to the largest volume stocks. Standard errors are robust to heteroskedasticity and within-group autocorrelation. *, **, *** denote significance at 10%, 5%, 1%, respectively.

	(1) $HFTvolume_{i,t}$	(2) $HFTtrades_{i,t}$	(3) $messages_{i,t}$	(4) $dvol_{i,t}$	(5) $invmidquote_{i,t}$	(6) $volatility_{i,t}$	(7) $FR2_{i,t}$
All	17.32***	4.48**	31,346.12***	-10.88***	-0.07***	11.13**	0.09***
T1	11.66***	10.70***	3,899.01***	-0.0002	-0.12***	9.91	0.04***
T2	8.00***	-0.42	11,364.54***	-1.52***	-0.005	2.19	0.07***
T3	21.32***	4.27***	39,026.05***	-12.36***	0.02**	27.45	0.10***

Source: Created by the authors using output from data analysis in STATA.

Appendix 3. Main results

Table 5 Second stage results for HFT impact on systematic risk

This table shows results for the second stage regressions that is the final step to analyze the causal relationship between high frequency trading and systematic risk. The model specification is:

$$SR_{i,p} = \alpha_i + \gamma_p + \beta\widehat{HFT_{i,p}} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

where SR_{ip} denotes systematic risk measure for stock i in month p, i.e., commonality in returns - R^2_{Comr}, and commonality in liquidity - R^2_{ComLIQ}, $\widehat{HFT_{i,p}}$ is the predicted value of HFT for stock i in month p from the first stage regression (12) (aggregated from daily predicted values), $CV_{i,p}$ is a vector of control variables. It includes daily trading volume, volatility and 1/midquote. $FR_{i,p}$ is the fragmentation proxy $FR2_{i,p}$. We include stock and time fixed effects to eliminate any stock-specific or time effects influencing our commonality measures. $\widehat{HFT_{i,p}}$ is the instrumented variable from first stage regressions identifying high frequency trading activity. Second stage regressions are performed for different terciles and whole sample period (All). Trading volume by country terciles are constructed from all stocks by country according to total trading volume in the whole sample period where Tercile 1 (T1) refers to the smallest and Tercile 3 (T3) to the largest volume stocks. It means that each of the three terciles - top, middle and lowest – contains stocks of all 12 countries. The same logic applies to average liquidity and average volatility terciles. Time period terciles are constructed by taking all observations for time period before breakpoint date 2008.10.13 (P1), and after the breakpoint date (P2). Standard errors are robust to heteroskedasticity and within-group autocorrelation, *t*-statistics are in parenthesis under coefficients. *, **, *** denote significance at 10%, 5%, 1%, respectively. Panel A represents results for systematic return risk (dependent variable R^2_{Comr}), and Panel B reports regressions for systematic liquidity risk (dependent variable R^2_{ComLIQ}).

Panel A: Impact of HFT on systematic return risk

Data sample	R^2_{Comr}	Control variables			
		$FR2_{i,p}$	$dvol_{i,p}$	$volatility_{i,p}$	$invmidquote_{i,p}$
All	7.197***	-189.034	-0.000	-0.184***	-40.692*
	(3.551)	(-1.344)	(-0.475)	(-2.677)	(-1.800)
Trading volume by country terciles (T1 – smallest)					
T1	18.424***	-583.490*	-0.000	-0.195**	41.549
	(4.631)	(-1.706)	(-0.033)	(-2.490)	(1.633)
T2	20.435**	-314.089	0.000	-0.343**	-108.526***
	(2.409)	(-1.137)	(0.384)	(-2.136)	(-2.741)
T3	-3.782	-110.132	-0.000***	-0.136	-153.754
	(-1.408)	(-0.603)	(-3.423)	(-1.554)	(-1.258)
Average liquidity by country terciles (T1 – smallest)					
T1	15.639***	-789.898***	0.000***	-0.248***	-0.248***
	(4.714)	(-2.643)	(4.448)	(-3.132)	(-3.132)
T2	11.606**	-328.701	-0.000	-0.227***	-65.847*
	(2.056)	(-1.069)	(-1.414)	(-3.003)	(-1.666)
T3	-4.952*	-3.782	-110.132	-0.136	-153.754
	(-1.772)	(-1.408)	(-0.603)	(-1.554)	(-1.258)
Average volatility by country terciles (T1 – smallest)					
T1	-0.863	364.741*	-0.000***	2.530***	601.053*
	(-0.340)	(1.847)	(-4.005)	(2.774)	(1.824)
T2	10.748***	-272.006	-0.000	1.338**	-2.931
	(2.622)	(-1.003)	(-0.974)	(2.502)	(-0.042)
T3	12.343***	-677.907***	0.000**	-0.229***	-42.600*
	(2.971)	(-2.652)	(2.130)	(-3.350)	(-1.771)

Table 5 - *Continued*

Data sample	R^2_{Comr}	Control variables			
		$FR2_{i,p}$	$dvol_{i,p}$	$volatility_{i,p}$	$invmidquote_{i,p}$
Time period before 2008.10.13 (break point) – (P1) and after 2008.10.13 (P2)					
P1	7.811**	-174.162	-0.000	-0.136**	-26.475
	(2.435)	(-0.922)	(-0.651)	(-2.327)	(-0.875)
P2	-9.369	-105.186	-0.000	-0.078	-50.653
	(-0.440)	(-0.303)	(-1.577)	(-0.191)	(-0.465)

Panel B: Impact of HFT on systematic liquidity risk

Data sample	R^2_{ComLIQ}	Control variables			
		$FR2_{i,p}$	$dvol_{i,p}$	$volatility_{i,p}$	$invmidquote_{i,p}$
All	13.481***	-290.732**	0.000***	-0.071	-20.534
	(6.327)	(-2.116)	(5.185)	(-1.352)	(-1.085)
Trading volume by country terciles (T1 – smallest)					
T1	29.259***	-960.126***	0.000***	-0.057***	63.315**
	(7.155)	(-2.830)	(4.765)	(-2.810)	(2.172)
T2	29.829***	-37.944	0.000***	0.117	-137.467***
	(3.652)	(-0.147)	(3.147)	(1.008)	(-4.285)
T3	3.671	472.694***	0.000	-0.076	-133.940
	(1.331)	(2.787)	(0.796)	(-0.956)	(-1.266)
Average liquidity by country terciles (T1 – smallest)					
T1	18.635***	-977.627***	0.000***	-0.022	-0.999
	(5.509)	(-2.776)	(4.561)	(-0.824)	(-0.041)
T2	30.338***	-691.368**	-0.000***	0.034	-68.607***
	(4.850)	(-2.071)	(-3.251)	(0.361)	(-2.888)
T3	2.943	408.195**	0.000	-0.016	-39.762
	(1.044)	(2.440)	(0.613)	(-0.160)	(-0.453)
Average volatility by country terciles (T1 – smallest)					
T1	14.931***	-41.876	0.000***	1.300	-525.822
	(5.079)	(-0.197)	(4.996)	(1.523)	(-1.606)
T2	10.064**	55.661	0.000	0.674	48.543
	(2.388)	(0.207)	(1.330)	(1.309)	(0.795)
T3	14.129***	-816.797***	0.000**	-0.078	-27.479
	(3.375)	(-3.490)	(2.130)	(-1.497)	(-1.387)
Time period before 2008.10.13 (break point) – (P1) and after 2008.10.13 (P2)					
P1	21.530***	-495.336**	0.000***	-0.064	-14.754
	(6.219)	(-2.538)	(5.581)	(-1.336)	(-0.653)
P2	-6.255	-846.759**	-0.000	-0.108	69.073
	(-0.262)	(-1.973)	(-0.926)	(-0.283)	(1.008)

F- statistic from first stage regressions test of instrumental relevance are in range from 10.6 to 198.3. The whole panel consists of 32,233 stock-month observations.

Source: created by the authors using output from data analysis in STATA.

Table 6 Country-specific second stage results for HFT impact on systematic risk

This table shows results for second stage regressions that is the final step to analyze the causal relationship between high frequency trading and systematic risk. The model specification is:

$$SR_{i,p} = \alpha_i + \gamma_p + \beta\widehat{HFT_{i,p}} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

where SR_{ip} denotes systematic risk measure for stock i in month p, i.e., commonality in returns - R^2_{Comr}, and commonality in liquidity - R^2_{ComLIQ}, $\widehat{HFT_{i,p}}$ is the predicted value of HFT for stock i in month p from the first stage regression (12) (aggregated from daily predicted values), $FR_{i,p}$ is the fragmentation proxy $FR2_{i,p}$, $CV_{i,p}$ is a vector of control variables. It includes such measures as the daily trading volume, volatility and 1/midquote. We include stock and time fixed effects to eliminate any stock-specific or time effects influencing our commonality measures. $\widehat{HFT_{i,p}}$ is the instrumented variable from first stage regressions identifying high frequency trading activity. Second stage regressions are performed for every country separately. Standard errors are robust to heteroskedasticity and within-group autocorrelation, t-statistics are in parenthesis under coefficients. *, **, *** denote significance at 10%, 5%, 1%, respectively. Panel A represents results for systematic return risk (dependent variable R^2_{Comr}), and Panel B reports regressions for systematic liquidity risk (dependent variable R^2_{ComLIQ}).

Panel A: Country-specific impact of HFT on systematic return risk

Country	Adj R^2, #obs	R^2_{Comr}	Control variables			
			$FR2_{i,p}$	$dvol_{i,p}$	$volatility_{i,p}$	$invmidquote_{i,p}$
Sweden	0.51	-3.220	898.147	-0.000**	-6.261***	-68.548
	1,987	(-0.650)	(1.193)	(-2.045)	(-3.984)	(-0.403)
France	0.44	26.841	-395.266	0.000	-5.649**	-502.450
	2,239	(1.512)	(-0.660)	(0.219)	(-2.250)	(-0.448)
Germany	0.33	63.003	-1,794.295	-0.000	-2.439	1,585.995
	2,367	(0.541)	(-0.364)	(-1.288)	(-0.617)	(0.300)
United	0.41	178.963***	-3,956.159***	0.000***	-4.843***	102.648
Kingdom	8,546	(3.036)	(-3.034)	(2.981)	(-3.492)	(1.075)
Spain	0.41	-23.657	1504.112**	-0.000**	0.783	18.742
	1,955	(-1.663)	(2.054)	(-2.322)	(0.433)	(0.058)
Italy	0.33	-0.784	-222.402	-0.000	-0.014	-106.638
	1,968	(-0.204)	(-0.384)	(-0.677)	(-0.184)	(-0.498)
Norway	0.38	9.571*	409.809	0.000	-1.594	-3.051
	1,973	(1.969)	(0.387)	(0.814)	(-1.386)	(-0.172)
The	0.39	13.064	320.455	-0.000	2.010*	-40.281
Netherlands	2,008	(0.815)	(0.683)	(-0.993)	(1.681)	(-0.700)
Denmark	0.34	8.876	-615.561	-0.000	0.198	-132.329
	1,825	(0.647)	(-0.292)	(-0.126)	(0.676)	(-0.846)
Finland	0.30	12.056	1,113.225	-0.000	-3.471**	142.915***
	1,970	(1.177)	(1.602)	(-0.383)	(-2.428)	(2.900)
Austria	0.24	71.258*	-91.631	0.000	-0.309*	-1,940.878***
	1,262	(1.802)	(-0.134)	(1.548)	(-1.676)	(-3.178)
Belgium	0.23	-6.956	-109.691	0.000	-1.265***	60.448*
	1,872	(-0.610)	(-0.187)	(0.442)	(-3.609)	(1.844)

Table 6 - Continued

Panel B: Country-specific impact of HFT on systematic liquidity risk

Country	Adj R^2, #obs	R^2_{ComLIQ}	Control variables			
			$FR2_{i,p}$	$dvol_{i,p}$	$volatility_{i,p}$	$invmidquote_{i,p}$
Sweden	0.17	-0.317	1,041.445	-0.000	-2.862*	180.179**
	1,999	(-0.042)	(1.008)	(-0.825)	(-1.864)	(2.601)
France	0.14	2.537	-20.645	-0.000	-2.353	-1,576.972**
	2,239	(0.133)	(-0.037)	(-0.830)	(-0.721)	(-2.159)
Germany	0.11	77.716	-3,264.161	0.000	0.394	2,369.061
	2,369	(0.621)	(-0.612)	(0.343)	(0.102)	(0.413)
United	0.21	154.442**	-3,546.865**	0.000**	-4.349***	49.199
Kingdom	8,544	(2.457)	(-2.581)	(2.467)	(-3.218)	(0.492)
Spain	0.13	-21.216	-416.910	-0.000	2.332	-156.798
	1,967	(-1.509)	(-0.493)	(-1.326)	(1.342)	(-0.566)
Italy	0.15	3.938	-813.145	0.000	-0.079	-103.649
	1,973	(0.919)	(-1.513)	(0.705)	(-1.400)	(-0.649)
Norway	0.08	8.164	-957.760	0.000	0.229	15.508
	1,703	(1.534)	(-0.832)	(0.625)	(0.214)	(0.760)
The	0.03	18.841	5.404	0.000**	1.374	142.555***
Netherlands	1,905	(1.332)	(0.014)	(2.450)	(1.276)	(4.274)
Denmark	0.06	10.642	-2,367.675*	0.000	0.158	224.983
	1,710	(0.849)	(-1.694)	(1.062)	(0.617)	(0.946)
Finland	0.03	-38.934***	1,395.159*	-0.000*	-0.534	-62.417
	1,846	(-3.031)	(1.752)	(-1.930)	(-0.449)	(-1.397)
Austria	0.06	-7.702	-1,087.851**	0.000	-0.022	128.876
	1,125	(-0.173)	(-2.415)	(0.021)	(-0.107)	(0.205)
Belgium	0.04	38.310***	-289.823	0.000***	-0.422	46.764
	1,566	(2.832)	(-0.420)	(3.127)	(-1.285)	(0.944)

F- statistic from first stage regressions test of instrumental relevance are in range from 8.3 to 52.9, except for Germany and the UK where F-statistic is below 1.

Source: created by the authors using output from data analysis in STATA.

Table 7 Economic significance of HFT impact on systematic risk

This table shows the economic significance in percent for both systematic risk measures (returns R^2_{Comr} and liquidity R^2_{ComLIQ}) for the whole panel and terciles. Since all R^2 values have been transformed, we have to perform a reverse transformation to be able to interpret the obtained coefficients. To calculate the effect of one standard deviation (σ) (or any value of interest) change in $HFTvolume_{i,p}$ on the value of our systematic risk measures (R^2_{LIQ} and R^2_r) following equation is used (Karolyi et al., 2012):

$$\Delta R^2 = \frac{e^{\alpha+\beta(\mu+\sigma)+\theta*Cv}}{1+\ e^{\alpha+\beta(\mu+\sigma)+\theta*Cv}} - \frac{e^{\alpha+\beta*\mu+\theta*Cv}}{1+\ e^{\alpha+\beta*\mu+\theta*Cv}}$$

where α denotes intercept, β is coefficient on our high frequency trading measure, both from our second stage regression. θ and Cv are vector of coefficients on time and stock fixed effects and other control variables and vector of means of same variables respectively. Trading volume by country terciles are constructed from all stocks by country according to total trading volume in the whole sample period, where Tercile 1 (T1) refers to the smallest and Tercile 3 (T3) to the largest volume stocks. It means that each of the three terciles - top, middle and lowest – contains stocks of all 12 countries. The same logic applies to average liquidity and average volatility terciles. Time period terciles are constructed by taking all observations for time period before breakpoint date 2008.10.13 (P1), and after the breakpoint date (P2).

Economic significance of HFT impact on systematic risk		
Data sample	R^2_{Comr}	R^2_{ComLIQ}
All	7.13%	9.52%
Trading volume by country terciles (T1 – smallest)		
T1	0.06%	0.00%
T2	29.00%	34.75%
T3	-1.37%	1.62%
Average liquidity by country terciles (T1 – smallest)		
T1	16.39%	15.96%
T2	8.17%	14.87%
T3	-3.40%	1.35%
Average volatility by country terciles (T1 – smallest)		
T1	-1.06%	14.83%
T2	0.22%	3.84%
T3	9.05%	5.69%
Time period before 2008.10.13 (break point) – (P1) and after 2008.10.13 (P2)		
P1	9.41%	21.26%
P2	-4.05%	-1.81%

Source: created by the authors using output from data analysis in STATA.

Table 8 Results for HFT impact on various individual stock and market measures

This table shows results for a number of regressions that analyze the causal relationship between HFT and individual stock and market measures. The model specification is:

$$M_{i,p} = \alpha_i + \gamma_p + \beta\widehat{HFT}_{i,p} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

where M_{ip} denotes the dependent variable for stock i in month p, i.e., average stock return $r_{i,p}$, average liquidity $LIQ_{i,p}$, average relative quoted spread $SPREAD_{i,p}$, average daily trading volume $dvol_{i,p}$, average stock return volatility $volatility_{i,p}$, and four monthly market measures for return, liquidity, volume and volatility. $\widehat{HFT}_{i,p}$ is the predicted value of HFT for stock i in month p from the first stage regression (12) (aggregated from daily predicted values), $FR_{i,p}$ is the fragmentation proxy $FR2_{i,p}$, $CV_{i,p}$ is a vector of control variables. It includes such measures as the daily trading volume, volatility and 1/midquote. Control for daily trading volume and volatility is excluded if the dependent variable is individual stock/market daily trading volume or volatility, respectively. We include stock and time fixed effects to eliminate any stock-specific or time effects influencing our measures. $\widehat{HFT}_{i,p}$ is the instrumented variable from first stage regressions identifying HFT activity. Standard errors are robust to heteroskedasticity and within-group autocorrelation, *t*-statistics are in parenthesis under coefficients. *, **, *** denote significance at 10%, 5%, 1%, respectively.

Variables	#obs, Adj R^2	$\widehat{HFT}_{i,p}$	Control variables			
			$FR2_{i,p}$	$dvol_{i,p}$	$volatility_{i,p}$	$invmidquote_{i,p}$
$r_{i,p}$	30,130	-0.206	18.830**	0.000	.002	-0.593
	0.16	(-1.454)	(2.04)	(0.27)	(-0.10)	(-0.21)
$LIQ_{i,p}$	29,647	0.018***	0.558***	0.000***	-0.000***	0.019
	0.81	(15.913)	(8.42)	(14.23)	(-3.75)	(0.51)
$SPREAD_{i,p}$	30,327	-3.533***	-90.588***	0.000***	0.086**	45.170***
	0.57	(-11.897)	(-5.01)	(-10.41)	(2.20)	(4.93)
$dvol_{i,p}$	30,338	-3,623,333***	139,888,490***		6,385.86***	-2,560,097***
	0.98	(-32.735)	(22.24)		(4.77)	(-5.30)
$volatility_{i,p}$	30,338	2.841**	-67.814*	0.000**		23.659***
	0.31	(2.325)	(-1.87)	(2.15)		(4.07)
Market return	30,185	0.417	3.576*	0.000	-0.002	-0.506
	0.79	(1.478)	(1.95)	(0.77)	(-0.93)	(-1.81)
Market liquidity	30,185	0.004***	0.414***	0.000***	-0.000***	-0.015**
	0.93	(6.607)	(11.77)	(5.13)	(-3.95)	(-2.44)
Market volume	30,338	-272,313***	1,451,809		1,675.031***	-281,182
	0.94	(-15.289)	(0.99)		(4.16)	(-1.55)
Market volatility	30,185	1.467***	-10.573**	0.000***		5.373***
	0.82	(15.254)	(-2.11)	(14.70)		(5.09)

Source: created by the authors using output from data analysis in STATA.

Appendix 4. Mediation tests

Figure 7. Mediation test for systematic return risk.

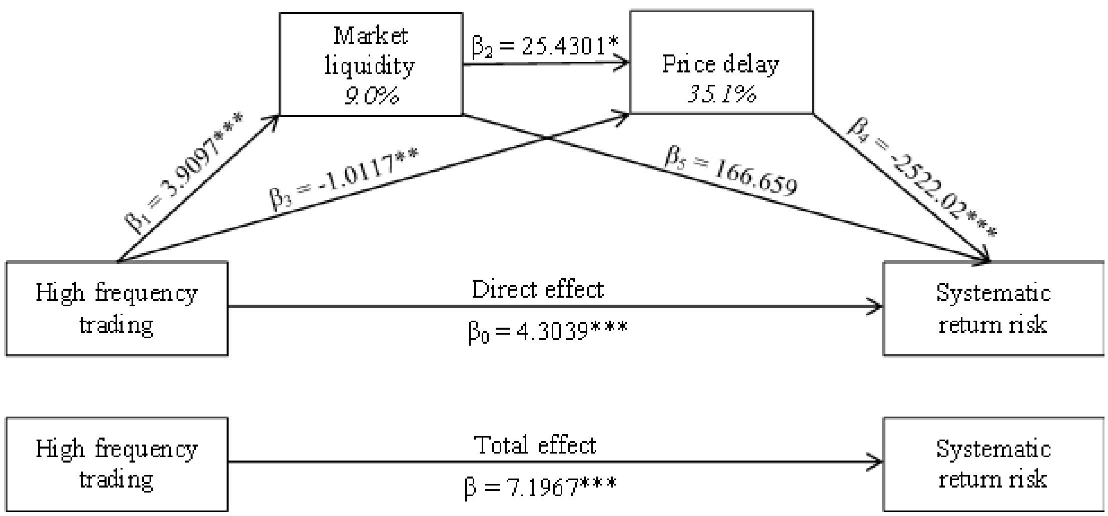
This graph depicts the scheme for mediational path to test market liquidity and price delay as potential mediators for the HFT and systematic return risk relationship. The serial multiple mediator model is applied and beta coefficients are shown on the arrows for each regression. Regressions used in the model are:

$$ML_{i,p} = \alpha_i + \gamma_p + \beta_1 \widehat{HFT_{i,p}} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

$$PD_{i,p} = \alpha_i + \gamma_p + \beta_3 \widehat{HFT_{i,p}} + \beta_2 ML_{i,p} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

$$R^2_{Comr} = \alpha_i + \gamma_p + \beta_0 \widehat{HFT_{i,p}} + \beta_5 ML_{i,p} + \beta_4 PD_{i,p} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

where $ML_{i,p}$ is market liquidity for stock i in month p calculated as the equally weighted average of the Amihud's liquidity measure for all stocks, $\widehat{HFT_{i,p}}$ is the predicted value of HFT for stock i in month p from the first stage regression (12) (aggregated from daily predicted values), $CV_{i,p}$ is a vector of control variables, $FR_{i,p}$ is the fragmentation proxy $FR2_{i,p}$, stock and time fixed effects are also included. $PD_{i,p}$ is the price delay measure for stock i in month p, R^2_{Comr} denotes systematic return risk measure for stock i in month p, i.e., commonality in returns. Specific indirect effect for each mediator is shown in percent. *, **, *** denote significance at 10%, 5%, 1%, respectively.



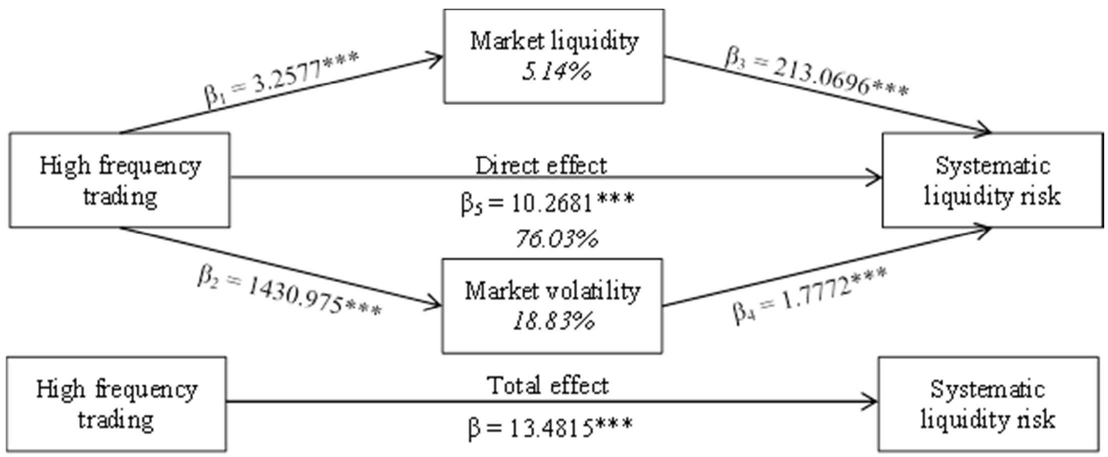
Source: created by the authors using output from data analysis in STATA.

Figure 8. Mediation test for systematic liquidity risk.

This graph depicts the scheme for mediational path to test market liquidity and market volatility as potential mediators for the HFT and systematic liquidity risk relationship. The parallel multiple mediator model is applied and beta coefficients are shown on the arrows for each regression. Regressions used in the model are:

$$ML_{i,p} = \alpha_i + \gamma_p + \beta_1 \widehat{HFT_{i,p}} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$
$$MV_{i,p} = \alpha_i + \gamma_p + \beta_2 \widehat{HFT_{i,p}} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$
$$R^2_{ComLIQ} = \alpha_i + \gamma_p + \beta_5 \widehat{HFT_{i,p}} + \beta_3 ML_{i,p} + \beta_4 MV_{i,p} + \delta CV_{i,p} + \phi FR_{i,p} + \tau_{i,p}$$

where $ML_{i,p}$ is market liquidity for stock i in month p calculated as the equally weighted average of the Amihud's liquidity measure for all stocks, $MV_{i,p}$is market volatility (in bps) for stock i in month p calculated as the average of monthly standard deviations of daily market returns, $\widehat{HFT_{i,p}}$ is the predicted value of HFT for stock i in month p from the first stage regression (12) (aggregated from daily predicted values), $CV_{i,p}$ is a vector of control variables, $FR_{i,p}$ is the fragmentation proxy $FR2_{i,p}$, stock and time fixed effects are also included. R^2_{ComLIQ} denotes systematic liquidity risk measure for stock i in month p, i.e., commonality in liquidity. Specific indirect effect for each mediator and direct effect are shown in percent. *, **, *** denote significance at 10%, 5%, 1%, respectively.



Source: created by the authors using output from data analysis in STATA.