Multimarket High-Frequency Trading and Commonality in Liquidity

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Abstract

This paper examines the effects of multimarket high-frequency trading (HFT) activity on liquidity co-movements across different markets. Multimarket trading by HFTs connects individual markets in a single network, which should induce stronger network-wide liquidity co-movements. We use the staggered introduction of an alternative trading platform, Chi-X, in European equity markets as our instrument for an exogenous increase in multimarket HFT activity. Consistent with our predictions, we find that liquidity co-movements within the aggregate network of European markets significantly increase after the introduction of Chi-X and even exceed liquidity co-movements within the home market. They are especially strong in down markets and for stocks with a higher intensity of HFT trading in the post-Chi-X period.

JEL classifications: G10, G11, G12

Keywords: Multimarket trading, High-frequency trading, Commonality in Liquidity, European equities, Liquidity risks

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1 Introduction

There are numerous benefits to high-frequency trading. Substantial academic literature confirms that, by acting competitively and processing information more efficiently, high-frequency traders (HFTs) generally improve market quality. They increase market liquidity (Brogaard 2010, Jovanovic and Menkveld 2016), reduce short-term volatility, at least during normal market conditions (Hasbrouck and Saar 2013, Hagströmer and Nordén 2013), and contribute positively to price discovery (Brogaard, Hendershott, and Riordan 2014). They reduce the trading costs of retail traders (Malinova, Park, and Riordan 2016), keep fragmented markets virtually consolidated (Menkveld 2013) and might even increase social welfare (Jovanovic and Menkveld 2016).

The various benefits generated by HFTs should not however overshadow potential risks, created by these market participants. In addition to an increase in adverse selection costs for other traders (Biais, Foucault, and Moinas 2015; Foucault, Kozhan, and Tham 2017), and the likely contribution of HFTs to high volatility during the Flash Crash (Kirilenko et al. 2017; Easley, López de Prado, and O'Hara 2011), the July 2011 International Organization of Securities Commissions (IOSCO) Technical Committee report emphasizes the effect HFT activity might potentially have on the transmission of extreme shocks across different markets and asset classes.[1] In their theoretical paper, Cespa and Foucault (2014) show that cross-asset learning leads to liquidity spillovers across asset classes, and a small drop in liquidity of one asset can even cause a marketwide liquidity crash. Bongaerts and Van Achter (2016) model implications of HFT for market stability to show that the combination of their superior speed and information processing skills leads to oligopolistic rents and occasional market freezes. Surprisingly, empirical evidence on transmission of liquidity shocks by HFTs is rather scarce.[2]

In this paper, we examine the effect of multimarket HFT activity on systematic liquidity comovements of stocks across different markets. Following Chordia, Roll, and Subrahmanyam (2000),

[1] See Section 3 of the July 2011 IOSCO Technical Committee report *"Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency"*.

[2] To the best of our knowledge, there are currently only two empirical papers that examine systemic risks, potentially generated by HFTs. Jain, Jain, and McInish (2016) analyze changes in systemic risk measures, caused by HFTs, on a single market, Tokyo Stock Exchange, as opposed to transmission of shocks across several markets. Ben-David, Franzoni, and Moussawi (2012) show that arbitrage activity between ETFs and their underlying securities, which can be potentially attributed to HFTs, can propagate shocks across these two asset classes.

we analyze co-variations of the stock's liquidity with the aggregate market liquidity and refer to these co-variations as commonality in liquidity. High-frequency traders share similar algorithms (Chaboud et al. 2014, Benos et al. 2015), which can lead to excess co-movements in their demand and supply, and consequently, to commonality in liquidity across stocks even within the same market.[3] However, HFTs often engage in trading across multiple markets, which essentially connects these markets in a single network and might facilitate cross-market liquidity spillovers.[4] Specifically, we hypothesize that multimarket HFT activity induces stronger commonality in liquidity for stocks traded within the aggregate network of markets, even after controlling for their liquidity co-movements within their home market.

Findings from prior studies suggest that stock liquidity co-movements can arise both through demand (Koch, Ruenzi, and Starks 2016, Kamara, Lou, and Sadka 2008) and supply channels (Coughenour and Saad 2004). As liquidity demanders, HFTs engage either in cross-market arbitrage strategies to exploit temporary mispricings between two markets, or directional trading strategies, to quickly trade on new information (Baron et al. 2016). In either case, excess co-movements in their demand can cause stronger commonality in liquidity across stocks, simultaneously traded by their algorithms. As liquidity suppliers, HFTs act as market makers, posting and monitoring quotes across multiple venues (Menkveld 2013). Since HFTs usually make markets in several assets, correlated fluctuations in their inventory levels can also induce stronger liquidity co-movements across stocks in their inventory portfolios.

We use the staggered entrance of Chi-X, an alternative platform for trading European equities, as an instrument for an increase in multimarket high-frequency trading activity. Two main competitive advantages of Chi-X at the time of its introduction, compared to national stock exchanges, are its lower execution fees, and its 22 to 84 times faster speed of order processing. Both of these features should arguably attract high-frequency traders. Jovanovic and Menkveld (2016) and Menkveld (2013) indeed find that one large HFT takes part in 70-80% of Chi-X trades for Dutch and Belgian index stocks, and almost 10% of all trades for these stocks on their home market,

[3]Prior studies by Huh (2011) and Boehmer and Shankar (2014) analyze the impact of algorithmic traders on the co-movement of liquidity and order flow within US and Indian equity markets, respectively.

[4]In their model, Lescourret and Moinas (2015) formally show that multimarket liquidity provision makes the liquidity of two markets interconnected. Tomio (2016) shows theoretically and empirically how multimarket arbitrage activity can contribute to the convergence of individual stock's liquidity between the two markets.

Euronext. Essentially, it is acting as a multimarket liquidity provider, with 4 in 5 of its trades being passive in both markets. Importantly, Menkveld (2013) also shows that Chi-X market shares jump above 10% with the entry of this HFT, and drop almost to zero on days when it is absent from the market.

Since trading of European major index stocks on Chi-X was introduced in several phases, it allows us to clearly identify the causal effect of multimarket HFT activity on the systematic liquidity co-variations of stocks across European equity markets. Variation in Chi-X entry times into 11 different markets in our sample should alleviate valid concerns about general time trends in commonality in liquidity, or any potential effects of the financial crisis. Further, for the staggered introduction of Chi-X to be a valid instrument, it must satisfy the exclusion restriction, i.e. its entry dates must not be related to contemporaneous changes in systematic stock liquidity co-movements other than through the effect of HFT activity. However, such a relation is rather unlikely, since it would mean that Chi-X was able to accurately predict changes in systematic liquidity co-movements of stocks traded across 11 European markets. Importantly, the introduction of Chi-X makes it easier to simultaneously engage in fast trading of all major European equities on a single trading platform, hitherto not possible at a comparable speed. Even though Chi-X might be a primary trading platform for HFTs, multimarket HFT trading activity between Chi-X and home markets makes the liquidity of multiple European markets interconnected, potentially inducing stronger liquidity co-movements within the aggregate network of European markets.[5]

To test our hypothesis, we derive two empirical predictions. First, if multimarket HFT activity induces stronger commonality in liquidity within the network of European markets, then we expect an increase in the stock's liquidity co-movements with the aggregate liquidity of the European market after the introduction of Chi-X. In the following, we refer to these co-movements as EU liquidity betas. Our second prediction is that EU liquidity betas should be higher for stocks with a more intense HFT trading in the post-Chi-X period.

[5]Note that correlated trading strategies of other traders, e.g., institutional investors, could also potentially induce stronger commonality in liquidity across different markets. However, these traders are less likely to engage in multimarket trading, which requires quick and simultaneous monitoring of several limit order books. By contrast, HFTs heavily invest in multimarket monitoring technology: e.g., Van Kervel (2015) empirically shows that executed trades of fast traders on one venue are followed by sizable cancellations on competing venues.

We test the two empirical predictions on the sample of 445 major European index stocks from 11 countries over the period from January 2004 to December 2014. Our results provide supporting evidence that commonality in liquidity within the aggregate network of European markets is significantly stronger after Chi-X introduction. Importantly, European-wide liquidity co-variations become more important than co-variations with the home market in the post-Chi-X period. Further, EU liquidity betas are especially high in down markets and, consistent with our second prediction, increase more for stocks with a more intense HFT market making activity. Overall, our findings suggest that multimarket HFT activity induces stronger liquidity co-movements across European markets by connecting them in a single network. Indeed, liquidity co-variations with home markets seem to have lost their significance in recent years, as each market now represents just a part of a greater system.

Understanding liquidity risks arising from multimarket HFT trading activity is important for policymakers, institutional investors, firms and virtually all market participants. Stronger co-variations in aggregate European liquidity make propagation of liquidity shocks easier across markets, increasing the risk of contagion and threatening the stability of global financial markets. Negative liquidity shocks are of special concern during crisis periods, because they imply higher transaction costs and the inability to trade assets quickly without large impact on their prices.

The details of our research design and main findings are as follows. We start with the analysis of home liquidity betas, estimated as the sensitivity of the stock's liquidity to the aggregate liquidity of the corresponding home market index (e.g., FTSE 100 for UK stocks) from Chordia et al.'s (2000) model. We use 5-minute relative spreads as our benchmark measure of liquidity. Consistent with prior studies of Huh (2011) and Boehmer and Shankar (2014), we find that home liquidity betas significantly increase in the post-Chi-X period, suggesting that correlated strategies of HFTs, trading between Chi-X and the home market, induce stronger liquidity co-movements of stocks in the same country.

In the next step, we examine EU liquidity betas, by adding fluctuations in liquidity of the FTSE Eurofirst 100, a pan-European index, to the model.[6] Consistent with our first prediction,

[6]Note that we exclude all stocks that are traded in the corresponding home market from the pan-European index to ensure that EU liquidity betas are not anyhow affected by the liquidity co-variations with the home market.

EU liquidity betas significantly increase by almost 40%, relative to their mean level in the pre-Chi-X period. We use Scandinavian stocks that are not part of Eurofirst 100 as our control group, and in line with expectations, we do not find any evidence of significantly higher EU liquidity betas for these stocks. After we control for liquidity co-movements with the aggregate European market, an increase in home liquidity betas drops by almost half and is overall lower, as compared to an increase in EU liquidity betas. For a group of major European countries, including the UK, Germany and France, home liquidity betas actually drop in the post-Chi-X period. Overall, our findings suggest that European-wide liquidity co-variations have become stronger than co-variations within the home market following an increase in multimarket high-frequency trading activity. Additionally, subperiod splits show that liquidity co-variations with the aggregate European market are especially high in down markets, implying that multimarket HFT activity makes European equity markets more susceptible to the transmission of liquidity shocks during crisis periods.

We then test for cross-sectional differences in EU liquidity betas, which might arise due to differences in the intensity of multimarket high-frequency trading in the post-Chi-X period. We use two proxies to measure the intensity of HFT activity, the *Chi-X market share* and the *Multimarket Trading* measure of Halling, Moulton, and Panayides (2013). We use the *Chi-X market share* as our proxy for liquidity supplying HFT activity, based on empirical evidence from Menkveld (2013). By contrast, the *Multimarket Trading* measure rather captures liquidity demanding HFT activity. We observe a larger increase in EU liquidity betas for stocks with larger Chi-X market shares, but not for stocks with higher measures of *Multimarket Trading*, indicating that stronger liquidity co-movements within the network of European markets in the post-Chi-X period are mostly driven by HFTs engaging in market making activity across multiple venues.

We further conduct robustness checks of our main analyses with two daily liquidity measures, the daily relative spread and the Amihud measure, because co-movements on the daily basis might be of higher importance to institutional and retail investors. We find that all our main results hold and are even stronger for the daily relative spread. We can therefore conclude that stronger intraday liquidity co-movements in the post-Chi-X period also aggregate to the daily level.

Our paper contributes to the ongoing debate on potential systemic risks, generated by high-frequency traders. Jain, Jain, and McInish (2016) use the introduction of a low-latency platform Arrowhead on the Tokyo Stock Exchange as an instrument for an increase in high-frequency trading, and find that correlated trading by HFTs may increase auto- and cross-correlation in limit orders as well as Adrian and Brunnermeier's (2011) measure of systemic risk (CoVaR). In related papers, Huh (2011) and Boehmer and Shankar (2014) examine the impact of algorithmic traders on the co-movement of liquidity and order flow separately for the US and the Indian equity market. Our study differs in two respects. First, we provide empirical evidence that HFT activity is likely to propagate liquidity shocks not only within stocks traded on the same market, but also within the aggregate network of markets. Further, we conduct a long-term study over a 10-year period, as opposed to the sample periods of less than one year in previous studies.

Our paper further adds to the literature on commonality in liquidity (Chordia, Roll, and Subrahmanyam 2000, Huberman and Halka 2001) and its sources (Coughenour and Saad 2004, Kamara, Lou, and Sadka 2008, Koch, Ruenzi, and Starks 2016). Karolyi, Lee, and van Dijk (2012) is a pioneering cross-country study that analyzes commonality in returns, liquidity and turnover in a sample of 40 developed and emerging countries. Importantly, their analysis documents the existence of strong liquidity co-movements of stocks within their home markets for all countries in their sample. Extending their results, we show that, following a rise in multimarket HFT trading activity, liquidity of a stock also systematically co-varies with the liquidity of the aggregate market network, and that these co-variations can even exceed its co-variations with the home market.

Lastly, we extend the literature on multimarket trading by analyzing the implications of multimarket high-frequency trading activity on potential liquidity risks. In contrast, the main focus of previous studies is either examining determinants of multimarket trading activity (Pulatkonak and Sofianos 1999, Halling et al. 2008, Baruch, Karolyi, and Lemmon 2007, Menkveld 2008) or studying its effects on liquidity levels through demand (Halling, Moulton, and Panayides 2013) and supply (Menkveld 2013, Van Kervel 2015, Lescourret and Moinas 2015) channels.

2 Institutional Background and Identification Strategy

2.1 Introduction of Chi-X

Prior to the introduction of the Markets in Financial Instruments Directive (MiFID) in November 2007, trading of European equities was virtually consolidated on national stock exchanges, with the majority of trades for British stocks executed on the London Stock Exchange (LSE), German stocks on Deutsche Boerse and French stocks on Euronext Paris. The European Union designed the MiFID to promote competition between exchanges by allowing entry of alternative platforms, so-called multilateral trading facilities (MTFs). Whereas equities can only be listed on national exchanges, MTFs provide a platform for trading these securities, bringing together third-party buyers and sellers.

The first and the largest of the European MTFs is Chi-X, introduced by Instinet six months ahead of MiFID in April 2007. Similar to many national stock exchanges, it is organized as an electronic limit order book with a price-time priority rule. Two main competitive advantages of Chi-X are its lower execution fees and faster speed of order processing, or low latency.[7] Chi-X operates a so-called "maker-taker" fee structure, charging liquidity demanders 0.30 bps and rebating liquidity providers with 0.20 bps. In contrast, national stock exchanges charged trading fees over 0.50 bps for each side of a trade at the time Chi-X was introduced.[8] Further, the Chi-X latency of 0.89 milliseconds was substantially lower than the latency of its main competitors. At the time, LSE needed around 20 milliseconds and Euronext Paris around 75 milliseconds to process a round-trip transaction, which is 22 to 84 times longer than the Chi-X processing time.[9]

Chi-X is also the first pan-European trading platform, enabling simultaneous trading of all major European equities on a single venue. Figure 1 demonstrates how Chi-X serves as a connection link for individual European markets on an example of LSE and Euronext Paris. Importantly, the entry of Chi-X into European equity markets was staggered in several phases. German (DAX30)

[7]There are many definitions for "latency". In this paper latency is defined as the time needed by the exchange trading engine to process a round-trip transaction.

[8]Even though their trading fees reduced over time, they remain substantially higher than 0.30 bps, charged by Chi-X. For example, LSE currently charges 0.45 bps for the first £2.5 bn of orders executed.

[9]He, Jarnecic, and Liu (2015) provide a detailed overview of fee structures and latencies of European national stock exchanges at the time of the introduction of Chi-X.

and Dutch (AEX) large-cap index stocks first started trading on its platform in April 2007. UK (FTSE100) and French (CAC40) stocks followed in July 2007 and October 2007, respectively. By the end of 2008, Chi-X expanded further into Belgian (BEL20), Scandinavian (OMXS30, OMXH25, OMXC20 and OBX), Spanish (IBEX35) and Italian (FTMIB) stocks. Figure 2 shows the timeline of Chi-X entrance into European equity markets and Appendix A lists Chi-X introduction dates for each country in our sample.

[Insert Figures 1 and 2 approximately here]

Chi-X market shares were initially low, but had increased to levels above 10% for the UK, France, Germany and the Netherlands by the end of 2008. By the beginning of 2010, they were already above 20% for these countries and started crossing the 10%-threshold for later entrants, such as Belgium, Sweden and Finland. Figure 3 and Table 1 present quarterly averages of Chi-X market shares by country. In 2011, Chi-X was taken over by BATS, a competitor MTF, resulting in its name change to BATS Chi-X Europe. However, the company still operates two separate limit order books: BATS CXE (Chi-X) and BATS BXE (BATS), which mainly differ in their fee structures.

[Insert Figure 3 and Table 1 approximately here]

By the end of 2014, Chi-X (BATS CXE) captured around 25% of trades for British, French, German, Dutch, Belgian, Finnish and Swedish stocks, and more than 15% of trades for remaining countries. Its market shares by far dominate the market shares of BATS and Turquoise, another MTF who entered the European market in fall 2008. In 2014, the Turquoise share was below 10% and the BATS BXE share below 5% for all major European stock indices.[10]

2.2 Identification Strategy

In our analysis, we use Chi-X entry as an instrument for an increase in multimarket high-frequency trading activity. For our instrument to be valid, it should be positively correlated with an increase

[10]Data on market fragmentation for all major European indices are provided by Fidessa on http://fragmentation.fidessa.com/europe.

in high-frequency trading. Indeed, several prior studies show that its reduced latency and rebates on liquidity provision attract high-frequency traders, especially those pursuing market making strategies. Jovanovic and Menkveld (2016) and Menkveld (2013) empirically analyze the entry of one large HFT trading Dutch and Belgian index stocks both in Chi-X and NYSE Euronext, the incumbent market. Specifically, Menkveld (2013) finds that around 80% of HFT trades are passive in both markets, i.e., it is essentially acting as a multimarket liquidity provider. Importantly, he shows that the HFT takes part in 70-80% of all Chi-X trades and almost 10% of all Euronext trades, which further supports the validity of our instrument. Chi-X market shares jump above 10% only with the entry of this large HFT, several months after the initial launch of Chi-X, and drop almost to zero on days when the HFT is absent from the market. Based on this evidence, we use the quarter when the average Chi-X market share for stocks in a country reaches the 10% threshold as the treatment quarter in our analysis.

He, Jarnecic, and Liu (2015) analyze determinants of Chi-X market shares for major European, Japanese and Australian stock indices. Their results confirm that Chi-X market shares are larger for stocks in countries in which the advantages to high-frequency traders are greater when compared to corresponding national stock exchanges: relatively lower latency and lower trading fees for liquidity providers result in higher Chi-X market shares for stocks in these countries. Consistent with prior studies on HFT (Hendershott and Moulton 2011, Hasbrouck and Saar 2013, Jovanovic and Menkveld (2016), Hagströmer and Nordén 2013), they further show that the introduction of Chi-X leads to a significant reduction in bid-ask spreads, thus improving overall market liquidity.

Importantly, the staggered introduction of Chi-X allows us to clearly identify the causal effect of multimarket HFT activity on systematic stock liquidity co-movements. Two valid concerns could be that our results are driven by general time trends in liquidity commonality, or are induced by an ongoing financial crisis. Arguably, the variation in Chi-X entry times across 11 countries in our sample reduces the influence of these concurrent effects and alleviates the above concerns. Our setup is similar to Hendershott, Jones, and Menkveld (2011), who use the staggered introduction of NYSE Autoquote as an instrument for an exogenous increase in algorithmic trading. Specifically, they use variation in the Autoquote phase-in schedule across NYSE stocks to identify the causal effect of algorithmic trading by comparing the liquidity of autoquoted stocks to the not yet autoquoted stocks in their sample. In our setup, we compare systematic liquidity co-movements for stocks already traded on Chi-X to those that have not started their trading yet, which essentially corresponds to difference-in-differences methodology.

Lastly, for the staggered introduction of Chi-X to be a valid instrument, it must satisfy the exclusion restriction, i.e., it should not be correlated with the error term in the explanatory equation. In other words, Chi-X entry dates must not be related to contemporaneous changes in systematic stock liquidity co-movements other than through the effect of HFT activity. We argue that such correlation with the error term is rather unlikely, since it would mean that Chi-X chooses its entry dates strategically and is able to accurately predict an increase in systematic liquidity co-movements across different countries. Further, we do not find any significant deviations of systematic stock liquidity co-movements from their unconditional means in the quarter preceding the introduction of Chi-X, which provides additional support for the exogeneity of our instrument.

3 Data and Sample Construction

3.1 Sample Construction

We download the composition of main European stock indices over the period January 2004 - December 2014 from the Thomson Reuters Tick History (TRTH) database. Countries covered in this paper are Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, and the United Kingdom. Table 2 lists the corresponding index for each country. Our initial sample consists of all stocks that constitute these indices during our sample period. If the composition of an index changes, we keep both old and new index constituents for the entire sample period to keep the number of firms in our sample constant.

We concentrate our analysis on the main European stock indices for two reasons. First, at the time of the introduction of Chi-X to each country, it is possible to trade only this country's main index constituents, with mid-cap and other stocks starting their trading only later on the Chi-X platform. Second, constituents of main indices represent the largest and the most liquid stocks in each country, which should encourage the active participation of high-frequency traders. Panel A of Table 2 reports the number of distinct firms and Panel B the number of firm-month observations for each country.

[Insert Table 2 approximately here]

The initial sample consists of 539 firms. In the first step, we filter out Reuters Instrument Codes (RICs) that appear to be erroneously reported as an index constituent by TRTH (Filter 1).[11] Appendix B provides details of our data cleaning procedure. We further require the stock price to be greater than £2 at the end of the previous trading day for UK stocks, and greater than €2 for other European stocks (Filter 2).[12] Lastly, we require the stock to be traded for at least 1,000 different 5-minute intervals in a given month. Excluding the stocks that do not satisfy the criteria above leaves 445 firms and 50,278 firm-months in our final sample.

3.2 Measuring Liquidity

Given that high frequency traders have relatively short trading horizons, we opt for the 5-minute quoted relative spread as the benchmark measure in our analysis.[13] Formally, we calculate the quoted relative spread, *qspread*, as

$$qspread_{i,t} = \frac{A_{i,t} - B_{i,t}}{(A_{i,t} + B_{i,t})/2},$$

where $A_{i,t}$ is the ask price and $B_{i,t}$ the bid price prevalent for stock i on its primary exchange at the end of the 5-minute interval t. We delete observations with negative spreads or spreads exceeding 20%, and winsorize the upper and lower 1% of the *qspread* distribution to avoid outliers.

Following Chordia, Roll, and Subrahmanyam (2000), we calculate first differences of the relative quoted spread, $\triangle qspread$, to capture fluctuations in intraday liquidity.[14] We further standardize

[11] RIC is the main stock identifier in TRTH, similar to the ticker in the NYSE TAQ database.

[12] This requirement is standard in previous studies with US data, for example, Amihud (2002), Acharya and Pedersen (2005), Kamara, Lou, and Sadka (2008) and Ben-Raphael, Kadan, and Wohl (2015).

[13] Prior studies on algorithmic trading also sample data on intervals of comparable length: Huh (2011) uses 5-minute intervals and Boehmer and Shankar (2014) 15-minute intervals. Spreads with higher frequency would include too much microstructure noise and is thus not appropriate for the purposes of our analysis. We also repeat our analysis with spreads, calculated over 10-minute intervals, but all results remain qualitatively similar.

[14] Taking first differences also helps us to overcome a potential econometric problem of nonstationarity of liquidity levels.

$\triangle qspread$ by the time-of-the-day mean and standard deviation to account for well-documented intraday patterns of bid-ask spreads.[15] Specifically, for stock i and interval t, $\triangle qspread_{i,t}$ is standardized by the monthly mean and standard deviation of $\triangle qspread$ estimated for stock i in the corresponding hour h across all days.

Arguably, liquidity co-variations on a daily basis might be more important for lower-frequency traders, such as institutional and retail investors. With short trading horizons of high frequency traders, it is *ex ante* not clear whether stronger intraday liquidity co-variations also aggregate to the daily level. Therefore, we also present results for daily closing bid-ask spreads and the Amihud measure of liquidity in our section with robustness checks.[16] We calculate the Amihud (2002) measure, *illiq*, for stock i on day d as the ratio of the absolute daily stock return, $|R_{i,d}|$, to the daily euro (pound) volume traded (in millions), $DVol_{i,d}$, on the stock's primary exchange:

$$illiq_{i,d} = \frac{|R_{i,d}|}{DVol_{i,d}}.$$

Following Amihud (2002), we winsorize the upper and lower 1% of the *illiq* distribution to avoid outliers.[17] Importantly, we find even stronger liquidity co-variations on the daily level in the post-Chi-X period, which suggests that intraday liquidity co-variations indeed aggregate to the daily level.

3.3 Summary statistics

Table 3 presents summary statistics of market capitalization (Panel A) and the relative quoted spread (Panel B) across all sample stocks separately for each country. Our main data source for prices, volume traded and bid-ask spreads is TRTH. Data on market capitalization, *firm size* (in millions of euros), are from Datastream. Appendix C provides a detailed description of variable definitions.

[15] McInish and Wood (1992) are the first to document a reverse J-shaped pattern in intraday spreads, which might falsely lead to excess co-movements in spreads at the beginning and at the end of the trading day. To avoid this bias, Huh (2011) and Boehmer and Shankar (2014) also standardize intraday spreads with their time-of-the-day mean and standard deviation.

[16] Results with equally-weighted average spreads, calculated over all 5-minute intervals during the day, are qualitatively similar.

[17] As in other studies, e.g., Koch, Ruenzi, and Starks (2016), we scale *illiq* by the factor 10^6 to obtain meaningful numbers (our daily euro/pound volume traded is in millions).

[Insert Table 3 approximately here]

As expected, all our sample stocks are generally large, with the average market capitalization of €15.8 billion. Market capitalization varies across different countries, with our smallest stocks located in Belgium and Norway (€4.7 and €5.8 billion, respectively) and our largest stocks in Germany and France (€25.4 and €28.8 billion, correspondingly).

The average relative spread constitutes 0.22% in the total sample. German and French stocks are the most liquid, with a spread value of 0.10-0.11%, around half as large as the sample average. They are followed by Dutch, UK and Scandinavian stocks, with their spread values in the range of 0.14% to 0.24%. Our least liquid stocks are located in Italy, Spain and Norway, with their spread values varying between 0.29% and 0.42%. Despite variation in liquidity levels across different countries, all our sample stocks are the largest and the most liquid stocks in their country and all of them represent constituents of main European equity indices.

4 HFT Activity and Liquidity Co-variations

Chaboud et al. (2014) and Benos et al. (2015) document that trading strategies of algo- and high-frequency traders are correlated across stocks, which can lead to correlated buy or sell pressure, and, therefore, to excess co-movements in stocks' liquidity. In this section, we empirically test whether HFTs induce stronger liquidity commonality across stocks traded in different markets, using the staggered entrance of Chi-X in Europe as our instrument for an exogenous increase in HFT activity. Based on the predictions of Lescourret and Moinas (2015), multimarket trading of HFTs between Chi-X and their home market should make the liquidity of the two markets interconnected, and thus facilitate cross-market liquidity spillovers. To start, we examine liquidity co-movements with the aggregate liquidity of the home market (Section 4.1). If HFTs induce stronger commonality in liquidity, we expect these co-movements to increase after the introduction of Chi-X trading in each country. We next turn to the analysis of liquidity co-movements with the aggregate liquidity of the European market, additionally controlling for fluctuations in home market liquidity (Section 4.2). Since Chi-X enables simultaneous trading of all major European equities on a single trading platform, previously not possible at a comparable speed, we expect the liquidity of stocks to co-vary more strongly with the aggregate European liquidity after the introduction of Chi-X. We further test whether European-wide commonality in liquidity is stronger in down markets and for stocks with higher intensity of HFT trading in the post-Chi-X period (Section 4.3).

4.1 Liquidity Co-variations in the Home Market: Pre- vs Post- Chi-X

Similar to Koch, Ruenzi, and Starks (2016), we conduct our analyses of liquidity co-variations in two steps. In the first step, we estimate the stock's liquidity co-variations with the aggregate liquidity of its home market. In the second step, we test whether these liquidity co-variations are stronger after the introduction of Chi-X trading in each country.

Estimating liquidity co-variations. For each stock and each month, we estimate the stock's liquidity co-variations with the aggregate liquidity of its home market from the market model of liquidity, employed by Chordia, Roll, and Subrahmanyam (2000). Specifically, we run time series regressions of $\Delta qspread_{i,t,d}$ on the change in the home market illiquidity, $\Delta qspread_{Home,t,d}$, for all 5-minute intervals t and all trading days d in a given month:

$$\Delta qspread_{i,t,d} = \alpha + \beta_{i,Home}\Delta qspread_{Home,t,d} + \varepsilon_{i,t,d}. \tag{1}$$

As in Kamara, Lou, and Sadka (2008) and Koch, Ruenzi, and Starks (2016), we calculate $\Delta qspread_{Home,t,d}$ as the cross-sectional value-weighted average of $\Delta qspread_{j,t,d}$ for all stocks in the home country index (e.g., FTSE100 for UK stocks) with $j \neq i$.[18] Our main coefficient of interest is $\beta_{i,Home}$, which captures the sensitivity of the stock's liquidity to the aggregate home market liquidity, or its systematic liquidity co-movement with the home market. In the following, we refer to $\beta_{i,Home}$ as home liquidity beta.

[Insert Figure 4 approximately here]

Figure 4 displays three-month moving averages of home liquidity betas, aggregated across all stocks in our sample. It depicts a significant overall increase in systematic liquidity co-movements of stocks over time, starting with the average liquidity beta of around 0.13 at the beginning of 2005,

[18] We require at least 70% of all stocks in the corresponding index to be traded in a given interval t, which ensures that the composition of the home market index does not fluctuate too much.

rising up first to 0.28 by 2009 and further to 0.47 by the end of 2014. These general time trends in liquidity betas can potentially be explained by the financial crisis of 2008-2009, turmoil on European financial markets in 2010-2011 due to the debt crisis in Greece, and subsequent market stabilization in 2012. Even though all these factors undoubtedly contribute to variation in liquidity betas, our aim is to separate the effect of multimarket HFT activity from other concurrent events. To this end, we use the staggered entry of Chi-X into European financial markets as our instrument for an exogenous increase in HFT activity, and compare home liquidity betas in the pre- and post-Chi-X periods in the next step.

Home liquidity co-variations: Pre- vs Post-Chi-X. We first start with the univariate analysis of the pre- and post-Chi-X home liquidity betas. For each country, Table 4 reports the averages of liquidity betas across all stocks and months in our sample, separately in the pre- and post-Chi-X periods. We further report the difference in liquidity betas between the two periods, $Diff$, and test whether it is significantly different from zero.

[Insert Table 4 approximately here]

Our benchmark definition of the post-Chi-X period is based on the month, when the average Chi-X market share for a given country index reaches 10%. Our reasons for choosing the 10% cutoff as our benchmark are twofold. First, we would like to ensure that there is a substantial amount of trading in the index constituents on the Chi-X platform. Indeed, Table 1 shows that when Chi-X is initially introduced in a country, its market share is usually at most 1%. It takes around one year for most of the countries to reach a market share of 10%, with Norway, Denmark and Spain taking exceptionally long - around three years after the initial introduction of the Chi-X platform. Our second reason for choosing the 10% cutoff point is based on empirical evidence from Menkveld (2013), who finds that the Chi-X market share for Dutch stocks jumps above 10% only with the entry of a multimarket high-frequency trader. We provide further robustness checks of our definition of the post-Chi-X period in Section 5.

From Table 4, we observe that the average post-Chi-X home liquidity beta increases by 0.27, from 0.19 to 0.46, and this increase is statistically significant at the 1% level. This finding provides the first empirical evidence consistent with our hypothesis that HFT activity induces stronger liquidity co-movements in the home market. Importantly, we observe a significant increase in home liquidity betas for all countries in our sample. Home liquidity betas in the UK, Germany and France increase by 0.28-0.30. The highest increase of 0.38 is observed for Swedish stocks and the lowest increase of 0.07-0.08 for Norwegian and Danish stocks, which can potentially be explained by the prolonged time period that Norway and Denmark take before their Chi-X market shares reach a significant level of 10%.

In the next step, we test our prediction in the multivariate setup, controlling for stock characteristics, time- and country-fixed effects. Specifically, we run a panel OLS regression of β_{Home}, estimated for each stock i in month m, on the dummy variable, $Post$, which equals 1 for all months after the country's Chi-X market share reaches 10%, and is zero otherwise. The vector of standardized control variables includes the log of market capitalization at the end of the previous month, $ln(firm\,size)_{i,m-1}$; the average 5-minute quoted spread, calculated over the previous month, $qspread_{i,m-1}$; the year-fixed, YFE, and country-fixed effects, CFE.[19] We allow standard errors to cluster at the firm level in order to account for cross-sectional dependence. Our specification is as follows:

$$\beta_{Home,i,m} = \alpha + \gamma_1 Post_{i,m} + \gamma_2 ln(firm\,size)_{i,m-1} + \gamma_3 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}. \quad (2)$$

The inclusion of year-fixed effects eliminates shocks to the systematic liquidity co-movements that are common to all countries, whereas country-fixed effects control for general levels of home liquidity betas within each country. Therefore, given the year- and country-fixed effects, our identification stems from cross-country variation in the *Post* dummy: we compare systematic liquidity co-movements for index stocks that have already started their trading on the Chi-X platform (and have reached a 10% market share) to those that are not traded yet, and thus represent the control group in the current month. For unrelated shocks to affect our results, they would have to be

[19]These control variables are standard in previous studies on commonality in liquidity (see, e.g., Koch, Ruenzi, and Starks 2016).

correlated with Chi-X entry dates across all countries in our sample, which, in our view, is rather unlikely.[20]

[Insert Table 5 approximately here]

Model (1) of Table 5 reports results for the total sample. Consistent with our expectations, home liquidity betas significantly increase on average by 0.07 after the introduction of Chi-X, which represents a 37% increase relative to their mean of 0.19 in the pre-Chi-X period. This 37% increase is both statistically and economically significant. Our control variables also display expected signs: larger stocks and stocks that are more liquid exhibit in general stronger systematic co-movements with aggregate home market liquidity, consistent with prior findings of Kamara, Lou, and Sadka (2008) and Koch, Ruenzi, and Starks (2016).

Models (2) to (4) present results for subsample splits across different countries. To conserve space, we pool 11 individual countries into three country groups, based on their Chi-X entry times. Model (2) reports our findings for the first group of major European countries, the indices of which started trading on Chi-X soon after its entry in 2007: the UK, France, Germany, the Netherlands and Belgium.[21] Surprisingly, we do not observe any significant increases in home liquidity betas for this country group, after we control for size, liquidity, year- and country-fixed effects. In contrast, we find a significant increase of 0.05 in home liquidity betas of four Scandinavian countries, which started trading on Chi-X in the first two quarters of 2008 (our second country group). Given their average pre-Chi-X home liquidity betas of 0.04-0.06, an increase of 0.05 suggests that liquidity co-movements with the home market have doubled for Scandinavian stocks. Model (4) shows an even more significant increase of 0.14 in home liquidity betas for our third group, consisting of Italy and Spain, which start trading on Chi-X in the last two quarters of 2008.

[20]Our specification is similar to that used by Christensen, Hail, and Leuz (2011) to identify the causal effects of the staggered introduction of Market Abuse and Transparency Directives on liquidity levels in European countries. Our setup is also close to Hendershott, Jones, and Menkveld (2011), who use the staggered introduction of NYSE Autoquote as an instrument for an exogenous increase in algorithmic trading.

[21]Note that Belgian stocks started trading on Chi-X only later, in mid-2008. However, we still choose to include them in the first group, since its national exchange, Euronext Brussels, is a part of the Euronext trading platform, also used in France (Euronext Paris) and the Netherlands (Euronext Amsterdam). All results remain robust if we exclude Belgium from the first country group.

We further test whether liquidity co-movements with the home market are stronger in up or down markets in the post-Chi-X period. To this end, we split the time series of each country's index return into terciles, and classify months in the top tercile of index return as up markets and those in the bottom tercile as down markets. Models (5) and (6) show significant increases in post-Chi-X home liquidity betas, both for down and up markets, correspondingly. Interestingly, increases in liquidity co-movements in the up markets of 0.11 are stronger, when compared to the increases in the down markets of 0.03. Overall, these findings suggest that HFTs can transmit both negative and positive liquidity shocks in home markets. However, they seem to be more active in the up markets, as liquidity levels generally improve with many noise traders entering the rising market.

4.2 European-wide Liquidity Co-variations: Pre- vs Post-Chi-X

Estimating liquidity co-variations in the European market. To examine liquidity co-movements with the aggregate European market, we add fluctuations in the European market illiquidity, $\Delta qspread_{EU,t,d}$, to equation (1). We calculate $\Delta qspread_{EU,t,d}$ as the cross-sectional value-weighted average of $\Delta qspread_{k,t,d}$ for all FTSE Eurofirst 100 index constituents, excluding stock i and all stocks j that belong to the home market index, $k \neq i$ and $k \neq j$:

$$\Delta qspread_{i,t,d}, = \alpha + \beta_{i,HomeExclEU} \Delta qspread_{Home,t,d} + \beta_{i,EU} \Delta qspread_{EU,t,d} + \varepsilon_{i,t,d}. \tag{3}$$

$\beta_{i,EU}$ now captures the sensitivity of the stock's liquidity to the aggregate European liquidity, after controlling for its liquidity co-movements with the home market, $\beta_{i,HomeExclEU}$. We refer to $\beta_{i,EU}$ as EU liquidity beta.

We choose FTSE Eurofirst 100 as our proxy for the aggregate European market, because it is a pan-European index, which consists of the 60 largest European companies ranked by market capitalization, and 40 additional companies chosen on the basis of their size and sector representation by the FTSE Group. Table 6 presents the composition of FTSE Eurofirst 100 during our sample period.

[Insert Table 6 approximately here]

We aggregate all statistics on the country level and report country codes in the first column. The second column shows the number of distinct companies in each country that represent a part of the index. As with home country indices, if the composition of Eurofirst 100 changes, we keep both old and new index constituents for the entire sample period to avoid any biases, such that the total number of companies in the index increases to 127 over 2004-2014. We report the average daily number of shares (in thousands) and euro volume (in millions) of index constituents traded in each country in the third and fourth columns, respectively. The last column displays the daily euro volume of index constituents for each country as a percentage of the total daily Eurofirst volume.[22]

Around one third of total Eurofirst volume can be attributed to UK stocks, another 20% to French stocks and around 15% to German stocks. Italy and Spain also have quite considerable shares, with around 10% each. The shares of the remaining countries, the Netherlands, Belgium and Finland, are either close to or below 5%. Note that, apart from 3 Finnish stocks, Scandinavian countries are not a part of Eurofirst 100. We exploit this feature in our future tests, using Scandinavian countries as our control group. Indeed, we would not expect the liquidity of Scandinavian stocks to co-vary with Eurofirst 100, if these stocks are not a part of the index. Further, we repeat all our analyses with STOXX ALL EUROPE 100, an alternative pan-European index, and find that our results remain robust (not tabulated).

[Insert Figure 5 approximately here]

Figure 5 displays the development of EU and home liquidity betas, estimated from equation (3), over our sample period. The solid line shows the three-month moving average EU liquidity betas, β_{EU}, and the dashed line the corresponding values for home liquidity betas, $\beta_{HomeExclEU}$, over 2005-2014. Importantly, both EU and home liquidity betas increase significantly over the decade. However, EU liquidity betas start dominating home liquidity betas in early 2008 and reach their peak level of 0.38 in 2011. By contrast, the level of home liquidity betas practically never exceeds

[22] In this table, we convert the pound volume for UK stocks into the equivalent euro volume, using daily EUR/GBP exchange rate.

0.30. These findings suggest that liquidity co-variations with the aggregate European market have become more important in recent years, as compared to the co-variations with the home market.

European-wide liquidity co-variations: Pre- vs Post-Chi-X. To examine the effect of multimarket HFT activity on European-wide liquidity co-variations, we first compute the difference between average pre- and post-Chi-X EU liquidity betas. Our univariate tests show that the average post-Chi-X EU liquidity betas increase by 0.18, from 0.15 to 0.33, and this increase is statistically significant at the 1% level. We do not report these results, but they are available upon request.

In the next step, we re-estimate our specification from equation (2) with $\beta_{i,EU}$ as the dependent variable, again controlling for firm size, average relative spread, year- and country-fixed effects. Panel A of Table 7 reports the results. It has the same layout as Table 5, presenting results first for the total sample, followed by subsample splits for three country groups and for subperiods of down and up markets.

[Insert Table 7 approximately here]

Consistent with univariate results, post-Chi-X EU liquidity betas significantly increase by 0.056 for our total sample, which represents a 37% increase relative to their mean level of 0.15 in the pre-Chi-X period. Importantly, this increase is driven mainly by stocks in our first (GB, FR, DE, NL, BE) and third (IT, ES) country groups. By contrast, Scandinavian countries do not display any significant increase in their liquidity co-variations with the aggregate European market in the post Chi-X period. These findings are consistent with our expectations, because stocks from the first and third groups contribute to a considerable amount of the total Eurofirst volume traded, whereas Scandinavian countries are not a part of this index and represent a control group in our setup.

Panel B shows the corresponding results for home liquidity betas, estimated after additionally controlling for EU liquidity betas from equation (3), $\beta_{i,HomeExclEU}$. For brevity, we report coefficients only on our main variable of interest, *Post*, but all regressions also include controls, year- and country-fixed effects. The coefficient on *Post* for home liquidity betas drops by more than half, from 0.07 to 0.033, after controlling for EU liquidity betas. This result suggests that liquidity co-variations with the home market become actually less important in the post-Chi-X period, after we control for liquidity co-movements with the aggregate European market. For our first country group (GB, FR, DE, NL, BE), liquidity co-variations with the home market even drop significantly in the post-Chi-X period (Model 2). The insignificant coefficient on *Post* from Table 5 for these countries can thus be decomposed into significant increase in EU liquidity betas and a simultaneous decrease in home liquidity betas. For Scandinavian countries, representing our control group, home liquidity betas are still significantly higher in the post-Chi-X period, consistent with our previous results from Table 5. Interestingly, for Italy and Spain, home liquidity betas also increase in the post-Chi-X period, which suggests that both EU and home liquidity co-variations become stronger for these countries in recent years.

The last two columns of both panels present results for subperiods of down and up markets, correspondingly. EU liquidity betas are significantly higher both in down and up markets in the post-Chi-X period, with a higher coefficient of 0.071 for down markets. In contrast, home liquidity betas increase significantly only in up markets. These findings suggest that with a rise in multimarket HFT activity European-wide liquidity co-variations dominate co-variations with the home market during crisis periods. We observe similar results in Figure 5. Consistent with our multivariate analysis, EU liquidity betas increase during the financial crisis of 2008-2009, whereas home liquidity betas simultaneously drop over this period.

Overall, our findings suggest that European-wide liquidity co-variations have become more important with an increase of multimarket high-frequency trading, which essentially connects different markets in a single network system. Importantly, they are significantly higher than co-variations with home market liquidity during downturn periods. Stronger European-wide liquidity co-variations in down markets should be of great concern for investors and regulators, since they imply that equity markets are now more susceptible to transmissions of negative liquidity shocks in periods when such shocks are more likely to occur.

4.3 Intensity of HFT Trading Activity and Liquidity Co-variations

Our analyses so far suggest that an exogenous increase in multimarket HFT activity leads to stronger liquidity co-movements across European markets. In this section, we conduct tests to examine heterogeneity in the treatment effects that arises due to differences in the intensity of HFT activity for stocks traded on the Chi-X platform. Specifically, we expect sensitivity to the aggregate European liquidity to be higher for stocks that are traded more intensely by multimarket high-frequency traders. To test for cross-sectional differences in liquidity co-movements, we split our sample by the median measure of HFT activity and introduce two dummy variables: *High HFT Activity*, equal to 1 for stocks with above median intensity of HFT activity, and *Low HFT Activity,* equal to 1 for those with below median intensity level. We then interact both of these dummies with our *Post* dummy and estimate the following specification:

$$\begin{aligned} \beta_{EU,i,m} &= \alpha + \gamma_1 High\,HFT\,Activity_{i,m} \cdot Post_{i,m} + \gamma_2 Low\,HFT\,Activity_{i,m} \cdot Post_{i,m} + \\ &+ \gamma_3 ln(firm\,size)_{i,m-1} + \gamma_4 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}. \end{aligned} \tag{4}$$

If our hypothesis holds, we expect γ_1 to be higher than γ_2, which would suggest that EU liquidity betas exhibit larger increases for stocks that are traded more intensely by HFTs after Chi-X introduction. We use the same set of control variables as in our specification (2), and continue to allow for clustering of standard errors at the firm level.

We employ two proxies to measure the intensity of HFT activity: *Chi-X market share* and the *Multimarket Trading* measure, proposed by Halling, Moulton, and Panayides (2013). We use the average monthly Chi-X market share as our proxy for liquidity supplying HFT activity, based on empirical evidence from Menkveld (2013): in his sample, around 70-80% of all Chi-X trades can be attributed to one large HFT that engages in market making both in the home market and on Chi-X. Moreover, Chi-X market shares jump to double-digit numbers with the HFT entry and drop almost to zero when it is absent from the market. Therefore, larger Chi-X market shares should correspond to a more intense market-making HFT activity in a stock.

Our second measure, *Multimarket Trading*, captures the correlation of unexpected trading volume between Chi-X and the home market, which can be attributed to liquidity demanding HFTs that engage in cross-market arbitrage strategies. Following Halling, Moulton, and Panayides (2013), we estimate it for each stock and month from the following VAR model:

$$\begin{aligned} \triangle Vol_{i,t}^{Home} &= \alpha_i^{Home} + \gamma_i^{Home} \triangle Vol_{i,t-1}^{Home} + \beta_i^{Chi-X} \triangle Vol_{i,t-1}^{Chi-X} + \delta_i ret_{i,t} + \varepsilon_{i,t}^{Home} \\ \triangle Vol_{i,t}^{Chi-X} &= \alpha_i^{Chi-X} + \gamma_i^{Chi-X} \triangle Vol_{i,t-1}^{Chi-X} + \beta_i^{Home} \triangle Vol_{i,t-1}^{Home} + \delta_i ret_{i,t} + \varepsilon_{i,t}^{Chi-X}, \end{aligned} \tag{5}$$

where $\triangle Vol_{i,t}$ is the change in the trading volume, calculated as the logarithm of the ratio of interval t to interval $t-1$ euro (pound) trading volume.[23] We also control for the firm's stock return in the home market, ret, to account for unexpected volume that might be related to trading on an information signal. *Multimarket Trading* for stock i in month m is calculated as the contemporaneous correlation between the unexpected trading volume in the home market, $\varepsilon_{i,t}^{Home}$, and on the Chi-X platform, $\varepsilon_{i,t}^{Chi-X}$. The higher the correlation in trading volume shocks between the two markets, the more intensive is the multimarket trading of this stock. Since trading across multiple markets requires costly technological investment and continuous monitoring, it is plausible to assume that multimarket trading between Chi-X and the home market is to a large extent driven by liquidity demanding high-frequency traders.

[Insert Table 8 approximately here]

Table 8 reports annual averages of the *Multimarket Trading* measure for each country since the introduction of Chi-X in 2007. On average, the correlation in unexpected trading volumes between Chi-X and the home market increases from 0.34 in 2007 to 0.68 in 2010, and continues to stay at this relatively high level until the end of our sample period. This considerable increase in the intensity of multimarket trading is also consistent with the rise in high-frequency trading over recent years.

[23] Similar to Halling, Moulton, and Panayides (2013), we use log-changes in trading volume to ensure stationarity of this variable.

We report our findings on the cross-sectional differences in liquidity co-movements in Table 9. The first three models use *Chi-X market share* and the last three models *Multimarket Trading* as our measure of HFT activity. For each of the two measures, we first present results for the total sample, followed by sample splits for down and up markets.

[Insert Table 9 approximately here]

Interestingly, the coefficients on the interactions of both *High HFT Activity* and *Low HFT Activity* with *Post*, γ_1 and γ_2, are positive and significant for both measures of HFT activity, suggesting that liquidity co-movements with the European market significantly increase for all our sample stocks in the post-Chi-X period. Consistent with our expectations, we observe a larger increase for stocks with a more intense HFT market making activity, captured by a higher γ_1 coefficient for *Chi-X market share* (Model 1). In contrast, we do not observe any differences between stocks with high and low level of *Multimarket Trading* (Model 4). These results indicate that stronger liquidity co-movements with the aggregate European market after the introduction of Chi-X are mostly driven by market making activity of high-frequency traders across multiple venues.

Next, we split our total sample into subperiods of down and up markets, using the same definition as in the previous section. For *Chi-X market share*, we observe that γ_1 continues to be higher than γ_2 in down markets, whereas they have the same value in up markets. For *Multimarket Trading,* we do not find any differences for down markets, and γ_2 is even higher than γ_1 for up markets. These results are consistent with our findings for the total sample and imply that stronger European-wide liquidity co-variations in down markets arise due to correlated fluctuations in inventory portfolios of market making HFTs.

5 Robustness checks

Daily liquidity measures. As our first robustness check, we repeat our analyses from Tables 5 and 7 with two daily liquidity measures: the daily relative spread and the Amihud measure, *illiq*.[24]

[24] Please refer to Section 3.2 for detailed definitions of both measures.

Ex ante, it is not clear whether intraday liquidity co-variations also aggregate to the daily level.[25] However, daily liquidity co-variations might be of higher importance for institutional and retail investors, because they have longer trading horizons than high-frequency traders.

Since there is now only one observation per day for each liquidity measure, we can no longer estimate liquidity betas on the monthly basis and therefore re-estimate equations (1) and (3) to obtain β_{Home}, β_{EU} and $\beta_{HomeExclEU}$ for each stock and each quarter. Afterwards, we re-estimate our specification from equation (2) with each of the three betas as the dependent variable. *Post* now takes value of 1 starting in the quarter when the country's Chi-X market share reaches 10%, and is zero otherwise. We also include firm size and average liquidity over the previous quarter as control variables. Panel A of Table 10 presents results. To conserve space, we only report the coefficient on *Post* for each specification. The first three columns present results for the daily relative spread and the last three columns for the Amihud measure.

[Insert Table 10 approximately here]

For daily relative spreads, we observe an even stronger increase of 0.18 in EU liquidity betas after the introduction of Chi-X (Model 1). Consistent with previous findings, home liquidity betas are either insignificant (β_{Home}) or even become negative, after controlling for European-wide liquidity co-variations ($\beta_{HomeExclEU}$). Models 2 and 3 present the corresponding results for subperiods of down and up markets. As before, we observe the highest increases in EU liquidity betas in down markets, whereas they drop insignificantly in the periods of market booms. The findings for the Amihud measure are similar, with the economic significance being comparable to the intraday spreads. Overall, we find stronger European-wide liquidity co-movements for daily liquidity measures in the post-Chi-X period and thus conclude that stronger intraday co-movements also aggregate to the daily level.

Assessing benchmark treatment dates. In the next step, we conduct placebo tests to assess whether our treatment dates, based on the month when the average Chi-X market share for a given country index reaches 10%, provide reasonably sharp identification with respect to

[25] For example, on a day with a situation similar to the Flash Crash, with large price declines across multiple stocks, followed by subsequent price reversals, their daily stock returns, and thus the Amihud (2002) measures, would still be close to zero, leading to potential underestimation of their liquidity co-variations during that day.

changes in systematic liquidity co-movements. In particular, we randomly assign our treatment dates between the first month of 2004 and the last month of 2014. Using 5,000 replications, we repeat our analyses from Tables 5 and 7 with 5-minute spreads and summarize the distributions of the coefficients and t-statistics on *Post* in Panel B of Table 10. We report the average, 5th and 95th percentiles across the 5,000 replications. We also report the percentiles of our actual estimates and t-statistics in the last row.

As expected, our average coefficients from the placebo regressions are close to zero for all specifications, with the 95th percentile not exceeding 0.01. Our actual estimates in the range of 0.03-0.07 fall within the 99th percentile of the distribution for all three liquidity betas, suggesting that they are significantly different from the placebo average. These results are also confirmed by comparing the actual t-statistics to its distribution from the placebo regressions in the lower part of the panel.

6 Conclusions

This paper examines the effects of multimarket HFT activity on systematic liquidity co-movements within a network of European markets. We use the staggered introduction of an alternative trading platform, Chi-X, in 11 European equity markets as our instrument for an exogenous increase in multimarket HFT activity. Our empirical identification strategy relies on the cross-country variation in Chi-X entry dates, which should alleviate potential concerns about general trends in liquidity commonality or concurrent, but unrelated, economic shocks. Importantly, Chi-X enables trading of all major European equities on a single trading platform, which was not previously possible at a comparable speed. Further, multimarket trading by HFTs between Chi-X and national stock exchanges connects individual markets in a single network, which should facilitate cross-market liquidity spillovers and induce stronger European-wide liquidity co-movements.

Consistent with our predictions, we find that liquidity co-movements within the aggregate European market significantly increase after the introduction of Chi-X in a given country and are even higher than liquidity co-movements within the corresponding home market. We further show that European-wide liquidity co-movements are stronger in down markets and for stocks with a higher intensity of HFT market making activity in the post-Chi-X period. Overall, our findings are consistent with the notion that multimarket HFT activity induces stronger network-wide liquidity co-movements, thus making propagation of liquidity shocks easier across different markets.

Empirical evidence in our paper suggests that market participants and policymakers currently underestimate potential liquidity risks, generated by HFTs. Stronger network-wide liquidity co-movements, especially during crisis periods, imply that equity markets are now more susceptible to negative liquidity shocks, exactly when such shocks are more likely to occur. Raising awareness of these risks should help institutional investors to manage their liquidity risks better and regulators to develop better policies aimed at the reduction of such risks on financial markets.

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Appendix A

Chi-X Inclusion Date

This table reports the date of Chi-X market entry for each country in our sample. We use the two letter country code to represent each country.

Country Name	Country Code	Chi-X Inclusion Date
Germany	DE	30/03/2007
Netherlands	NL	30/03/2007
United Kingdom	GB	29/06/2007
France	FR	28/09/2007
Sweden	SE	14/03/2008
Finland	FI	04/04/2008
Norway	NO	27/06/2008
Denmark	DK	27/06/2008
Belgium	BE	04/07/2008
Italy	IT	13/10/2008
Spain	ES	19/12/2008

Appendix B

Thomson Reuters Tick History (TRTH) Data Filtering

In the TRTH database, *RIC* is the main company identifier, similar to the ticker in the NYSE TAQ database. In this appendix, we provide details of our initial TRTH data cleaning procedure for filtering out RICs. First, we drop duplicate *RIC*s, with the first character equal to 0. Second, we retain only *RICs* with *Type* code equal to 113 or 256 to discard any non-equity assets. *Type* 113 means that the asset is equity, and the corresponding *RIC* is the company's current *RIC* in use. *Type* 256 means the asset is equity, but the company is using a different RIC now. Third, we drop *RICs* that do not end with ".L" (".DE", ".PA", ".AS", " .BR", ".HE", ".ST", ".OL", ".CO", ".MI" and ".MC") for UK (German, French, Dutch, Belgian, Finnish, Swedish, Norwegian, Danish, Italian and Spanish) stocks.

For stocks that change *RICs* during our sample period, we use the following procedure to merge new *RIC*s with old *RICs*. If the stock's *NewRICSymbol* is empty, this means that the corresponding *RIC* is the company's most recent identifier (new *RIC*). In this case, we use the corresponding *RIC* as the final *RIC*. If the stock's *NewRICSymbol* is not empty, we then use this reported *NewRICSymbol* as the final *RIC*. If a stock has more than one observation on a particular trading day, we keep the most recent *RIC* with *Type* 113 that has the highest trading volume.

Appendix C

Variable Definitions

Variable	Description	Source
Chi-X Market Share	Chi-X market share, defined as the ratio of the daily volume traded on Chi-X relative to the total daily volume traded on both Chi-X and the home exchange.	TRTH
$firm\,size$	Market capitalization (in €/£ million) at the end of each quarter t	Datastream
High HFT Activity	A dummy variable, which equals 1 for stocks with above median intensity of HFT activity in our sample, and is zero otherwise. We use either *Chi-X market share* or *Multimarket Trading* to measure intensity of HFT activity.	TRTH
illiq	The Amihud (2002) measure, calculated as the ratio of the absolute daily price change, $\lvert R_{i,d}\rvert$, to the daily euro (pound) volume traded (in millions) on the stock's primary exchange, $DVol_{i,d}$: $illiq_{i,d} = \frac{\lvert R_{i,d}\rvert}{DVol_{i,d}}$. We calculate $illiq(avg)$ as the quarterly average of the daily Amihud (2002) measure.	TRTH
Low HFT Activity	A dummy variable, which equals 1 for stocks with below median intensity of HFT activity in our sample, and is zero otherwise. We use either *Chi-X market share* or *Multimarket Trading* to measure intensity of HFT activity.	TRTH

Variable	Description	Source
Multimarket Trading	The *Multimarket Trading* measure of Halling, Moulton, and Panayides (2013), estimated from the following VAR model: $\triangle Vol_{i,t}^{Home} = \alpha_i^{Home} + \gamma_i^{Home} \triangle Vol_{i,t-1}^{Home} + \beta_i^{ChiX} \triangle Vol_{i,t-1}^{ChiX} + ret_{i,t} + \varepsilon_{i,t}^{Home}$ $\triangle Vol_{i,t}^{ChiX} = \alpha_i^{ChiX} + \gamma_i^{ChiX} \triangle Vol_{i,t-1}^{ChiX} + \beta_i^{Home} \triangle Vol_{i,t-1}^{Home} + ret_{i,t} + \varepsilon_{i,t}^{ChiX}$ where $\triangle Vol_{i,t}$ is the change in the trading volume, calculated as the logarithm of the ratio of interval t to interval $t-1$ euro (pound) trading volume; and $ret_{i,t}$ is the firm's stock return in the home market. *Multimarket Trading* for stock i in month m is calculated as the contemporaneous correlation between $\varepsilon_{i,t}^{Home}$ and $\varepsilon_{i,t}^{ChiX}$.	TRTH
POST	A dummy variable, which equals 1 for all months after the country's Chi-X market share reaches 10%, and is zero otherwise.	TRTH
qspread	The quoted relative spread, calculated as $qspread_{i,t} = \frac{A_{i,t} - B_{i,t}}{(A_{i,t} + B_{i,t})/2}$, where $A_{i,t}$ is the ask price and $B_{i,t}$ the bid price prevalent for stock i on its primary exchange at the end of the 5-minute interval t. We delete observations with negative spreads or spreads exceeding 20%, and winsorize the upper and lower 1% of the *qspread* distribution to avoid outliers.	TRTH
ret	The firm's stock return in the home market	TRTH

Figure 1: **Chi-X as a connection link for fragmented European markets**

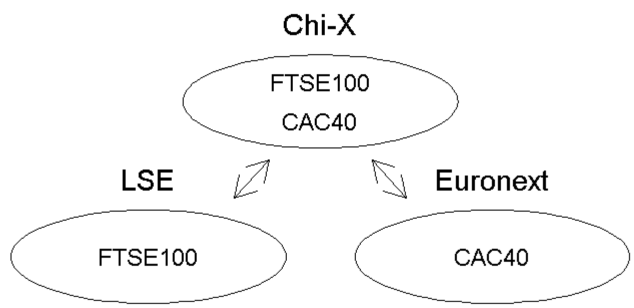

Figure 2: **Staggered entrance of Chi-X into European equity markets**

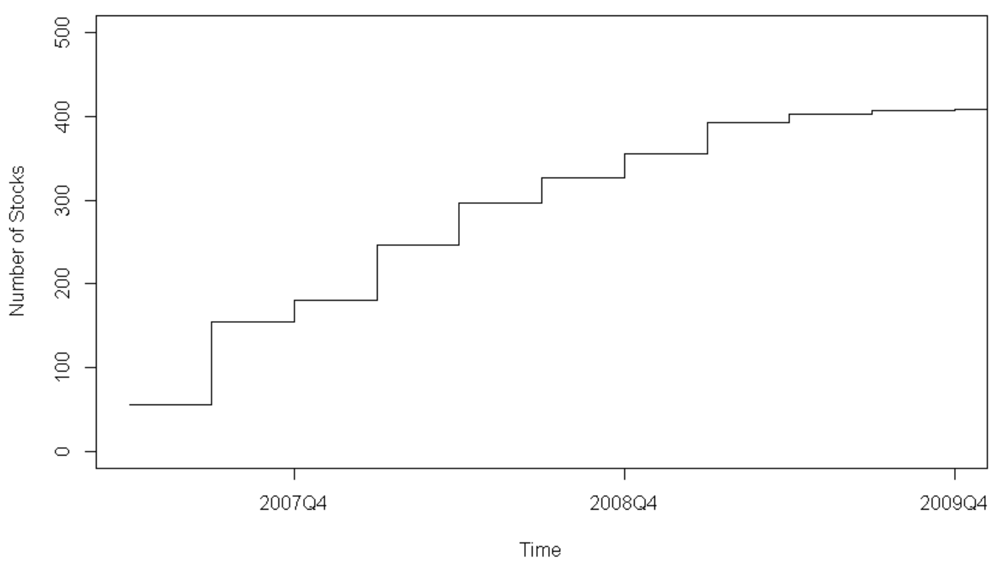

Figure 3: **Chi-X Market Share by Country.** This figure plots the time series of the average Chi-X market share for each country in our sample. The Chi-X market share for stock i on day d is calculated as $ChiXMrktShr_{i,t} = \frac{Volume_{i,d,c}}{Volume_{i,d,c}+Volume_{i,d,h}}$, where $Volume_{i,d,c}$ is the volume executed on Chi-X for stock i on day d and $Volume_{i,d,h}$ is the volume executed on its home stock exchange. It is then averaged quarterly for all stocks in the corresponding country. The vertical line shows the time when each country's Chi-X market share reaches 10%. Please refer to Appendix A for country code abbreviations.

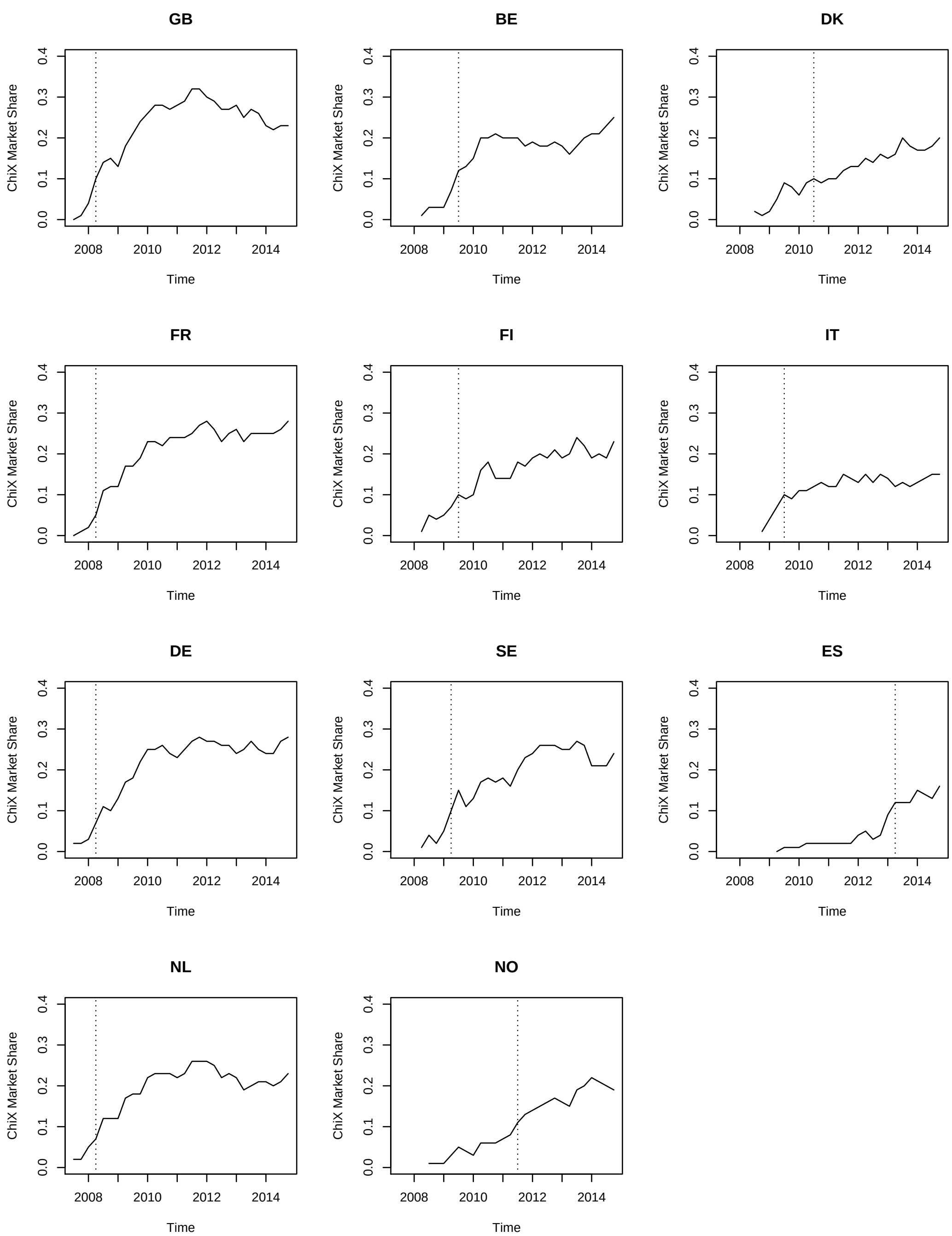

Figure 4: **Development of Aggregate Home Liquidity Betas over Time.** This figure displays three-month moving averages of home liquidity betas, aggregated across all stocks in our sample. For each stock and each month, we first estimate the following regression: $\Delta qspread_{i,t,d} = \alpha + \beta_{i,Home} \Delta qspread_{Home,t,d} + \varepsilon_{i,t,d}$, where $\Delta qspread_{i,t,d}$ is the change in the 5-minute relative quoted spread of firm i from interval $t-1$ to interval t on day d, and $\Delta qspread_{Home,t,d}$ is the cross-sectional value-weighted average of $\Delta qspread_{j,t,d}$ for all stocks in the home country index with $j \neq i$. We then calculate the average home liquidity beta ($\beta_{i,Home}$) for all stocks in each month over 2005-2014, and plot the three-month moving average liquidity beta to smooth out its variations across different months.

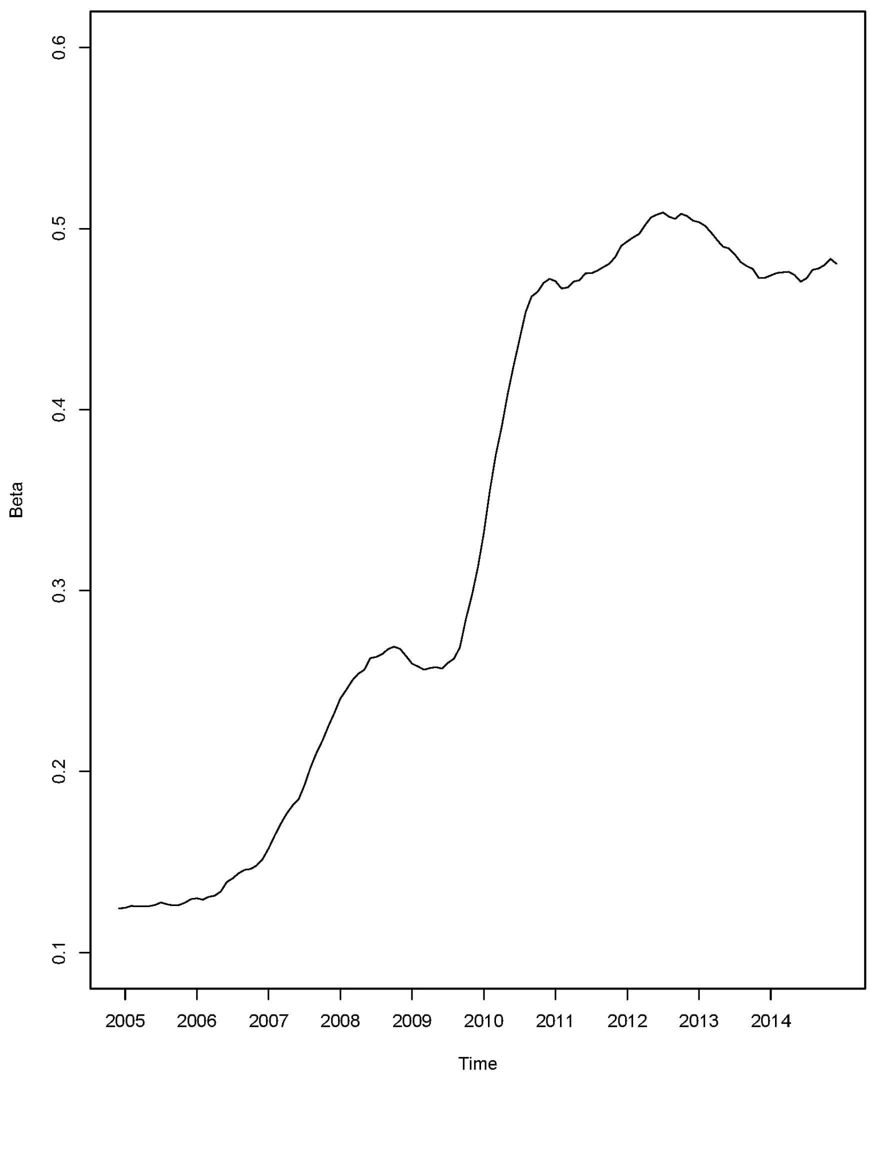

Figure 5: **Development of Aggregate EU and Home Liquidity Betas over Time.** This figure displays three-month moving averages of EU and home liquidity betas, aggregated across all stocks in our sample. For each stock and each month, we first estimate the following regression: $\Delta qspread_{i,t,d} = \alpha + \beta_{i,HomeExclEU} \Delta qspread_{Home,t,d} + \beta_{i,EU} \Delta qspread_{EU,t,d} + \varepsilon_{i,t,d}$, where $\Delta qspread_{i,t,d}$ is the change in the 5-minute relative quoted spread of firm i from interval $t-1$ to interval t on day d, $\Delta qspread_{Home,t,d}$ is the cross-sectional value-weighted average of $\Delta qspread_{j,t,d}$ for all stocks in the home country index with $j \neq i$, and $\Delta qspread_{EU,t,d}$ is the cross-sectional value-weighted average of $\Delta qspread_{k,t,d}$ for all FTSE Eurofirst100 index constituents, with $k \neq i$ and $k \neq j$. We then calculate the average EU ($\beta_{i,EU}$) and home ($\beta_{i,HomeExclEU}$) liquidity betas for all stocks in each month. The solid line shows the three-month moving average EU liquidity betas and the dashed line the corresponding values for home liquidity betas over 2005-2014.

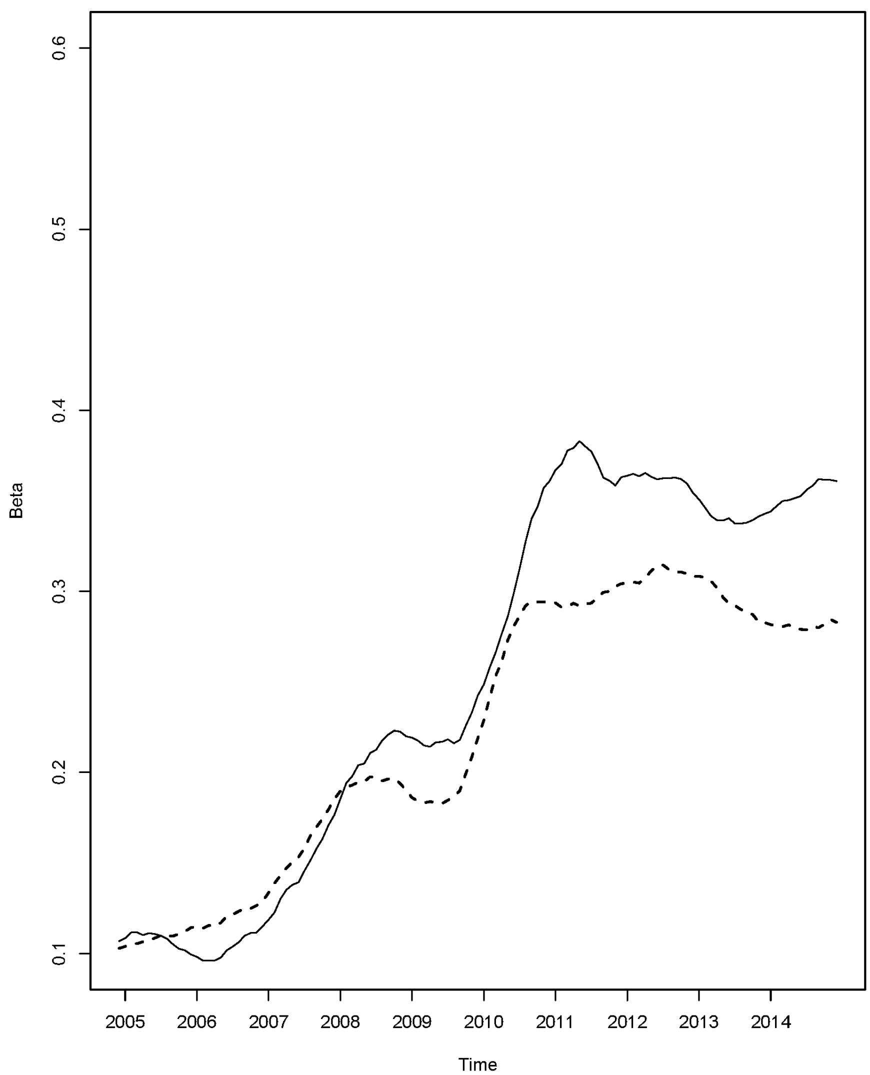

Table 1: **Chi-X Market Share by Country.** This table reports the quarterly averages of Chi-X market shares for each country in our sample. Chi-X market share for stock i on day d is calculated as $ChiXMrktShr_{i,t} = \frac{Volume_{i,d,c}}{Volume_{i,d,c}+Volume_{i,d,h}}$, where $Volume_{i,d,c}$ is the volume executed on Chi-X for stock i on day d and $Volume_{i,d,h}$ is the volume executed on its home stock exchange. It is then averaged quarterly for all stocks in the corresponding country. Please refer to Appendix A for country code abbreviations.

	GB	**FR**	**DE**	**NL**	**BE**	**FI**	**SE**	**NO**	**DK**	**IT**	**ES**
2007Q4	1.3%	0.9%	1.9%	2.4%							
2008Q1	4.3%	2.4%	3.0%	4.5%							
2008Q2	10.3%	5.4%	6.8%	7.4%	0.5%	1.0%	1.2%				
2008Q3	14.4%	10.8%	10.8%	12.2%	3.0%	5.1%	3.8%	1.4%	1.6%		
2008Q4	14.6%	11.8%	10.2%	11.6%	3.4%	4.0%	2.3%	0.8%	1.2%	1.0%	
2009Q1	13.0%	12.4%	12.5%	12.4%	3.0%	5.0%	4.7%	1.1%	1.9%	4.0%	
2009Q2	17.8%	17.2%	16.6%	16.8%	6.7%	6.5%	10.4%	3.0%	5.4%	6.8%	0.3%
2009Q3	20.5%	17.0%	18.1%	17.6%	11.8%	9.9%	14.9%	4.6%	9.0%	9.6%	0.7%
2009Q4	23.8%	19.3%	21.7%	18.0%	12.7%	9.2%	11.0%	3.6%	7.7%	9.4%	0.6%
2010Q1	26.2%	23.4%	24.9%	21.7%	15.3%	10.1%	13.3%	3.4%	6.0%	10.8%	0.7%
2010Q2	28.2%	22.6%	24.8%	23.0%	19.7%	15.7%	16.8%	5.6%	8.6%	11.3%	2.2%
2010Q3	27.5%	22.1%	25.9%	22.8%	19.7%	17.5%	17.9%	6.0%	9.8%	11.9%	2.1%
2010Q4	27.1%	23.8%	24.0%	22.9%	20.7%	14.0%	17.3%	6.1%	9.3%	12.7%	2.1%
...											
2011Q4	31.9%	27.2%	27.7%	25.5%	17.6%	17.3%	23.0%	13.2%	12.7%	14.4%	2.0%
...											
2012Q4	27.3%	25.3%	25.9%	22.6%	18.7%	20.5%	26.3%	16.7%	16.1%	14.8%	4.0%
...											
2013Q4	25.9%	25.3%	24.7%	20.9%	19.9%	22.2%	25.6%	20.1%	18.1%	12.4%	12.3%
...											
2014Q4	23.0%	27.5%	28.1%	23.1%	25.2%	22.6%	24.2%	19.1%	19.9%	15.1%	16.1%

Table 2: **Sample Construction.** This table presents details of our sample construction. Our initial sample consists of all stocks that constitute main European equity indices during our sample period, January 2004 - December 2014. We download the composition of these indices from the Thomson Reuters Tick History (TRTH) database. If the composition of an index changes, we keep both old and new index constituents for the entire sample period. We filter out RICs that appear to be erroneously reported as an index constituent by TRTH (Filter 1). See Appendix B for details of our data cleaning procedure. We further omit firms whose stock price is less than £2 at the end of the previous trading day for UK stocks and less than €2 for other European stocks (Filter 2). Finally, we retain a stock in a given month only if it is traded for at least 1,000 different 5-minute intervals. Panel A reports the number of distinct firms and Panel B the number of firm-month observations for each country in our sample. Please refer to Appendix A for country code abbreviations.

Panel A: Number of Distinct Firms

Country	Total	GB	FR	DE	NL	BE	FI	SE	NO	DK	IT	ES
Index		FTSE100	CAC40	DAX30	AEX	BFX	OMXH25	OMXS30	OBX	OMXC20	FTMIB	IBEX35
Initial Sample	539	180	44	40	40	16	32	39	35	27	46	40
Filter 1	446	144	43	37	35	9	25	34	26	20	41	32
Filter 2	446	144	43	37	35	9	25	34	26	20	41	32
Final Sample	445	144	43	37	35	9	25	34	26	20	40	32

Panel B: Number of Firm-Month Observations

Country	Total	GB	FR	DE	NL	BE	FI	SE	NO	DK	IT	ES
Index		FTSE100	CAC40	DAX30	AEX	BFX	OMXH25	OMXS30	OBX	OMXC20	FTMIB	IBEX35
Filter 1	51,667	16,415	5,293	4,190	3,443	1,052	2,901	4,408	2,859	2,547	3,831	4,728
Filter 2	50,446	16,413	5,248	4,176	3,364	1,020	2,872	4,407	2,837	2,547	3,751	3,811
Final Sample	50,278	16,338	5,224	4,172	3,359	1,012	2,871	4,406	2,833	2,509	3,744	3,810

Table 3: **Summary Statistics.** Panel A of this table reports cross-sectional summary statistics of market capitalization, *firm size* (in € million), across all sample stocks separately for each country. Panel B reports corresponding summary statistics for the 5-minute relative quoted spread measure, *qspread*. Our main data source for prices, volume traded and bid-ask spreads is Thomson Reuters Tick History (TRTH). Data on market capitalization are from Datastream. We censor the upper and lower 1% of the *firm size* and *qspread* to avoid outliers. We also delete observations with *qspread* < 0 or *qspread* > 0.2. Appendix C provides a detailed description of variable definitions.

Panel A: Summary Statistics for *firm size*

Country	N	Mean	Median	StDev	Min	Max
GB	144	15,886	6,000	21,605	1,401	86,968
FR	43	28,843	15,923	26,590	4,547	102,791
DE	37	25,494	15,979	21,540	3,975	75,077
NL	35	18,001	7,854	23,652	1,373	91,188
BE	9	4,771	2,591	4,047	1,221	13,148
FI	25	8,000	3,678	9,760	1,501	33,115
SE	34	13,097	6,409	13,434	1,188	52,408
NO	26	5,859	2,362	7,959	611	33,580
DK	20	7,551	3,992	9,363	1,298	34,037
IT	40	11,199	6,549	13,213	1,512	52,022
ES	32	16,196	7,984	20,568	2,252	77,742
Total	445	15,863	7,299	20,264	611	102,791

Panel B: Summary Statistics for *qspread*

Country	N	Mean	Median	StDev	Min	Max
GB	144	0.0021	0.0011	0.0053	0.0001	0.2000
FR	43	0.0010	0.0007	0.0015	<0.0001	0.1633
DE	37	0.0011	0.0007	0.0014	<0.0001	0.1331
NL	35	0.0014	0.0008	0.0024	0.0001	0.1848
BE	9	0.0024	0.0015	0.0026	<0.0001	0.0735
FI	25	0.0019	0.0013	0.0020	0.0001	0.1672
SE	34	0.0022	0.0018	0.0018	0.0002	0.1639
NO	26	0.0033	0.0022	0.0047	<0.0001	0.1961
DK	20	0.0024	0.0017	0.0024	0.0002	0.1524
IT	40	0.0042	0.0013	0.0089	0.0001	0.1967
ES	32	0.0029	0.0012	0.0062	0.0001	0.1524
Total	445	0.0022	0.0011	0.0046	<0.0001	0.2000

Table 4: **Liquidity Co-movements with the Home Market: Univariate Analysis.** For each stock and each month, we first estimate the following regression: $\Delta qspread_{i,t,d} = \alpha + \beta_{i,Home} \Delta qspread_{Home,t,d} + \varepsilon_{i,t,d}$, where $\Delta qspread_{i,t,d}$ is the change in the 5-minute relative quoted spread of firm i from interval $t-1$ to interval t on day d, and $\Delta illiq_{Home,t,d}$ is the cross-sectional value-weighted average of $\Delta qspread_{j,t,d}$ for all stocks in the home country index with $j \neq i$. For each country, we then calculate the average home liquidity beta ($\beta_{i,Home}$) across all stocks and months in our sample, separately for the pre- and post-Chi-X periods. We further report the difference between the pre- and post-Chi-X average liquidity betas, $Diff$, and the statistics of the t-test for the null-hypothesis that this difference equals zero. Please refer to Appendix A for country code abbreviations.

	Total	**GB**	**FR**	**DE**	**NL**	**BE**	**DK**	**FI**	**NO**	**SE**	**IT**	**ES**
Pre Chi-X	0.19	0.24	0.31	0.21	0.16	0.10	0.06	0.04	0.06	0.04	0.20	0.26
Post Chi-X	0.46	0.54	0.59	0.50	0.36	0.19	0.14	0.24	0.13	0.42	0.54	0.54
Diff	0.27	0.30	0.28	0.29	0.20	0.09	0.08	0.20	0.07	0.38	0.34	0.28
t-stat	39.70	27.19	14.02	8.97	10.05	6.46	14.64	24.33	8.46	29.09	27.35	27.80

Table 5: **Liquidity Co-movements with the Home Market: Multivariate Analysis.** This table reports results of the following panel OLS regressions: $\beta_{Home,i,m} = \alpha + \gamma_1 Post_{i,m} + \gamma_2 ln(firm\, size)_{i,m-1} + \gamma_3 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}$, where $\beta_{Home,i,m}$ is the home liquidity beta, estimated for stock i in month m, and $Post$ is a dummy variable that equals 1 for all months after the country's Chi-X market share reaches 10%, and zero otherwise. We include the year- and country-fixed effects and allow standard errors to cluster at the firm level. Model (1) reports results for the total sample, Models (2)-(4) present results for sample splits by three country groups and Models (5) and (6) the corresponding results for subperiods of down and up markets. We classify months in the top tercile of the country's index return as up markets and in the bottom tercile as down markets. Please refer to Appendix C for a detailed description of variable definitions. *, ** and *** denote significance at the 1%, 5% and 10% levels, respectively.

	Total (1)	GB FR DE NL BE (2)	FI SE NO DK (3)	IT SE (4)	down mkt (5)	up mkt (6)
POST	0.074 ***	-0.003	0.050 ***	0.144 ***	0.028 ***	0.109 ***
ln(firm size)	0.048 ***	0.061 ***	0.003	0.046 ***	0.049 ***	0.046 ***
qspread	-0.009 ***	-0.023 ***	-0.037 ***	0.002	-0.011 ***	-0.007 *
Constant	-0.041 ***	-0.052 ***	-0.015	0.121 ***	-0.044 ***	-0.022
N	50728	30136	12320	8272	17765	16356
R-Squared	0.64	0.58	0.58	0.71	0.63	0.65
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

Table 6: **Composition of FTSE Eurofirst 100.** This table presents details of the composition of the FTSE Eurofirst 100 index over 2004-2014, aggregated on the country level. Column (1) reports the corresponding country code abbreviation from Appendix A. Column (2) shows the number of distinct index constituents from each country. Column (3) displays the average daily number of shares (in thousands) and column (4) the average daily euro volume (in millions) traded in each country. The last column shows the percentage of total Eurofirst euro volume traded in each country.

Country	N	Share Volume	Euro Volume	Weight
GB	48	636,712.1	5,000.4	33.4%
FR	28	88,429.3	2,949.0	19.7%
DE	16	60,356.1	2,328.7	15.6%
NL	12	73,904.5	877.5	5.9%
BE	5	27,595.2	495.8	3.3%
FI	3	33,642.4	352.8	2.4%
IT	6	240,160.2	1,360.5	9.0%
ES	9	192,605.6	1,598.9	10.7%
Total	127	1,353,405.4	14,963.6	100%

Table 7: **Liquidity Co-movements with the European market: Multivariate Analysis.** Panel A of this table reports results of the following panel OLS regressions: $\beta_{EU,i,m} = \alpha + \gamma_1 Post_{i,m} + \gamma_2 ln(firm\,size)_{i,m-1} + \gamma_3 qspread_{i,m-1}) + YFE + CFE + \varepsilon_{i,m}$, where $\beta_{EU,i,m}$ is the EU liquidity beta, estimated for stock i in month m, and $Post$ is a dummy variable that equals 1 for all months after the country's Chi-X market share reaches 10%, and zero otherwise. We include the year- and country-fixed effects and allow standard errors to cluster at the firm level. Model (1) reports results for the total sample, Models (2)-(4) present results for sample splits by three country groups, and Models (5) and (6) the corresponding results for subperiods of down and up markets. We classify months in the top tercile of the country's index return as up markets and in the bottom tercile as down markets. Panel B presents the corresponding results with $\beta_{HomeExclEu,i,m}$, estimated after additionally controlling for EU liquidity betas from equation (3), as the dependent variable. Please refer to Appendix A for country code abbreviations and Appendix C for a detailed description of variable definitions. *, ** and *** denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: EU Beta

	Total	GB FR DE NL BE	FI SE NO DK	IT ES	down mkt	up mkt
	(1)	(2)	(3)	(4)	(5)	(6)
POST	0.056 ***	0.019 **	0.008	0.049 ***	0.071 ***	0.066 ***
ln(firm size)	0.027 ***	0.035 ***	0.014 **	0.020 **	0.028 ***	0.022 ***
qspread	-0.030 ***	-0.017 **	-0.043 ***	-0.049 ***	-0.031 ***	-0.042 ***
Constant	0.252 ***	0.238 ***	0.142 ***	0.208 ***	0.284 ***	0.226 ***
N	51097	30281	12383	8433	17827	16443
R-Squared	0.49	0.52	0.47	0.43	0.46	0.49
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

Panel B: Home Beta, after Controlling for EU Beta

	(1)	(2)	(3)	(4)	(5)	(6)
POST	0.033 ***	-0.012 **	0.022 ***	0.150 ***	0.007	0.066 ***
Constant	-0.019 **	-0.022 *	0.011	0.078 ***	-0.027 ***	0.226 ***
N	51097	30281	12383	8433	17827	16443
R-Squared	0.50	0.44	0.40	0.41	0.51	0.49
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

Table 8: **Multimarket Trading by Country.** This table reports annual averages of the *Multimarket Trading* measure, proposed by Halling, Moulton, and Panayides (2013), for each country over the period of 2007, when Chi-X started trading first stocks on its platform, until the end of our sample period in 2014. Please refer to Appendix A for country code abbreviations and Appendix C for a detailed description of the estimation procedure for the *Multimarket Trading* measure.

	GB	**FR**	**DE**	**NL**	**BE**	**FI**	**SE**	**NO**	**DK**	**IT**	**ES**	**Total**
2007	0.33	0.32	0.30	0.41								0.34
2008	0.52	0.57	0.51	0.60	0.30	0.31	0.37	0.22	0.17	0.20		0.38
2009	0.68	0.75	0.67	0.75	0.58	0.52	0.59	0.37	0.38	0.51	0.16	0.54
2010	0.72	0.82	0.75	0.82	0.70	0.66	0.74	0.57	0.60	0.66	0.43	0.68
2011	0.72	0.76	0.74	0.75	0.67	0.69	0.70	0.63	0.57	0.66	0.35	0.66
2012	0.71	0.77	0.73	0.77	0.71	0.67	0.74	0.68	0.61	0.63	0.43	0.68
2013	0.67	0.78	0.75	0.76	0.65	0.66	0.69	0.66	0.62	0.65	0.51	0.67
2014	0.67	0.79	0.74	0.76	0.65	0.64	0.70	0.69	0.61	0.66	0.59	0.68

Table 9: **Intensity of HFT Trading Activity and Liquidity Co-movements with the European market.** This table reports results of the following panel OLS regressions: $\beta_{EU,i,m} = \alpha + \gamma_1 High\, HFT\, Activity_{i,m} \cdot Post_{i,m} + \gamma_2 Low\, HFT\, Activity_{i,m} \cdot Post_{i,m} + Controls + YFE + CFE + \varepsilon_{i,m}$, where $\beta_{EU,i,m}$ is the EU liquidity beta, estimated for stock i in month m; *Post* is a dummy variable that equals 1 for all months after the country's Chi-X market share reaches 10%; and *High (Low) HFT Activity* is a dummy variable that equals 1 for stocks with the above (below) median intensity of HFT activity in our sample. Models (1)-(3) use *Chi-X market share* and Models (4)-(6) use *Multimarket Trading* to measure intensity of HFT activity. The vector of standardized control variables includes $ln(firm\, size)$, the log of market capitalization at the end of the previous month; *qspread*, the average relative quoted spread, calculated over the previous month, the year- and country-fixed effects. Standard errors are clustered at the firm level. Models (1) and (4) report results for the total sample, and Models (2), (3), (5) and (6) for subperiods of down and up markets. We classify months in the top tercile of the country's index return as up markets and in the bottom tercile as down markets. Please refer to Appendix C for a detailed description of variable definitions. *, ** and *** denote significance at the 1%, 5% and 10% levels, respectively.

	Total (1)	down mkt (2)	up mkt (3)	Total (4)	down mkt (5)	up mkt (6)
High Chi-X Shr*POST	0.044 ***	0.047 ***	0.041 ***			
Low Chi-X Shr*POST	0.038 ***	0.038 ***	0.041 ***			
High MltiMrkt*POST				0.041 ***	0.042 ***	0.038 ***
Low MltMrkt*POST				0.041 ***	0.043 ***	0.044 ***
ln(firm size)	0.025 ***	0.025 ***	0.019 ***	0.025 ***	0.026 ***	0.019 ***
qspread	-0.030 ***	-0.030 ***	-0.042 ***	-0.030 ***	-0.030 ***	-0.042 ***
Constant	0.249 ***	0.272 ***	0.223 ***	0.250 ***	0.273 ***	0.223 ***
N	51130	17842	16452	51130	17842	16452
R-Squared	0.49	0.46	0.49	0.49	0.46	0.49
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

Table 10: **Robustness checks.** Panel A of this table reports results of the following panel OLS regressions, based on daily liquidity measures: $\beta_{X,i,q} = \alpha + \gamma_1 Post_{i,q} + \gamma_2 ln(firm\,size)_{i,q-1} + \gamma_3 qspread_{i,q-1}) + YFE + CFE + \varepsilon_{i,q}$, with each of the three betas, β_{Home}, β_{EU} and $\beta_{HomeExclEU}$, as the dependent variable. β_{Home} is estimated for stock i and quarter q from equation (1). β_{EU} and $\beta_{HomeExclEU}$ are estimated for stock i and quarter q from equation (3). *Post* is a dummy variable that equals 1 for all quarters after the country's Chi-X market share reaches 10%, and zero otherwise. We include the year- and country-fixed effects and allow standard errors to cluster at the firm level. To conserve space, we only report the coefficient on *Post* for each specification. The first three columns show the results for the daily relative spread and the remaining three columns for the Amihud illiquidity measure. Models (1) and (4) report results for the total sample, and Models (2), (3), (5) and (6) the corresponding results for subperiods of down and up markets. We classify quarters in the top tercile of the country's index return as up markets and in the bottom tercile as down markets. Please refer to Appendix C for a detailed description of variable definitions. *, ** and *** denote significance at the 1%, 5% and 10% levels, respectively. Panel B summarizes the distributions of the coefficients and t-statistics from placebo regressions, based on 5-minute spreads, in which we randomly assign *Post* 5,000 times between the first month of 2004 and the last month of 2014. We report the average, 5th and 95th percentiles across the 5,000 replications. We report the percentiles of our actual coefficient estimates and t-statistics in the last row.

Panel A: Daily Liquidity Measures

	qspread			illiq		
	total	down mkt	up mkt	total	down mkt	up mkt
	(1)	(2)	(3)	(4)	(5)	(6)
β_{Home}	0.019	0.132 ***	-0.236 ***	0.021 *	0.035 ***	0.033
β_{EU}	0.182 **	0.302 ***	-0.134	0.050 ***	0.091 ***	0.033
$\beta_{HomeExclEU}$	-0.116 ***	-0.099 *	-0.133	-0.045 ***	-0.077 ***	-0.020
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

Panel B: Placebo regressions

	β_{Home}	β_{EU}	$\beta_{HomeExclEU}$
Coefficient on Post			
Mean	0.00	0.00	0.00
5th percentile	-0.01	-0.01	-0.01
95th percentile	0.01	0.01	0.01
percentile of actual estimate	>99%	>99%	>99%
t-statistic on Post			
Mean	0.09	0.06	0.07
5th percentile	-1.58	-1.64	-1.63
95th percentile	1.72	1.74	1.75
percentile of actual estimate	>99%	>99%	>99%