Commonality in Intraday Liquidity and Multilateral Trading Facilities: Evidence from Chi-X Europe*

Olga Klein† and Shiyun Song‡

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Abstract

This paper examines the effects of Chi-X, a pan-European multilateral trading facility, on intraday liquidity co-movements within European equity markets. Chi-X enables simultaneous trading of all European equities on a single trading platform. Further, it induces an increase in multi-market trading between Chi-X and the home exchange, connecting individual markets in a single network. Greater market consolidation combined with an increase in multi-market trading should induce stronger network-wide liquidity co-movements. Consistent with our predictions, we find that Europe-wide liquidity co-movements increase after the Chi-X entry. The increase is stronger in down markets and for stocks with more intense trading on Chi-X.

JEL classifications: G10, G11, G12

Keywords: Market consolidation, Multi-market trading, High-frequency trading, Commonality in Liquidity, European equities, Liquidity risks

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†The corresponding author. Warwick Business School, CV4 7AL Coventry, UK. E-mail: olga.klein@wbs.ac.uk. Tel: +44 24765 28956. Declarations of interest: none.

‡The Vanguard Group, 19301 Paoli, PA, USA. E-mail: shiyun_song@vanguard.com. Tel: +1 6105030616. Declarations of interest: none.

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Abstract

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JEL classifications: G10, G12, G15

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1 Introduction

The change of the European financial markets regulation in November 2007, the Markets in Financial Instruments Directive (MiFID), allowed for entry of multilateral trading facilities (MTFs). MTFs are alternative platforms, which act as competitors of the incumbent exchanges, such as the London Stock Exchange, NYSE Euronext and Deutsche Börse. Prior academic literature confirms that, by increasing competition for the order flow, MTFs generally improve market liquidity (He et al., 2015; Gresse, 2017). However, the benefits of MTFs stand against potential risks, associated with their entry. Hoffmann (2016) shows that trades, executed on alternative platforms, carry significantly more private information than those executed in the primary markets, increasing adverse selection risks for MTF liquidity suppliers. By enabling trading of all European equities on a single platform, MTFs might also facilitate the transmission of liquidity shocks across markets. Surprisingly, empirical evidence on systematic liquidity co-movements across stocks traded on different venues is rather scarce.[1]

In this paper, we examine the effect of the introduction of Chi-X, the first and the largest pan-European MTF, on systematic liquidity co-movements of stocks across European markets. Following Chordia et al. (2000), we analyze co-variations of the stock's liquidity with the aggregate market liquidity and refer to these co-variations as commonality in liquidity. Specifically, we hypothesize that Europe-wide commonality in liquidity, i.e. systematic stock liquidity co-movements with the aggregate European market, increases after the introduction of Chi-X. Our reasoning behind this argument is twofold. First, the introduction of Chi-X facilitates simultaneous trading of a basket of European equities on a single trading platform. According to previous literature (Koch et al., 2016; Kamara et al., 2008), correlated demand for a basket of securities leads to stronger commonality in their liquidity. Second, reduced latency and rebates for liquidity suppliers on Chi-X should in particular attract high-frequency traders (HFTs).[2] High-frequency traders share similar algorithms (Chaboud et al., 2014; Benos et al., 2015), which can lead to excess co-movements in

[1]To the best of our knowledge, Jain et al., 2020 is the only paper to examine the impact of MTFs on liquidity co-movements of stocks, traded by these platforms. Another related study is Ben-David et al. (2012) who show that arbitrage activity between ETFs and their underlying securities can propagate shocks across these two asset classes.

[2]Jovanovic and Menkveld (2016) and Menkveld (2013) 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, Euronext.

their demand and supply, and consequently, to commonality in liquidity across stocks, traded by their algorithms.[3] Further, HFTs often engage in trading across multiple markets, e.g. between Chi-X and the home exchange. Such multi-market HFT trading essentially connects European markets in a single network and might facilitate cross-market liquidity spillovers.[4] Based on these two reasonings, we expect that Europe-wide liquidity co-movements become stronger for stocks that are more intensely traded on Chi-X and that are more likely to be traded by multi-market HFTs.

Our second hypothesis is that Europe-wide liquidity co-movements should be stronger in down markets. Longin and Solnik, 2001 confirm this relation for returns, showing that return correlation across international equity markets increases during market downturns. Liquidation is costlier in down markets, compared to up markets (Saar, 2001; Chiyachantana et al., 2004). Nevertheless, investors are more likely to liquidate their portfolios when a negative return shock hits the market in fear of further price declines and potentially greater losses. The resulting simultaneous selling pressure across all European stocks should lead to stronger co-movements in their liquidity in down markets, as opposed to up markets.

Because trading of European major index stocks on Chi-X was introduced in several phases, this staggered entrance allows us to clearly identify the causal effect of Chi-X entry on Europe-wide commonality in liquidity. 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. To address potential endogeneity concerns, it is rather unlikely that Chi-X was able to accurately predict changes in systematic liquidity co-movements of stocks traded across 11 European markets.

We test our predictions on a sample of 445 major European index stocks from 11 countries over the period from January 2004 to December 2014. Our results provide supporting evidence for our first hypothesis that commonality in liquidity within the aggregate network of European markets is stronger after Chi-X introduction. Consistent with our second hypothesis, we also find that

[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 multi-market liquidity provision makes the liquidity of two markets interconnected. Tomio (2016) shows theoretically and empirically how multi-market arbitrage activity can contribute to the convergence of individual stock's liquidity between two markets.

Europe-wide liquidity co-movements are stronger in down markets. Overall, our findings suggest that the introduction of Chi-X induces stronger liquidity co-movements across European markets by connecting them in a single network.

Understanding liquidity risks arising from entry of MTFs on European markets 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 use the average one-minute quoted spread as our benchmark measure of liquidity.[5] Whereas HFTs have shorter trading horizons of milli-, micro- or nanoseconds, we need to compare liquidity co-movements over intervals of the same length both in the pre- and post-Chi-X period. The average time between two quote updates at the beginning of our sample in 2004-2005 constitutes 43 seconds. To be able to obtain meaningful values for liquidity co-movements in our control period, we have therefore chosen 60 seconds as our benchmark interval length.[6]

Using Chordia et al.'s (2000) market model of liquidity, we estimate EU liquidity beta as the sensitivity of the stock's liquidity to the aggregate liquidity of the FTSE Eurofirst 100, a pan-European index. We additionally control for the fluctuations in liquidity of the corresponding home market index (e.g., FTSE 100 for UK stocks).[7] In the following, we refer to the sensitivity of the stock's liquidity to its home market liquidity as home liquidity beta.

Consistent with our first prediction, EU liquidity betas significantly increase by 19%, 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. In line with expectations, we do not find any evidence of significantly

[5] In Section 5.2, we show that all main results remain unchanged if we use the effective spread, the realized spread or the intraday price impact instead.

[6] Given the relatively short trading horizons of high-frequency traders, we would expect liquidity co-variations to be even stronger if measured on a millisecond (or shorter) basis. Therefore, estimating liquidity betas over 1-minute intervals, if anything, makes it potentially harder for us to find evidence of stronger liquidity co-variations in the post Chi-X period. We also show in Section 5.2 that our main results hold over longer time intervals of five minutes and aggregate to the daily level.

[7] 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.

higher EU liquidity betas for these stocks. Importantly, Chi-X entry has the strongest effect on EU betas for more isolated stocks on peripheral markets (Italy and Spain), compared to already well-integrated stocks on core European markets (the UK, France and Germany).

We also find supporting evidence for our second hypothesis that liquidity co-variations with the aggregate European market have become stronger in down markets. This result implies that the introduction of Chi-X makes European equity markets more susceptible to the transmission of liquidity shocks during crisis periods. In contrast, we find that liquidity co-movements with home markets increase significantly only during market upturns. This finding is consistent with Longin and Solnik (2001) who show that return correlations are lower in up markets. Thus, positive return shocks appear to be more dispersed across countries in time, whereas negative return shocks are more likely to affect all countries at once.

We then test whether cross-sectional differences in EU liquidity betas are related to differences in the level of market consolidation and the intensity of multi-market high-frequency trading in the post-Chi-X period. We use the average monthly share of volume traded on Chi-X, *Chi-X market share*, and the *Multimarket Trading* measure of Halling et al. (2013) as our proxies for the level of market consolidation and the intensity of multi-market HFT activity, respectively. Consistent with expectations, we observe a larger increase in EU liquidity betas for stocks with larger Chi-X market shares and with a more intense multi-market activity.

Finally, we examine the entry of Turquoise, the second pan-European MTF, in September 2008. We formulate two countervailing predictions for the entry of Turquoise on Europe-wide commonality in liquidity. On the one hand, Turquoise presents another opportunity for fast trading of major European equities on a single platform, which should result in a further increase in EU liquidity betas. On the other hand, Turquoise competes directly with Chi-X for the order flow, potentially increasing market fragmentation for European stocks. A higher degree of market fragmentation should result in weaker Europe-wide liquidity co-movements. Overall, we observe lower EU liquidity betas in down markets after the entry of Turquoise, consistent with the latter prediction. Thus, the entry of a competitor appears to alleviate the problem of increased Europe-wide commonality in liquidity in down markets.

We also consider two potential alternative explanations of our empirical findings. First, the observed increase in Europe-wide liquidity co-movements could be also explained by a launch of exchange-traded funds (ETFs) that track broad European stock indices. Indeed, simultaneous trading in the underlying securities of ETFs results in stronger liquidity co-movements (Agarwal et al., 2018). To test this alternative explanation, we download from Bloomberg all ETFs that track Euro Stoxx 50 and MSCI Europe with inception dates within the timeline of the staggered entry of Chi-X into European markets. Overall, we find no evidence to support the argument of the ETF launch as the source of an increase in Europe-wide liquidity co-movements.

Second, we test for "phantom liquidity" as another potential source of stronger cross-market liquidity co-movements. Phantom liquidity refers to the same limit order posted by the same trader across multiple markets to maximize chances of its execution. Upon execution of one order, the orders still outstanding on other venues are canceled. Such simultaneous order cancellations can also result in stronger cross-market liquidity co-movements. In contrast to frequent quote updates by HFT market makers, "phantom" order cancellations represent longer-lasting liquidity withdrawals.[8] To proxy for the degree of phantom liquidity, we estimate the sensitivity in the depth of the limit order book on the home exchange to Chi-X trades. Overall, we observe that EU liquidity betas display a significant increase only for stocks with low levels of phantom liquidity, which is not consistent with the phantom liquidity hypothesis.

We conduct robustness checks of our main analyses, using the five-minute quoted spread as well as the one-minute realized spread, effective spread and price impact. We obtain virtually identical results for all of these alternative intraday liquidity measures. Since co-movements on the daily basis might be of higher importance to institutional and retail investors, we further estimate quarterly liquidity betas, based on the daily relative spread and the Amihud measure. All our main results for EU liquidity betas continue to hold and turn out even stronger for the daily measures.

Our paper contributes to the literature on potential liquidity risks, generated by MTFs. The closest paper to ours is Jain et al. (2020) who document an increase in liquidity co-movements for stocks that start trading on two MTFs, Turquoise and NYSE-Arca Europe. We complement

[8] Van Kervel (2015) documents that the execution on one venue triggers not only immediate cancellations on competing venues, but is also followed by further cancellations even after 10 seconds since the original execution.

their study by analyzing the entry of Chi-X, which is the first pan-European MTF. It also has the largest market share of around 25%, as compared to around 5% for Turquoise.[9] Whereas Jain et al. (2020) examines daily liquidity co-movements, we analyze commonality in intraday liquidity, using 1-minute average quoted spreads as our benchmark liquidity measure. Overall, our findings are consistent with the results of Jain et al. (2020). In addition to stronger daily liquidity co-movements, we also find stronger commonality in intraday liquidity, potentially associated with an increase in market consolidation and multi-market HFT trading after the Chi-X entry. In contrast to Jain et al. (2020), our findings imply that the increase in Europe-wide liquidity co-movements should be rather attributed to the entry of Chi-X, as opposed to Turquoise, for larger stocks in our sample.

Our paper further adds to the literature on commonality in liquidity (Chordia et al. 2000, Huberman and Halka 2001) and its sources (Coughenour and Saad 2004, Kamara et al. 2008, Koch et al. 2016). Karolyi et al. (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 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 multi-market trading by analyzing the implications of multi-market trading activity on potential liquidity risks. In contrast, the main focus of previous studies is either examining determinants of multi-market trading activity (Pulatkonak and Sofianos, 1999; Halling et al., 2008; Baruch et al., 2007; Menkveld, 2008) or studying its effects on liquidity levels through demand (Halling et al., 2013) and supply (Menkveld, 2008; Van Kervel, 2015; Lescourret and Moinas, 2015) channels.

[9] Market share statistics for all European venues provided by CBOE Global Markets at https://markets.cboe.com/europe/equities/market_share/market/venue/.

2 Institutional Background and Hypothesis Development

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 Börse and French stocks on Euronext Paris. The European Union designed the MiFID to promote competition between exchanges by allowing the entry of 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. Importantly, Chi-X is the first pan-European trading platform, enabling simultaneous trading of all major European equities on a single venue. Two further competitive advantages of Chi-X are its lower execution fees and faster speed of order processing, or low latency.[10] 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.[11] 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.[12]

[Insert Figure 1 approximately here]

The entry of Chi-X into European equity markets was staggered in several phases. Figure 1 shows the timeline of Chi-X entrance into European equity markets. German (DAX30) and Dutch

[10]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.

[11]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.

[12]He et al. (2015) provide a detailed overview of fee structures and latencies of European national stock exchanges at the time of the introduction of Chi-X.

(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.

[Insert Table 1 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. Table 1 and Figure IA1 in the Internet Appendix 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. Subsequently, CBOE took over BATS Chi-X Europe in 2017. However, the company still operates two separate limit order books: CXE (Chi-X) and BXE (BATS), which mainly differ in their fee structures. By the end of 2014, Chi-X (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.[13]

2.2 Hypothesis Development and Identification Strategy

Hypothesis 1. We hypothesize that systematic stock liquidity co-movements with the aggregate European market increase after the introduction of Chi-X. The entry of Chi-X is associated with two important changes in European financial landscape. First, it consolidated the market by allowing trading of all major European equities on a single platform. Market consolidation makes it easier for investors to trade simultaneously a basket of European stocks, which should lead to an increase in stock liquidity co-movements with each other. Consistent with our prediction, Kaul et al. (2016) and Jain et al. (2020) document that liquidity co-movements are stronger for stocks traded on the same platform.

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

Second, reduced latency and rebates on liquidity provision on the Chi-X platform encouraged an increase in high-frequency trading.[14] Findings from prior studies suggest that stock liquidity co-movements can arise both through demand (Koch et al. 2016, Kamara et al. 2008) and supply channels (Coughenour and Saad 2004). As liquidity demanders, HFTs engage either in cross-market arbitrage strategies to exploit temporary mispricings between markets, or directional trading strategies, to quickly trade on new information (Baron et al. 2016). In either case, their correlated trading strategies lead to correlated buy or sell pressure (Chaboud et al., 2014; Benos et al., 2015). Therefore, excess co-movements in HFT demand can cause stronger commonality in liquidity across stocks. 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.

Hypothesis 2. We further hypothesize that systematic liquidity co-movements within the European market become stronger in periods of market downturns rather than market upturns. Longin and Solnik (2001) already show this phenomenon for returns, i.e. return correlation across international equity markets increases during market downturns. Therefore, negative return shocks are likely to be systemic, i.e. they affect all countries at once, whereas positive shocks are more dispersed across countries in time.[15] When a negative return shock hits the market, investors are more likely to liquidate their portfolios in fear of further price declines and even greater losses. However, it is exactly at that time when the liquidation is most costly. Indeed, Saar (2001) and Chiyachantana et al. (2004) show theoretically and empirically that investors pay a liquidity premium for trading on the same side of the market. Further, Chiyachantana et al. (2004) empirically

[14] Prior studies by Jovanovic and Menkveld (2016) and Menkveld (2013) show that one large HFT trading Dutch and Belgian index stocks accounts for 70-80% of all Chi-X trades and almost 10% of all trades on the home exchange, NYSE Euronext. He et al. (2015) also 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.

[15] We also find evidence of the increased return correlation during market downturns across countries in our sample. In down markets, correlation across country index returns equals 0.79, as compared to 0.66 in up markets. The z-statistics for the test of equality of two correlation coefficients is 4.49, suggesting a significantly higher return correlation in down markets.

find this premium to be more pronounced in down markets. In addition, in down markets, investors do not have to engage in time-consuming information gathering, because they can only sell stocks that they are already holding.[16] Overall, an increase in simultaneous selling pressure across all stocks in major European stock indices should result in Europe-wide liquidity co-variations that are stronger in down markets rather than up markets.

The staggered introduction of Chi-X allows us to clearly identify its effect 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 et al. (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 auto-quoted stocks to the not yet auto-quoted 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 trading yet, which essentially corresponds to a difference-in-differences methodology.

3 Data and Sample Construction

3.1 Sample Construction

We download the composition of 11 main European stock indices over the period January 2004 - December 2014 from the Thomson Reuters Tick History (TRTH) database: BEL20 (Belgium), OMXC20 (Denmark), OMXH25 (Finland), CAC40 (France), DAX30 (Germany), MIB40 (Italy), AEX20 (the Netherlands), OBX (Norway), IBEX35 (Spain), OMXS30 (Sweden), and FTSE100 (the United Kingdom). 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.

[16] We assume that short-selling is not available to a median investor in the market.

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 presents the details of our sample construction.

[Insert Table 2 approximately here]

In the first step, we filter out Reuters Instrument Codes (RICs) that appear to be erroneously reported as an index constituent by TRTH.[17] Appendix A provides details of our data cleansing procedure. Our initial sample consists of 446 firms. 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.[18] Lastly, we require the stock to be traded for at least 1,000 different 1--minute intervals in a given month. Excluding the stocks that do not satisfy the criteria above leaves 445 firms and 50,728 firm-months in our final sample. Table IA1 in the Internet Appendix reports the number of distinct firms and the number of firm-month observations, separately for each country.

3.2 Measuring Liquidity

We opt for the one-minute average quoted spread, *qspread*, as the benchmark liquidity measure in our analysis. Arguably, the quoted spread measured over seconds or milliseconds would better correspond to relatively short trading horizons of high-frequency traders. However, to address our research question, we need to compare liquidity co-movements over intervals of the same length in both pre- (2004-2007) and post-Chi-X (2008-2014) periods. Trading is not so active at the beginning of our sample in 2004-2005, with the average time of 43 seconds between two quote updates.[19] We

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

[18] This requirement is standard in previous studies with US data, for example, Amihud (2002), Acharya and Pedersen (2005), Kamara et al. (2008) and Ben-Raphael et al. (2015).

[19] For example, the average time between quote updates for UK stocks constitutes 50 seconds, for Italian stocks 62 seconds and for Danish stocks 100 seconds at the beginning of our sample period (not tabulated).

therefore choose 60 seconds as our benchmark interval length to compute the quoted spread.[20] We provide a series of robustness checks for our benchmark liquidity measure in Section 5 and the Internet Appendix.

Formally, we calculate *qspread* as

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

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

Following Chordia et al. (2000), we calculate first differences of the quoted spread, $\triangle qspread$, to capture fluctuations in intraday liquidity.[21] We further standardize $\triangle qspread$ by the time-of-the-day mean and standard deviation to account for well-documented intraday patterns of bid-ask spreads.[22] 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.

3.3 Summary statistics

Panel B of Table 2 presents summary statistics of market capitalization and the 1-minute average quoted spread across all stocks in our sample. 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 B provides a detailed description of variable definitions.

As expected, our sample stocks are generally large, with the average market capitalization of €15.8 billion. Table IA2 in the Internet Appendix presents summary statistics, separately for each

[20]Prior studies on algorithmic trading sample data on longer intervals: Huh (2011) uses 5-minute intervals and Boehmer and Shankar (2014) 15-minute intervals. We repeat our analysis with average spreads, calculated over 5-minute intervals, but all results remain qualitatively similar.

[21]Taking first differences also helps us to overcome a potential econometric problem of non-stationarity of liquidity levels.

[22]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.

country. 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 quoted spread constitutes 0.16% in the total sample. German, French and Dutch stocks are the most liquid, with a spread value of 0.09-0.10%, around half as large as the sample average. They are followed by UK, Belgian, Finnish, Italian and Spanish stocks, with their spread values in the range of 0.15% to 0.18%. Our least liquid stocks are located in Sweden, Denmark and Norway, with their spread values varying between 0.20% and 0.27%. 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 Chi-X Entry and Liquidity Co-movements

In this section, we first test whether the staggered entrance of Chi-X in Europe induces stronger liquidity co-movements of stocks with the aggregate liquidity (Section 4.1). Since Chi-X enables simultaneous trading of all major European equities on a single trading platform, we expect the liquidity of stocks to co-vary more strongly with the aggregate European liquidity after its introduction. We further test whether Europe-wide commonality in liquidity is stronger in down markets (Section 4.1) as well as for stocks with higher Chi-X market shares and higher intensity of HFT trading (Section 4.2). Finally, we analyze the entry of Turquoise, the second MTF (after Chi-X) to combine all major European indices on a single platform, and its effect on Europe-wide liquidity co-movements (Section 4.3).

4.1 Europe-wide Liquidity Co-variations: Pre- vs Post-Chi-X

Similar to Koch et al. (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 the European 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 the European market from the market model of liquidity, employed by Chordia et al. (2000). Specifically, we run time series regressions of $\Delta qspread_{i,t,d}$ on liquidity changes of the aggregate European market, $\Delta qspread_{EU,t,d}$, for all stocks i in all 1-minute intervals t and all trading days d. We additionally control for liquidity changes of the corresponding home market, $\Delta qspread_{Home,t,d}$:

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

As in Kamara et al. (2008) and Koch et al. (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 $j \neq i$.[23] The coefficient $\beta_{i,Home}$ 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. 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 i's home market index, $k \neq i$ and $k \neq j$. The coefficient $\beta_{i,EU}$ captures the sensitivity of the stock's liquidity to the aggregate European liquidity, after controlling for its liquidity co-movements with the home market, $\beta_{i,Home}$. We refer to $\beta_{i,EU}$ as the EU liquidity beta.

We choose the 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 3 presents the composition of FTSE Eurofirst 100 during our sample period.

[Insert Table 3 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

[23] 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.

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.[24]

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.

[Insert Figure 2 approximately here]

Figure 2 displays the development of EU and home liquidity betas, estimated from equation (1), over our sample period. The solid line shows the six-month moving average home liquidity beta, β_{Home}, and the dashed line the corresponding values for EU liquidity beta, β_{EU}, over 2004-2014. The vertical dashed line shows the launch of Chi-X in the second quarter of 2007. Both EU and home liquidity betas increase significantly over the decade from 0.05-0.08 to 0.20-0.25, correspondingly. These findings suggest that liquidity co-variations with the aggregate European market have become as important as those with the home market over recent years. The general increase in liquidity betas over time can potentially be explained by the financial crisis of 2008-2009 as well as the turmoil on European financial markets in 2010-2011 due to the Greek debt crisis. These periods of market downturns are highlighted by gray shaded vertical bars in the figure. Even though all these factors undoubtedly contribute to the variation in liquidity betas, our aim is to separate the effect of the Chi-X entry from other concurrent events. Fortunately, the staggered entry of Chi-X into European financial markets allows for a clear identification of its causal effect.

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

Liquidity co-variations: Pre- vs Post-Chi-X. To examine the effect of Chi-X entry on home and Europe-wide liquidity co-variations, we first compute the difference between average pre- and post-Chi-X liquidity betas. 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%. 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 multi-market high-frequency trader. We provide further robustness checks of our definition of the post-Chi-X period in Section 5.

Our univariate tests show that the average post-Chi-X EU liquidity betas increase by 0.09, from 0.07 to 0.16, and this increase is statistically significant at the 1% level. This finding represents the first empirical evidence for our hypothesis that Chi-X entry induces stronger Europe-wide liquidity co-movements. We also find that the average post-Chi-X home liquidity betas significantly increase by 0.19, from 0.12 to 0.31, presumably because of an increase in multi-market trading by HFTs between Chi-X and the home exchange.

In the next step, we test our predictions in the multivariate setup, controlling for stock characteristics, time- and country-fixed effects. Specifically, we run a panel OLS regression of β_{EU}, 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 quoted spread, calculated over the previous month, $qspread_{i,m-1}$; the year-fixed, YFE, and country-fixed effects, CFE.[25] We allow standard errors to cluster at the firm level in order to account for cross-sectional dependence. Our specification is as follows:

[25] These control variables are standard in previous studies on commonality in liquidity (see, e.g., Koch et al. 2016).

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

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 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 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 correlated with Chi-X entry dates across all countries in our sample, which, in our view, is rather unlikely.[26] Panel A of Table 4 reports the results for the total sample, followed by subsample splits for three country groups and for sub-periods of down and up markets. Panel B shows the corresponding results for home liquidity betas, $\beta_{i,Home}$, as the dependent variable.

[Insert Table 4 approximately here]

Consistent with univariate results, post-Chi-X EU liquidity betas significantly increase by 0.013 for our total sample (Model 1 of Panel A), which represents a 19% increase relative to their mean level of 0.07 in the pre-Chi-X period. Home liquidity betas also increase after the Chi-X entry: An increase of 0.030 (Model 1 of Panel B) represents a 25% increase relative to their pre-Chi-X mean of 0.12. Our control variables display expected signs: larger stocks and stocks that are more liquid exhibit in general stronger systematic co-movements with aggregate market liquidity, consistent with prior findings of Kamara et al. (2008) and Koch et al. (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.

[26] Our specification is similar to that used by Christensen et al. (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 et al. (2011), who use the staggered introduction of NYSE Autoquote as an instrument for an exogenous increase in algorithmic trading.

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.[27] On aggregate, the increase in EU and home liquidity betas in this group is of approximately the same magnitude as for the total sample, because British, German and French stocks account for the majority of observations. Further, with the combined volume weight of around 68% in the FTSE Eurofirst 100, these countries indeed represent the core of the European financial market.

Model (3) presents results for the four Scandinavian countries as our second country group, which started trading on Chi-X in the first two quarters of 2008. Whereas their home liquidity betas significantly increase by 0.033, Scandinavian stocks do not display any significant increase in their EU liquidity betas in the post Chi-X period. However, because the vast majority of Scandinavian stocks do not constitute a part of Eurofirst 100, we do not expect their liquidity to co-move with the European market.

Model (4) presents results for Italy and Spain as our third group, which start trading on Chi-X in the last two quarters of 2008. Importantly, we observe a significantly larger increase in EU betas of 0.075 for Italy and Spain, compared to our first country group (UK, FR. DE, NL, BE) in Model (2) of Panel A. An increase in respective home betas for these countries is insignificant (Model 4 of Panel B). Taken together with an approximately equal pre-Chi-X average EU and home betas of 0.12, our overall findings imply that EU betas have become more important than home betas for Italian and Spanish stocks after the introduction of Chi-X. Therefore, it appears that Chi-X entry has the strongest effect on EU betas for previously more isolated stocks on peripheral markets (IT, ES), compared to stocks on core European markets (UK, FR, DE).

Additionally, we re-estimate home liquidity betas from equation (1), without controlling for liquidity changes of the aggregate European market, $\Delta qspread_{EU,t,d}$. Table IA3 in the Internet Appendix presents results for equation (2) with these home liquidity betas as dependent variables. All results are virtually identical to Panel B of Table 4.

[27] 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.

Overall, our findings are consistent with H1 that Europe-wide liquidity co-variations significantly increase with the introduction of Chi-X. Importantly, we find that EU liquidity betas are significantly higher than home liquidity betas for more isolated stocks on peripheral markets, compared to stocks with already high liquidity co-variations on core European markets.

To test H2, we next analyze liquidity betas during market downturns and market upturns, respectively. We expect stronger increases in EU liquidity betas during market downturns. Longin and Solnik (2001) show that negative return shocks are more likely to affect all countries at once, i.e. they are more likely to be systemic, which should result in simultaneous selling pressure across all European stocks. We split the time series of each country's index return, and classify months with positive index returns as up markets and those with negative returns as down markets. Models (5) and (6) of Panel A present results for down and up markets, correspondingly. Consistent with our expectations, an increase in EU liquidity betas is significantly higher in down markets in the post-Chi-X period, but not in up markets. This result is in contrast to our findings for home liquidity betas, which increase significantly only in up markets (Model 6 of Panel B). Consistent with Longin and Solnik (2001), our findings for up markets imply that positive return shocks are less correlated between countries. Overall, we find that Europe-wide liquidity co-variations have become stronger during crisis periods. Stronger Europe-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.

4.2 Market consolidation and intensity of multi-market HFT trading

Our analyses so far suggest that the entry of Chi-X resulted in stronger Europe-wide liquidity co-movements. One potential explanation could be an increase in market consolidation, because Chi-X enables simultaneous trading of all major European equities on a single platform. Another (non-mutually exclusive) explanation could be an increase in multi-market HFT trading, which induces correlated trading in the stock between the Chi-X and the home exchange. In this section, we conduct tests of these two candidate explanations by examining heterogeneity in the treatment effects that arises due to differences in 1) the level of market consolidation , and 2) the intensity of multi-market activity for stocks traded on the Chi-X platform.

To test the first candidate explanation, we use the average monthly share of volume traded on Chi-X, *Chi-X market share,* as our proxy for the level of market consolidation. Higher volumes traded on Chi-X signal higher levels of stock exposure to the aggregate European market. Therefore, we expect sensitivity to the aggregate European liquidity to be higher for stocks that are traded more intensely on Chi-X. To test for cross-sectional differences in liquidity co-movements, we split our sample by the median Chi-X market share and introduce two dummy variables: *High*, equal to 1 for stocks with above median Chi-X market share, and *Low,* equal to 1 for those with below median share. We then interact both of these dummies with our *Post* dummy and estimate the following specification:

$$\begin{aligned}\beta_{EU,i,m} \quad = \quad & \alpha + \gamma_1 High_{i,m} \cdot Post_{i,m} + \gamma_2 Low_{i,m} \cdot Post_{i,m} + \gamma_3 ln(firm\,size)_{i,m-1} \\ & + \gamma_4 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}. \end{aligned} \tag{3}$$

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 on Chi-X. 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.

[Insert Table 5 approximately here]

We report our findings on the cross-sectional differences in liquidity co-movements in Panel A of Table 5. Model (1) presents results for the total sample. To conserve space, we do not report coefficients for control variables, but they are included in all regressions. The coefficient on the interaction of $High$ and $Post$, γ_1, is positive and significant, whereas the interaction of *Low* and *Post*, γ_2, is not. Consistent with our expectations, these findings suggest a stronger increase in EU liquidity betas for stocks that are more intensely traded on Chi-X, i.e. those with higher levels of market consolidation. Next, we split our total sample into sub-periods of down and up markets, respectively, using the same definition as in the previous section. For down markets in Model (2), we observe that interactions of *Post* with both *High* and *Low* are statistically significant, but the coefficient on the former is significantly higher. For up markets in Model (3), we do not observe any statistically significant differences between the coefficients on the two interaction terms. Overall, we conclude that an increase in Europe-wide liquidity co-variations in down markets is especially high for stocks with higher trading intensity on Chi-X.

To test the second explanation, we use the Halling et al. (2013) measure of *Multimarket Trading* to proxy for the intensity of multi-market HFT activity. *Multimarket Trading* captures the correlation of unexpected trading volume within a one-minute time interval between Chi-X and the home market. We estimate this measure for each stock i and day d from the following VAR model:

$$
\begin{aligned}
\triangle Vol_{i,t}^{Home} &= \alpha_i^{Home} + \gamma_i^{Home}\triangle Vol_{i,t-1}^{Home} + \beta_i^{Chi-X}\triangle Vol_{i,t-1}^{Chi-X} + \delta_i ret_{i,t} + \varepsilon_{i,t}^{Home} \\
\triangle Vol_{i,t}^{Chi-X} &= \alpha_i^{Chi-X} + \gamma_i^{Chi-X}\triangle Vol_{i,t-1}^{Chi-X} + \beta_i^{Home}\triangle Vol_{i,t-1}^{Home} + \delta_i ret_{i,t} + \varepsilon_{i,t}^{Chi-X},
\end{aligned} \tag{4}
$$

where $\triangle Vol_{i,t}$ is the change in the trading volume, calculated as the logarithm of the ratio of the 1-minute interval t to interval $t-1$ euro (pound) trading volume.[28] 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 on day d 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, $\varepsilon_{i,t}^{Chi-X}$. We then average the obtained daily correlations for each month m. The higher the correlation in trading volume shocks between the two markets, the more intensive is the multi-market trading of this stock. Since trading across multiple markets requires costly technological investment and continuous monitoring, it is plausible to assume that multi-market trading between Chi-X and the home market is to a large extent driven by high-frequency traders. On average, the correlation in unexpected trading volumes between Chi-X and the home market increases from 0.25 in 2008 to 0.35 in 2011, consistent with the rise in high-frequency trading

[28] Similar to Halling et al. (2013), we use log-changes in trading volume to ensure stationarity of this variable.

over these years. It subsequently drops to less than 0.10 in 2014, which implies that cross-market strategies have become less profitable towards the end of our sample period.

We re-estimate equation (4), splitting our sample by the median *Multimarket Trading* measure. Model (4) in Panel A of Table 5 presents the corresponding results for the total sample. Models (5) and (6) present results for down and up market splits, respectively. As in our previous analysis with the Chi-X market share, we observe a higher coefficient on $High \cdot Post$ than on $Low \cdot Post$, for the total sample and in down markets. Overall, these findings are consistent with the second candidate explanation that Europe-wide liquidity co-movements are stronger for stocks more intensely traded by multi-market HFT traders.

4.3 Entry of Turquoise

We further conduct an additional analysis of the entry of Turquoise, the second MTF (after Chi-X) to start trading all major European indices on a single platform. It was launched in 2008 by a consortium of nine founding investment banks.[29] The main objective of its founding members was to decrease execution costs for their clients. Whereas the soft launch with 5 firms per country took place in mid-August 2008, it was not until September 2008 that Turquoise started trading stocks from 13 major European indices.[30] Italian stocks started trading in October 2008, followed by Spanish stocks in February 2009. Overall, empirical predictions for the effect of Turquoise on Europe-wide liquidity co-variations are not straightforward. On the one hand, Turquoise presents another opportunity (also for HFTs) to trade all European stocks on a single venue, which can result in stronger co-variations. On the other hand, it competes directly with Chi-X for attracting the order flow, which increases market fragmentation for the European basket of stocks and can therefore result in overall weaker liquidity co-variations.

To determine which of the two predictions dominates, we re-estimate our equation (2), now adding a dummy variable, $Post_{Turq}$. $Post_{Turq}$ equals 1 for all months after Turquoise starts trading the main stock index of a country, and is zero otherwise. Model 1 in Panel B of Table 5

[29] Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, Merrill Lynch, Morgan Stanley, UBS, BNP Paribas and Societe Generale.

[30] Hengelbrock and Theissen (2009) provide a detailed overview of the entry of Turquoise on European financial markets.

reports the results for the total sample. As in our benchmark model (Model 1 in Panel A of Table 4), the coefficient on $Post_{Chi-X}$ shows a significant increase of 0.012 in EU liquidity betas for our total sample, relative to the pre-MTF period (2004Q1-2007Q1). $Post_{Turq}$ captures an additional change in EU liquidity betas after the entry of Turquoise.[31] Although the coefficient on $Post_{Turq}$ is insignificant, the total effect on EU liquidity betas, measured as the sum of the coefficients on $Post_{Chi-X}$ and $Post_{Turq}$, is still 0.012. In other words, EU liquidity betas increase after the entry of Chi-X and remain at the same increased level after the entry of Turquoise. Our findings are overall consistent with previous results of Jain et al. (2020), who document an increase in liquidity commonality across stocks traded on Turquoise. However, our findings imply that this increase should be rather attributed to the prior entry of Chi-X for our sample of larger stocks.[32]

In addition to Jain et al. (2020), we further analyze changes in EU liquidity betas in down and up markets in Models (2) and (3), respectively. Overall, we observe similar coefficients on $Post_{Chi-X}$ as in our benchmark Models (5) and (6) in Panel A of Table 4. Importantly, the coefficient on $Post_{Turq}$ is significantly negative for the subsample of down markets, suggesting a marginal decrease of 0.01 in EU liquidity betas after the entry of Turquoise. The total effect, relative to the pre-MTF period, is however still positive, i.e. $0.027 - 0.01 = 0.017$. In up markets, both $Post_{Chi-X}$ and $Post_{Turq}$ are insignificant. Overall, our empirical findings, based on the entry of Turquoise, are rather consistent with the "competition" hypothesis. The entry of Turquoise implies additional competition for Chi-X for the order flow, resulting in greater market fragmentation for European stocks. Consequently, we observe weaker Europe-wide liquidity co-variations in down markets. Thus, the entry of a competitor helps to alleviate the problem of increased systematic liquidity co-movements across European stocks in down markets.

[31] Since Turquoise entered after Chi-X, $Post_{Turq}$ only equals 1 if $Post_{Chi-X}$ is also equal to 1. Therefore, $Post_{Turq}$ can be regarded as the interaction term, $Post_{Chi-X} \cdot Post_{Turq}$, measuring the additional effect of Turquoise on EU liquidity betas.

[32] In contrast to our study, the sample of Jain et al. (2020) includes all stocks traded on Turquoise. Apart from differences in the sample composition, Jain et al. (2020) use the closing bid-ask spreads to estimate liquidity co-variations on a daily level, as opposed to 1-minute average quoted spreads in our study.

5 Alternative Explanations and Robustness Checks

5.1 Alternative explanations

Launch of Europe-wide ETFs. One potential alternative explanation for an increase in Europe-wide equity liquidity co-movements could be launch of ETFs tracking broad European stock indices, such as Euro Stoxx 50 and MSCI Europe. Agarwal et al. (2018) show that simultaneous trading in the underlying securities of ETFs leads to greater commonality in liquidity between them. Therefore, if the launch of Europe-wide ETFs overlaps with the entry of Chi-X, an increase in correlated demand for their underlying stocks could also explain our empirical findings. With this argument, we would then also expect to find an increase in Europe-wide liquidity co-movements after an ETF launch.

To test this alternative explanation, we download from Bloomberg ETFs that track Euro Stoxx 50 and MSCI Europe and the inception dates of which lie within the timeline of the staggered entry of Chi-X into European markets. Specifically, we identify 6 ETFs that satisfy the above criteria: Deka Euro Stoxx 50 ETF (inception: March 31, 2008), Deka MSCI Europe ETF (August 29, 2008), Amundi Euro Stoxx 50 ETF (September 1, 2008), Invesco Euro Stoxx 50 ETF (March 18, 2009), Invesco MSCI Europe ETF (March 23, 2009), and HSBC MSCI Europe MTF (November 3, 2010). We re-estimate our specifications from Table 4 with EU liquidity betas as dependent variables, now replacing $Post$ with $Post_{ETF}$. $Post_{ETF}$ is a dummy variable, which equals 1 for all months after the launch of the corresponding ETF, and is zero otherwise. Panel A of Table 6 reports the average coefficient on $Post_{ETF}$ and the average t-statistics across all ETFs.

[Insert Table 6 approximately here]

On average, we do not observe a significant increase in EU liquidity betas after the launch of ETFs, the inception dates of which overlap with the Chi-X entry (Model 1). $Post_{ETF}$ is only marginally significant at the 10% level in down markets (Model 2), with its coefficient of 0.008 being three times lower than the corresponding coefficient of 0.025 on $Post_{Chi-X}$ in Model (5) in Panel A of Table 4. Interestingly, we find a significant effect of the launch of ETFs on EU liquidity betas in up markets (Model 3), suggesting that liquidity co-movements of their underlying stocks are stronger due to an increase in ETF demand in the rising markets. In contrast, the effect of Chi-X entry on EU liquidity betas is only significant in down markets. Whereas positive liquidity shocks are rather benign, correlated liquidity decreases in down markets are of greater concern: liquidity dries up exactly when investors need to liquidate their positions.

Overall, our empirical findings, based on the launch of Europe-wide ETFs, are inconsistent with the notion that an increase in EU liquidity betas is driven by increased correlated demand for the underlying stocks of these ETFs. The overall insignificant effect of ETFs entering the market simultaneously with Chi-X can probably be explained by the fact that the first ETF offering broad exposure to European equities, iShares Euro Stoxx 50 ETF, started trading on the Deutsche Börse as early as April 11, 2000, which precedes the entry of Chi-X by seven years. Therefore, we suppose that the major effect of ETFs on liquidity commonality for European stocks takes place in the pre-Chi-X period.

Placebo tests. Further, we conduct placebo tests, in which we randomly assign our *Post* dummy between the first month of 2004 and the last month of 2014. Using 5,000 replications, we repeat our analyses from Table 4 and summarize the distributions of the coefficients and t-statistics on *Post* in Panel B of Table 6. 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 0.013-0.03 fall within the 99th percentile of the distribution for both liquidity betas, suggesting that they are significantly different from the placebo average. These results are also confirmed by the actual t-statistics to its distribution from the placebo regressions in the lower part of the panel.

Phantom liquidity. Another alternative explanation for our empirical results is a phenomenon referenced as "phantom liquidity" in the SEC's (2010) release on equity market structure.[33] Phantom liquidity refers to the same single limit order posted across multiple markets. Posting a limit order is much less costly than submitting a market order and posting across multiple venues max-

[33]See the 2010 Securities and Exchange Commission Concept Release on Equity Market Structure.

imizes the chances of the limit order execution. After the execution on one of the venues, all outstanding orders on other venues are canceled. Such simultaneous order cancellations could also increase the liquidity co-movements across markets. Quote updates by HFT market makers also result in simultaneous order cancellations. However, the reduction in liquidity is only temporary, as it is replenished after market makers repost their new quotes.[34] In contrast, order cancellations associated with phantom liquidity represent a longer-lasting withdrawal of liquidity from the market. Van Kervel (2015) documents that an execution on one venue is followed by cancellations of limit orders on the same side on competing venues of around 60% of the trade size within 100 ms. Further, the effect becomes stronger with the time horizon and continues to hold even after 10 seconds.

We use the sensitivity in the depth of the limit order book on the home exchange to Chi-X trades as a proxy for phantom liquidity. Specifically, we estimate a modified equation (10) from Van Kervel (2015) for each stock-day:

$$\begin{aligned} \triangle DepthAsk_{i,t}^{Home} &= \alpha_i^{Home} + \gamma_{1,i}^{Home} Buy_{i,t}^{Home} + \gamma_{2,i}^{Home} Sell_{i,t}^{Home} + \\ &+ \boldsymbol{\beta_{1,i}^{Chi-X}} Buy_{i,t}^{Chi-X} + \boldsymbol{\beta_{2,i}^{Chi-X}} Sell_{i,t}^{Chi-X} + \varepsilon_{i,t}^{Home}. \end{aligned} \tag{5}$$

where $\triangle DepthAsk_{i,t}^{Home}$ is the change in the depth quoted at the best ask on the home exchange (in pounds/euros) within the one-minute interval t for stock i; $Buy_{i,t}^{Home}$ is the one-minute buy volume (in pounds/euros) for stock i on the home exchange; $Sell_{i,t}^{Home}$ is the corresponding sell volume on the home exchange. $Buy_{i,t}^{Chi-X}$ and $Sell_{i,t}^{Chi-X}$ are defined similarly for the buy and sell volume traded on Chi-X, respectively. We also run regressions, using changes in the depth quoted at the best bid ($\triangle DepthBid_{i,t}^{Home}$) as the dependent variable. To capture the long-lasting effect of liquidity withdrawals, we opt for a longer time interval of one minute. All results remain robust if we use one second instead.[35]

[34] Baruch and Glosten (2013) show theoretically that it is rational for market makers to manage their undercutting risk by rapidly canceling their quotes and replacing them with new randomly chosen ones.

[35] We obtain similar results for the sensitivity of the depth of the Chi-X limit order book to trades on the respective home exchange (not tabulated).

Our main coefficient of interest is β_1 for regressions with $\triangle DepthAsk^{Home}$ as the dependent variable. Specifically, β_1 shows the pound/euro change in the depth on the ask side of home exchange after a 1 pound/euro purchase trade on Chi-X. For regressions with $\triangle DepthBid^{Home}$ as the dependent variable, our main coefficient of interest is β_2, respectively. The more negative values of β_1 and β_2 imply stronger sensitivity in the depth of the limit order book on the home exchange to Chi-X trades. Thus, we associate more negative values of β_1 and β_2 with a higher level of phantom liquidity. Van Kervel (2015) documents that β_1 and β_2 are symmetrical and lie in the range of -0.20 to -0.40, dependent on the length of the time interval. We also find the symmetric monthly average value of -0.28 for β_1 and β_2 in our sample.

Next, we split our sample by the median value of β_1 and β_2, and define two dummy variables: *High Phantom Liq*, equal to 1 for stocks with below median values, and *Low Phantom Liq,* equal to 1 for those with above median values. We then interact both of these dummies with our *Post* dummy and re-estimate equation (3) above.

[Insert Table 7 approximately here]

Models (1) to (3) of Table 7 present results for *High Phantom Liq* based on β_1, i.e. the sensitivity of the ask side of the limit order book on home exchange to purchase trades on Chi-X. Models (4) to (6) present corresponding results for *High Phantom Liq* based on β_2, i.e. the sensitivity of the bid side of the limit order book on home exchange to sale trades on Chi-X. To conserve space, we do not report coefficients for control variables, but they are included in all regressions. For the total sample, we observe that EU liquidity betas display a significant increase only for stocks with low levels of phantom liquidity, both for ask and bid sides of the book (Models 1 and 4). These results also hold for down (Models 2 and 5) and up (Models 3 and 6) markets. Overall, our empirical findings are inconsistent with the explanation that phantom liquidity is a source of stronger cross-market liquidity co-movements.

5.2 Robustness checks

Alternative intraday liquidity measures. As our first robustness check, we repeat our analyses from Table 4 with two alternative intraday liquidity measures: the five-minute average quoted spread and the one-minute realized spread. We use a longer time window of five minutes to check the robustness of our results and to make them comparable to previous studies on algorithmic trading that also sample data on longer intervals (Huh, 2011;Boehmer and Shankar, 2014). We also use an alternative measure of the one-minute realized spread, which should better capture profitability of presumably the most common multi-market HFT trading strategy - the market making strategy. Specifically, we calculate the realized spread as

$$rspread_{i,j} = \frac{2|P_{i,j} - M_{i,j+60s}|}{M_{i,j}},$$

where $P_{i,j}$ is the transaction price of stock i at time j on its primary exchange, and $M_{i,j}$ is the midpoint quote, calculated as the average of the prevailing bid and ask quotes at time j ($M_{i,j} = \frac{A_{i,j}+B_{i,j}}{2}$). $M_{i,j+60s}$ represents the one-minute (or 60-second) forward midpoint quote. We then average all realized spreads for each stock i within each minute t to calculate the one-minute average realized spread.

[Insert Table 8 approximately here]

We re-estimate equation (1), using these alternative liquidity measures, to obtain β_{Home} and β_{EU} for each stock and each month. Afterwards, we re-estimate our specification from equation (2) with each of these two betas as the dependent variable. As before, we include the firm size, the average liquidity over the previous month, year- and country-fixed effects as control variables. Panel A of Table 8 presents the results. To conserve space, we only report the coefficient on *Post* for each specification.

Models (1)-(3) present results, using the five-minute average quoted spread, for the total sample, down and up markets, respectively. Importantly, we obtain greater economic magnitude of coefficients, compared to previous results from Table 4. This finding implies that the liquidity co-movements measured over one-minute intervals do not dissipate within the next five minutes, but actually become stronger. The results for the one-minute realized spread in Models (4)-(6) are virtually identical to benchmark specifications in Table 4. All main results also hold if we use the one-minute average effective spreads or price impacts to estimate our liquidity betas (Table IA4 in the Internet Appendix).

Daily liquidity measures. It is *ex ante* not clear whether stronger intraday liquidity co-variations are also significant on the daily level. Arguably, daily liquidity co-variations might be of higher importance for lower-frequency traders, such as institutional and retail investors. Therefore, we also present results for daily quoted bid-ask spreads and the Amihud (2002) measure of illiquidity in Panel B of Table 8.[36]

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.[37] Since there is now only one observation per day for each liquidity measure, we can no longer estimate liquidity betas on a monthly basis and therefore re-estimate equation (1) on a quarterly basis. In equation (2), *Post* now takes value of 1 starting in the quarter when the country's Chi-X market share reaches 10%, and is zero otherwise.

For daily quoted spreads, we observe a considerably stronger increase of 0.18 in EU liquidity betas after the introduction of Chi-X (Model 1), whereas home liquidity betas decrease by -0.11. Models (2) and (3) present the corresponding results for 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 also find stronger Europe-wide liquidity co-movements for daily liquidity measures in the post-Chi-X period.

[36] 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.

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

6 Conclusions

This paper examines the effects of the market entry of Chi-X, a pan-European MTF, on systematic liquidity co-movements within a network of European national markets. The staggered introduction of Chi-X in 11 European equity markets allows us to clearly identify its effect on Europe-wide commonality in liquidity. Importantly, Chi-X enables trading of all major European equities on a single trading platform, which was not hitherto possible at a comparable speed. Further, multi-market 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 Europe-wide liquidity co-movements.

Consistent with our expectations, we find that liquidity co-movements within the aggregate European market significantly increase after the introduction of Chi-X, especially in down markets. We further show that Europe-wide liquidity co-movements are stronger for stocks with higher Chi-X market shares and higher multi-market trading activity in the post-Chi-X period. Overall, our findings are consistent with the notion that the introduction of MTFs is associated with stronger network-wide liquidity co-movements, thus facilitating propagation of liquidity shocks across markets.

Empirical evidence in our paper suggests that market participants and policymakers currently underestimate potential liquidity risks, generated by MTFs. 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 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* 225 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.

B 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
illiq	The Amihud (2002) measure, calculated as the ratio of the absolute daily price change, $\|R_{i,d}\|$, to the daily euro (pound) volume traded (in millions) on the stock's primary exchange, $DVol_{i,d}$. We calculate *illiq* as the quarterly average of the daily Amihud (2002) measure.	TRTH
Multimarket Trading	The *Multimarket Trading* measure of Halling et al. (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 the one-minute 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 on day d is calculated as the contemporaneous correlation between $\varepsilon_{i,t}^{Home}$and $\varepsilon_{i,t}^{ChiX}$. We then average the obtained daily correlations for each month m.	TRTH

Variable	Description	Source
Phantom Liq	The measure of phantom liquidity, estimated as β_1 from the modified equation (10) in Van Kervel (2015): $\triangle DepthAsk_{i,t}^{Home} = \alpha_i^{Home} + \gamma_{1,i}^{Home} Buy_{i,t}^{Home} + \gamma_{2,i}^{Home} Sell_{i,t}^{Home} + \boldsymbol{\beta_{1,i}^{Chi-X}} Buy_{i,t}^{Chi-X} + \boldsymbol{\beta_{2,i}^{Chi-X}} Sell_{i,t}^{Chi-X} + \varepsilon_{i,t}^{Home}$ where $\triangle DepthAsk_{i,t}^{Home}$ is the one-minute change in the depth quoted at the best ask on the home exchange (in pounds/euros) within the time interval t for stock i; $Buy_{i,t}^{Home}$ is the one-minute buy volume (in pounds/euros) for stock i on the home exchange; $Sell_{i,t}^{Home}$ is the corresponding sell volume on the home exchange. $Buy_{i,t}^{Chi-X}$ and $Sell_{i,t}^{Chi-X}$ are defined similarly for the buy and sell volume traded on Chi-X, respectively. For regressions with $\triangle DepthBid_{i,t}^{Home}$ as the dependent variable, the phantom liquidity is proxied by β_2.	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

Variable	Description	Source
qspread	The one-minute quoted spread, calculated as $$qspread_{i,j} = \frac{A_{i,j} - B_{i,j}}{(A_{i,j} + B_{i,j})/2},$$ where $A_{i,j}$ is the ask price and $B_{i,j}$ the bid price prevalent for stock i at time j on its primary exchange. We then average all quoted spreads for each stock i within each minute t to calculate the 1-minute average quoted spread. 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
realized spread	The one-minute realized spread, calculated as $$rspread_{i,j} = \frac{2\lvert P_{i,j} - M_{i,j+60s}\rvert}{M_{i,j}},$$ where $P_{i,j}$ is the transaction price of stock i at time j on its primary exchange, and $M_{i,j}$ is the midpoint quote, calculated as the average of the prevailing bid and ask quotes at time j ($M_{i,j} = \frac{A_{i,j} + B_{i,j}}{2}$). $M_{i,j+60s}$ represents the 1-minute (or 60-second) forward midpoint quote. We then average all realized spreads for each stock i within each minute t to calculate the 1-minute average realized spread.	TRTH
ret	The firm's stock return in the home market	TRTH

Figure 1: **Staggered entrance of Chi-X into European equity markets.** This figure shows the timeline of Chi-X entrance into European equity markets. The dates of Chi-X entry into European equity markets are 30/03/2007 for Germany (DE) and the Netherlands (NL); 29/06/2007 for the United Kingdom (GB), 28/09/2007 for France (FR), 14/03/2008 for Sweden (SE), 04/04/2008 for Finland (FI), 27/06/2008 for Norway (NO) and Denmark (DK), 04/07/2008 for Belgium (BE), 13/10/2008 for Italy (IT) and 09/12/2008 for Spain (ES).The dotted lines highlight the time of Chi-X market entry for each country in our sample. We use the two letter country code to represent each country.

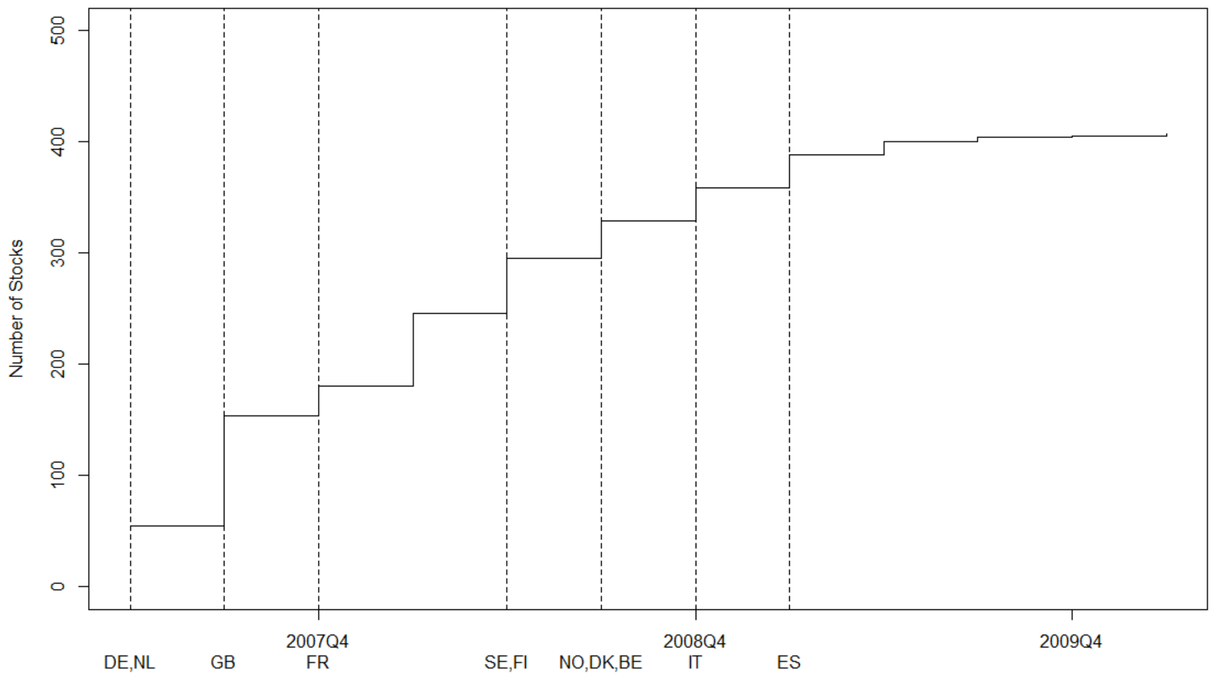

Figure 2: **Development of Aggregate EU and Home Liquidity Betas over Time.** This figure displays six-month moving averages of EU and home liquidity betas, aggregated across all stocks in our sample. For each stock and each month, we first estimate the following regression: $\Delta qspread_{i,t,d} = \alpha + \beta_{i,Home}\Delta qspread_{Home,t,d} + \beta_{i,EU}\Delta qspread_{EU,t,d} + \varepsilon_{i,t,d}$, where $\Delta qspread_{i,t,d}$ is the change in the 1-minute average 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 ($\beta_{i,Home}$) liquidity betas for all stocks in each month. The solid line shows the six-month moving average home liquidity betas and the dashed line the corresponding values for EU liquidity betas over 2004-2014. The vertical line shows the launch of Chi-X in the second quarter of 2007. Periods of market downturns, defined as months when the aggregate market return is below zero, are highlighted with gray shaded vertical bars.

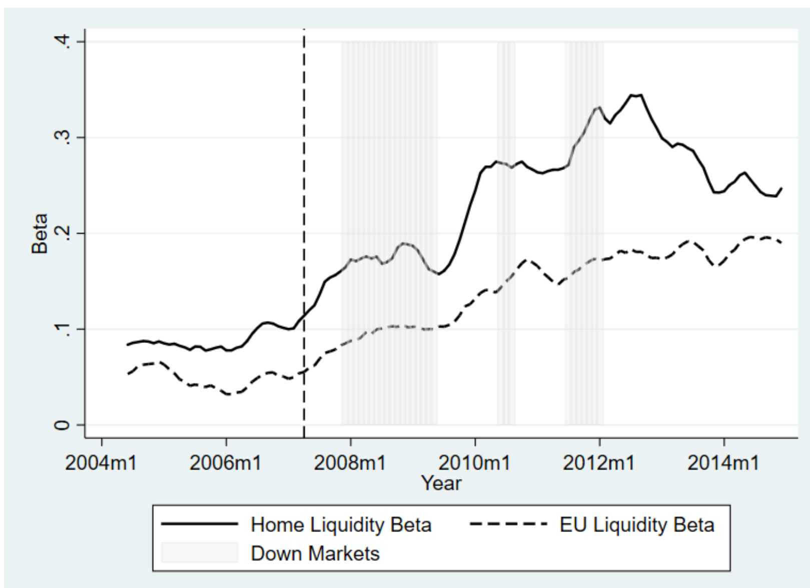

Table 1: **Chi-X Market Share by Country.** This table reports the quarterly averages of Chi-X market shares for each country in our sample. Chi-X market share for stock i on day d is calculated as $ChiXMrktShr_{i,t} = \frac{Volume_{i,d,c}}{Volume_{i,d,c}+Volume_{i,d,h}}$, where $Volume_{i,d,c}$ is the 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.

	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 and Summary Statistics.** Panel A of 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. Appendix A provides 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. Finally, we retain a stock in a given month only if it is traded for at least 1,000 different 1-minute intervals. Column (2) reports the number of distinct firms and Column (3) reports the number of firm-month observations in our sample. Panel B of this table reports cross-sectional summary statistics of market capitalization, *firm size* (in € million), and the 1-minute average quoted spread , *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 B provides a detailed description of variable definitions.

Panel A: Sample Construction

	Firms	Firm-Month Obs
Initial Sample	446	52,384
Stock price > £2/€2	446	50,895
Traded for 1,000 1-min intervals	445	50,728

Panel B: Summary Statistics

	N	Mean	Median	StDev	Min	Max
firm size	445	15,863	7,299	20,264	611	102,791
qspread	445	0.0016	0.0014	0.0009	0.0004	0.0073

Table 3: **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. 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 4: **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 from equation (1), 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 when the country's index return is positive as up markets and as down markets when it is negative. Panel B presents the corresponding results with $\beta_{Home,i,m}$, estimated from equation (1), as the dependent variable. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: EU liquidity beta, β_{EU}

	Total (1)	GB FR DE NL BE (2)	FI SE NO DK (3)	IT ES (4)	down mkt (5)	up mkt (6)
Post	0.013 ***	0.012 ***	0.010	0.075 ***	0.025 ***	0.004
	(3.38)	(2.60)	(1.36)	(7.33)	(6.79)	(0.78)
Ln(firm size)	0.033 ***	0.024 ***	0.029 ***	0.064 ***	0.035 ***	0.032 ***
	(9.51)	(5.61)	(3.98)	(13.05)	(8.83)	(9.37)
Qspread	-0.004	0.001	-0.026 ***	-0.021 ***	-0.006 *	-0.003
	(-1.35)	(0.30)	(-3.50)	(-5.48)	(-1.89)	(-0.88)
N	50,728	30,136	12,320	8,272	18,603	32,125
R^2	0.48	0.53	0.40	0.47	0.50	0.47
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Home liquidity beta, β_{Home}

	Total (1)	GB FR DE NL BE (2)	FI SE NO DK (3)	IT ES (4)	down mkt (5)	up mkt (6)
Post	0.030 ***	0.023 ***	0.033 ***	-0.007	0.002	0.058 ***
	(7.38)	(5.19)	(9.19)	(-0.74)	(0.53)	(11.16)
Ln(firm size)	0.054 ***	0.075 ***	0.012 ***	0.035 ***	0.057 ***	0.052 ***
	(14.31)	(14.91)	(3.88)	(11.02)	(14.56)	(13.57)
Qspread	-0.013 ***	-0.009 *	-0.018 ***	-0.016 ***	-0.014 ***	-0.012 ***
	(-4.03)	(-1.93)	(-2.78)	(-4.18)	(-4.70)	(-2.98)
N	50,728	30,136	12,320	8,272	18,603	32,125
R^2	0.59	0.57	0.44	0.44	0.60	0.60
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **Liquidity Co-movements with the European market: Cross-sectional Tests.** Panel A of this table reports results of the panel OLS regressions: $\beta_{EU,i,m} = \alpha + \gamma_1 High_{i,m} \cdot Post_{i,m} + \gamma_2 Low_{i,m} \cdot Post_{i,m} + Controls + YFE + CFE + \varepsilon_{i,m}$, where $\beta_{EU,i,m}$ is the EU liquidity beta, estimated for stock i in month m from equation (1); *Post* is a dummy variable that equals 1 for all months after the entry of Chi-X; and *High (Low)* is a dummy variable that equals 1 for stocks with the above (below) median *Chi-X market share* (Models 1-3) or *Multimarket Trading* (Models 4-6) in our sample. Appendix B provides a detailed description of variable definitions. Panel B reports the analysis for the entry of Turquoise, another pan-European trading platform that entered the market after Chi-X. $Post_{Turq}$ is a dummy variable that equals 1 for all months after the entry of Turquoise, and zero otherwise. The vector of standardized control variables in all regressions 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. Models (2) and (5) present results for down markets, and Models (3) and (6) for up markets. We classify months when the country's index return is positive as up markets and as down markets when it is negative. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Cross-sectional tests

	Chi-X market share			Multimarket trading		
	total	down mkt	up mkt	total	down mkt	up mkt
β_{EU}	(1)	(2)	(3)	(4)	(5)	(6)
$High \cdot Post$	0.021 ***	0.034 ***	0.013 *	0.017 ***	0.029 ***	0.009
	(4.32)	(7.34)	(1.94)	(3.27)	(6.27)	(1.40)
$Low \cdot Post$	0.001	0.013 **	-0.007	0.005	0.021 ***	-0.004
	(0.17)	(2.41)	(-1.04)	(1.12)	(4.69)	(-0.66)
N	50,728	18,603	32,125	42,164	15,514	26,650
R^2	0.48	0.50	0.47	0.53	0.54	0.53
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Entry of Turquoise

	total	down mkt	up mkt
β_{EU}	(1)	(2)	(3)
$Post_{Chi-X}$	0.012 ***	0.027 ***	0.002
	(3.07)	(7.04)	(0.38)
$Post_{Turq}$	-0.004	-0.010 ***	0.000
	(-1.49)	(-2.73)	(0.11)
N	51,097	18,663	32,434
R^2	0.47	0.49	0.47
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

Table 6: **Alternative Explanation: Launch of ETFs.** Panel A of this table reports the average coefficient on $Post_{ETF}$, estimated from the following panel OLS regressions: $\beta_{EU,i,m} = \alpha + \gamma_1 Post_{ETF,i,m} + \gamma_2 ln(firm\, size)_{i,m-1} + \gamma_3 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}$, where $\beta_{EU,i,m}$ is the EU liquidity beta, estimated for stock i in month m from equation (1). $Post_{ETF}$ is a dummy variable that equals 1 for all months after the launch of ETFs that track the Euro Stoxx 50 or the MSCI Europe stock indices and the inception dates of which lie within the timeline of the staggered entry of Chi-X into European markets. 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) and (3) present results for down and up markets, respectively. We classify months when the country's index return is positive as up markets and as down markets when it is negative. Panel B summarizes the distributions of the coefficients and t-statistics from placebo regressions, 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. Appendix B provides a detailed description of variable definitions. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Launch of Europe-wide ETFs

β_{EU}	total (1)	down mkt (2)	up mkt (3)
$Post_{ETF}$	0.004	0.008 *	0.061 ***
	(1.23)	(1.90)	(7.00)
N	51,097	18,663	32,434
R^2	0.47	0.49	0.47
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

Panel B: Placebo regressions

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

Table 7: **Alternative Explanation: Phantom Liquidity.** This table reports results of the following panel OLS regressions: $\beta_{EU,i,m} = \alpha + \gamma_1 High\,Phantom\,Liq_{i,m} \cdot Post_{i,m} + \gamma_2 Low\,Phantom\,Liq_{i,m} \cdot Post_{i,m} + Controls + YFE + CFE + \varepsilon_{i,m}$, where $\beta_{EU,i,m}$ is the EU liquidity beta, estimated for stock i in month m from equation (1); and *High (Low) Phantom Liq* is a dummy variable that equals 1 for stocks with the above (below) median phantom liquidity in our sample. Models (1)-(3) show results for the phantom liquidity on the ask side and Models (4)-(6) on the bid side of the limit order book. 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. Models (2) and (5) present results for down markets, and Models (3) and (6) for up markets. We classify months when the country's index return is positive as up markets and as down markets when it is negative. Appendix B provides a detailed description of variable definitions. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Ask side			Bid side		
	total	down mkt	up mkt	total	down mkt	up mkt
β_{EU}	(1)	(2)	(3)	(4)	(5)	(6)
High · Post	0.004	0.020 ***	-0.007	0.004	0.020 ***	-0.006
	(0.77)	(4.26)	(-1.12)	(0.87)	(4.23)	(-1.01)
Low · Post	0.018 ***	0.029 ***	0.011 *	0.018 ***	0.029 ***	0.010
	(3.53)	(6.62)	(1.65)	(3.44)	(6.67)	(1.55)
N	42,296	15,562	26,734	42,296	15,562	26,734
R^2	0.53	0.54	0.53	0.53	0.54	0.53
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: **Robustness Checks.** Panel A of this table reports results of the following panel OLS regressions, using alternative liquidity measures of 5-minute quoted spread and 1-minute realized spread: $\beta_{X,i,m} = \alpha + \gamma_1 Post_{i,m} + \gamma_2 ln(firm\,size)_{i,m-1} + \gamma_3 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,q}$, with each of the two betas, β_{Home} and β_{EU}, as the dependent variable. β_{Home} and β_{EU} are estimated for each stock i and month m from equation (1). 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. Models (1)-(3) show the results for the 5-minute quoted spread and Models (4)-(6) for the 1-minute realized spread. Models (1) and (4) report results for the total sample, Models (2) and (5) for down markets, and Models (3) and (6) for up markets. We classify months when the country's index return is positive as up markets and as down markets when it is negative. Panel B presents the corresponding results with liquidity betas, estimated quarterly from daily quoted spread (Models 1-3) and the Amihud illiquidity measure (Models 4-6). Appendix B provides a detailed description of variable definitions. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Alternative intraday liquidity measures

	5-min qspread			1-min realized spread		
	total	down mkt	up mkt	total	down mkt	up mkt
	(1)	(2)	(3)	(4)	(5)	(6)
β_{EU}	0.014 ***	0.032 ***	-0.004	0.014 ***	0.022 ***	0.011
β_{Home}	0.064 ***	0.037 ***	0.089 ***	0.040 ***	0.004	0.076 ***
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: Daily liquidity measures

	daily qspread			illiq		
	total	down mkt	up mkt	total	down mkt	up mkt
	(1)	(2)	(3)	(4)	(5)	(6)
β_{EU}	0.182 **	0.302 ***	-0.023	0.050 ***	0.091 ***	0.033
β_{Home}	-0.116 ***	-0.088	-0.123 **	-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

Internet Appendix

Figure IA1: **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%.

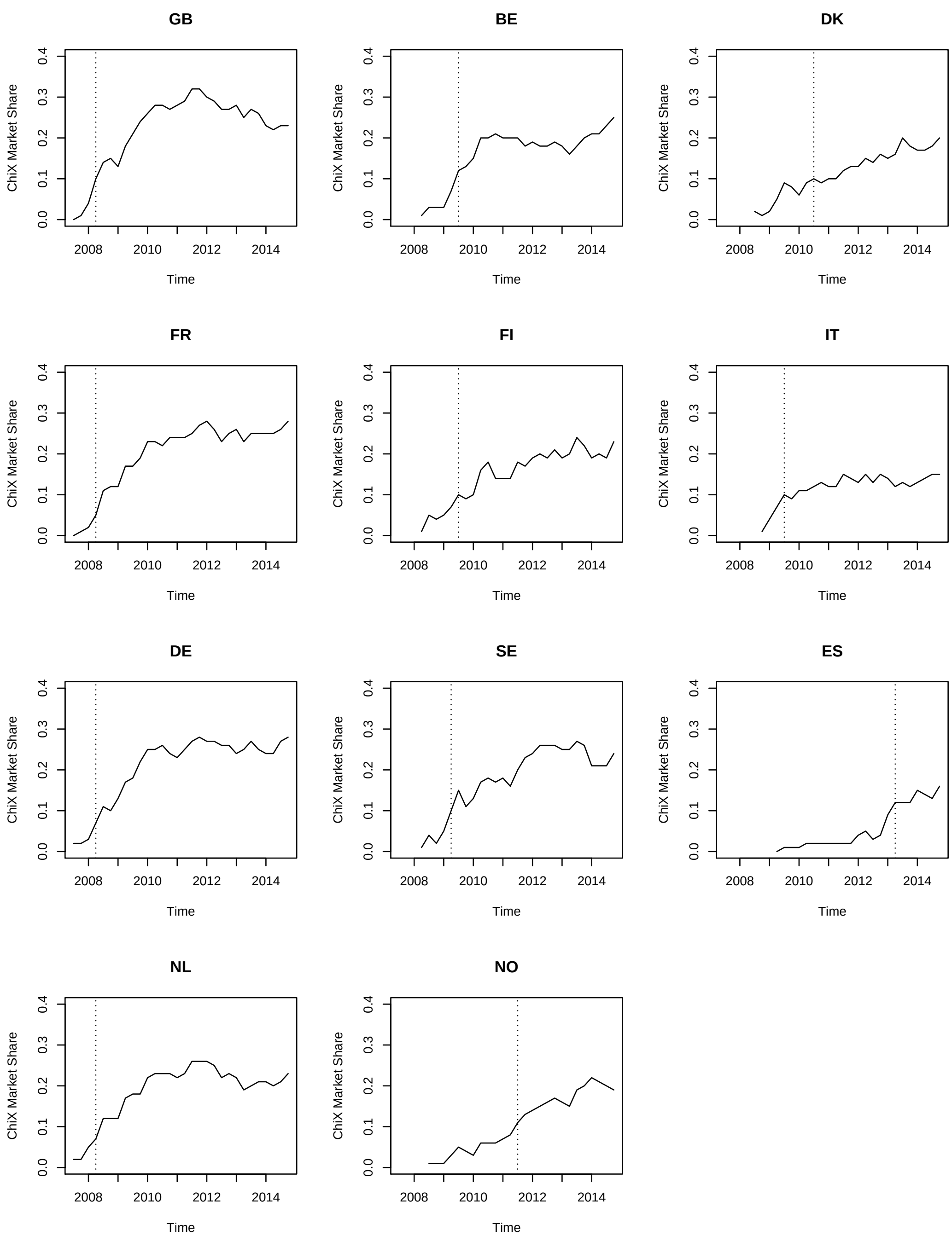

Table IA1: **Sample Construction.** This table presents details of our sample construction. Our initial sample consists of all stocks that constitute main European equity indices during our sample period, January 2004 - December 2014. We download the composition of these indices from the Thomson Reuters 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. Appendix A provides details of our data cleansing 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. Finally, we retain a stock in a given month only if it is traded for at least 1,000 different 1-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.

Panel A: Number of Distinct Firms

	GB	FR	DE	NL	BE	FI	SE	NO	DK	IT	ES
Initial Sample	144	43	37	35	9	25	34	26	20	41	32
Stock price > £2 / €2	144	43	37	35	9	25	34	26	20	41	32
Traded for 1,000 1-min intervals	144	43	37	35	9	25	34	26	20	40	32

Panel B: Number of Firm-Month Observations

	GB	FR	DE	NL	BE	FI	SE	NO	DK	IT	ES
Initial Sample	16,415	5,293	4,190	3,443	1,052	2,901	4,408	2,859	2,547	4,548	4,728
Stock price > £2 / €2	16,316	5,290	4,179	3,431	1,036	2,891	4,388	2,541	2,543	4,468	3,812
Traded for 1,000 1-min intervals	16,241	5,266	4,175	3,426	1,028	2,891	4,387	2,537	2,505	4,461	3,811

Table IA2: **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 1-minute average 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 B 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	0.0017	0.0015	0.0010	0.0005	0.0073
FR	43	0.0009	0.0008	0.0004	0.0005	0.0026
DE	37	0.0009	0.0008	0.0005	0.0004	0.0022
NL	35	0.0010	0.0009	0.0004	0.0006	0.0020
BE	9	0.0018	0.0017	0.0006	0.0011	0.0029
FI	25	0.0016	0.0015	0.0005	0.0009	0.0029
SE	34	0.0020	0.0019	0.0006	0.0012	0.0047
NO	26	0.0027	0.0024	0.0013	0.0013	0.0067
DK	20	0.0021	0.0018	0.0006	0.0013	0.0035
IT	40	0.0015	0.0014	0.0006	0.0006	0.0038
ES	32	0.0017	0.0016	0.0007	0.0006	0.0038
Total	445	0.0016	0.0014	0.0009	0.0004	0.0073

Table IA3: **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 from equation (1), without controlling for liquidity changes of the aggregate European market, $\Delta qspread_{EU,t,d}$. 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 when the country's index return is positive as up markets and as down markets when it is negative. Appendix B provides a detailed description of variable definitions. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Total	GB FR DE NL BE	FI SE NO DK	IT ES	down mkt	up mkt
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.034 ***	0.024 ***	0.036 ***	0.003	0.007	0.061 ***
	(7.68)	(5.15)	(8.49)	(0.28)	(1.34)	(11.18)
Ln(firm size)	0.056 ***	0.076 ***	0.015 ***	0.040 ***	0.059 ***	0.054 ***
	(14.80)	(15.08)	(4.17)	(10.67)	(15.03)	(14.00)
Qspread	-0.012 ***	-0.007	-0.018 ***	-0.014 *	-0.013 ***	-0.010 **
	(-3.17)	(-1.43)	(-2.84)	(-1.92)	(-3.57)	(-2.47)
N	50,728	30,136	12,320	8,272	18,603	32,125
R^2	0.61	0.59	0.48	0.43	0.60	0.62
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA4: **Robustness Checks: Effective Spread and Intraday Price Impact.** This table replicates Panel A from Table 8, using alternative liquidity measures of the 1-minute average effective spread (Models 1-3) and the 1-minute average price impact (Models 4-6). The effective spread is calculated as $espread_{i,j} = \frac{2|P_{i,j}-M_{i,j}|}{M_{i,j}}$ and the price impact as $prcimp_{i,j} = \frac{2|M_{i,j+60s}-M_{i,j}|}{M_{i,j}}$, where $P_{i,j}$ is the transaction price of stock i at time j on its primary exchange, and $M_{i,j}$ is the midpoint quote, calculated as the average of the prevailing bid and ask quotes at time j ($M_{i,j} = \frac{A_{i,j}+B_{i,j}}{2}$). $M_{i,j+60s}$ represents the 1-minute (or 60-second) forward midpoint quote. We then average all effective spreads and price impacts for each stock i within each minute t. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	1-min effective spread			1-min price impact		
	total	down mkt	up mkt	total	down mkt	up mkt
	(1)	(2)	(3)	(4)	(5)	(6)
β_{EU}	0.012 ***	0.023 ***	0.005	0.015 ***	0.024 ***	0.011
β_{Home}	0.032 ***	-0.002	0.062 ***	0.050 ***	0.005	0.094 ***
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes