Three Essays in Transaction Cost Analysis

by

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Declarations

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that Chapters 1 of this thesis is a product of joint work with Prof. Rui Albuquerque and Dr. Chen Yao, Chapters 2 of this thesis is a product of joint work with Dr. Olga Klein, and Chapters 3 of this thesis is a product of joint work with Prof. Roman Kozhan and Prof. Wing Wah Tham.

Abstract

This thesis studies the impact of transaction costs on stocks prices and examine the impact of institutional investors and high frequency traders (HFTs) on market quality and transaction costs. It is comprised of three chapters.

Chapter 2 uses a clean and novel field experiment to study how stock prices of publicly listed companies respond to changes in transaction costs. Using the SEC's pilot program that increased the tick size for approximately 1,200 randomly chosen stocks, we find a decrease in market capitalization of $7 billion for stocks affected by the larger tick size relative to a control group. We find that the increase in the present value of transaction costs accounts for a small percentage of the price decrease. We study channels of price variation due to changes in expected returns: investor horizon, liquidity risk, and information risk. The evidence suggests that trading frictions affect the cost of capital.

Chapter 3 examines the effects of multimarket high-frequency trading (HFT) activity on liquidity co-movements across different markets. Multimarket trading by HFTs connects individual markets in a single network, which should induce stronger network-wide liquidity co-movements. We use the staggered introduction of an alternative trading platform, Chi-X, in European equity markets as our instrument for an exogenous increase in multimarket HFT activity. Consistent with our predictions, we find that liquidity co-movements within the aggregate network of European markets significantly increase after the introduction of Chi-X and even exceed liquidity co-movements within the home market. They are especially strong in down markets and for stocks with a higher intensity of HFT trading in the post-Chi-X period.

Chapter 4 studies optimality of trade execution by institutional trading desks. We document the presence of negative autocorrelation in intraday stock return and show that the temporary price pressure is larger at the beginning and the end of the day. Institutional trading volume exhibits similar intraday pattern. We relate the periodity of price pressure to trading desks' performance using a proprietary database of institutional investor trades. We find that execution quality is the worst at the end of the day yet institutional trading volume is also surprisingly high. Poorer performing brokers in terms of execution shortfall trade more in the last hour of the day, have a higher execution cost at the end of the day, and carry out less order splitting at the end of the day. Our findings suggest that intraday price pressure stems from end of the day clustering of under-performing trading desks strategies results in higher trading costs and poorer execution quality. A trading strategy exploiting this intraday predictability yields a monthly return of 16.11%. Our results have implications on the impact of broker selection and execution strategy on trading costs.

Chapter 1

Introduction

An efficient and well-functioning market is fundamental for the economy growth. Transaction cost is an important ingredient of efficient markets, as large transaction costs may erode or eliminate the value added by portfolio managers and impede efficient information dissemination. Keim and Madhavan (1995) show that investors who try to follow a particular index are concerned about execution and trading cost. This is also highlighted by Schwartz and Steil (2002) in a survey of chief investment officers (CIOs) of 72 major asset management firms in North America, Europe and Australia with an asset management of $2.1 trillion, show that large institutions rank execution cost and speed as important determinants of how they choose brokers. Further, the last decade has witnessed a dramatic increase in high frequency trading on the market, which has significantly reduced the transaction cost and reshaped the market. Given this, transaction cost analysis has attracted attentions from both academic researchers and industry practitioners.

In this thesis, we are interested in answering several novel and important research questions that are not yet explored in the literature. First, we investigate the price effects of wider tick size using a novel and clean field experiment and the direct and indirect mechanisms through which this happens. Our analysis shows for the first time in the literature that transaction costs have a significant impact on a firm's cost of capital. Second, we examine the effect of multi-market HFT activity on systematic liquidity co-movements of stocks across different markets. While a number of papers have shown that high frequency traders (HFTs) generally reduce transaction costs and improve market quality, our study generates an important implications that significant risks induced by HFTs should not be overshadowed by the potential benefits. Finally, we study whether and how sub-optimal execution strategies by trading desks may lead to predictable patterns in trading volume and return predictability among common stocks.

In Chapter 2, we investigate the stock price effects of the Tick Size Pilot Program, a two-year experiment launched on October 3, 2016 by the U.S. Securities and Exchange Commission (SEC) as mandated by the U.S. Congress to increase the tick size from 1 cent to 5 cents for a number of randomly chosen stocks. This field experiment provides a unique opportunity to study the effect of exogenous shocks to liquidity on stock prices and to estimate the liquidity premium. Stock prices may change as a result of changes in transactions costs *directly* through an effect on the present value of future trading costs as in Amihud and Mendelson (1986), Constantinides (1986), Vayanos (1998), Vayanos and Vila (1999) and others, as well as *indirectly* due to changes in expected returns caused by changes in liquidity risk as in Acharya and Pedersen (2005) or by changes in information risk as in Easley and O'Hara (2004) and O'Hara (2003). In this paper, we ask how large is the liquidity premium in response to the tick size change and what are its sources of variation.

We provide empirical evidence of a causal negative impact of a larger tick size on stock prices and calculate the liquidity premium implied by the change in tick size. The sources of stock price variation appear different across the various treated stocks in the program. We show that the decline in stock prices is associated with an increase in spreads and in price impact, and with a reduction in volume for groups 1 and 2 stocks. For these stocks, we show that there is an increase in investor horizon consistent with the view that transactions costs have a direct effect over stock prices holding expected returns constant, as in Amihud and Mendelson (1986). However, for group 3 stocks, we show that there is a change in quoted spreads but no change in effective spreads or in trading volume. We also study the indirect effect on stock prices through expected returns (net of transactions costs) of the change in tick size. We show that there is no statistically significant change in liquidity risk across all test groups. However, we show that all stocks experience a decline in price efficiency suggesting that information risk and thus expected returns increased for the treated stocks. This evidence is consistent with firm's cost of capital being affected by market microstructure features.

In Chapter 3, we examine the effect of multimarket HFT activity on systematic liquidity co-movements of stocks across different markets. Following Chordia, Roll, and Subrahmanyam (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. High-frequency traders share similar algorithms (Chaboud et al. 2014, Benos et al. 2015), which can lead to excess co-movements in their demand and supply, and consequently, to commonality in liquidity across stocks even within the same market. However, HFTs often engage in trading across multiple markets, which essentially connects these markets in a single network and might facilitate cross-market liquidity spillovers. Specifically, we hypothesize that multimarket HFT activity induces stronger commonality in liquidity for stocks traded within the aggregate network of markets, even after controlling for their liquidity co-movements within their home market.

We use the staggered entrance of Chi-X, an alternative platform for trading European equities, as an instrument for an increase in multimarket high-frequency trading activity. Two main competitive advantages of Chi-X at the time of its introduction, compared to national stock exchanges, are its lower execution fees, and its 22 to 84 times faster speed of order processing. Both of these features should arguably attract high-frequency traders.

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

In Chapter 4, we postulate that sub-optimal execution by trading desks leads to predictable patterns in trading volume and return predictability among common stocks. We divide the trading day into 13 half-hour trading intervals to study the nature of intraday return predictability. Consistent with the previous literature and Heston et al. (2010), we find the presence of negative autocorrelation in intraday stock return. Intraday negative autocorrelation in returns is often associated with temporary price pressure due to risk-averse intermediaries charging price impact for temporarily holding the position in the absence of a natural counterparty. For example, Kraus and Stoll (1972) shows the existence of price pressures by studying large institutional trades. These transitory price effects, intraday return reversal and their relation to intraday pattern of how trading desks work their trades are the focus of this study.

We find that temporary price pressure is larger and more prevalent at the beginning and the end of the trading day. This suggests the predictability of large uninformed institutional trades within a trading day. While Guercio and Tkac (2002), Frazzini and Lamont (2008), and Lou (2012) find evidence of persistent fund flows into and out of mutual funds that induces return predictability across days, it is unlikely that fund flows explains the intraday pattern of institutional trades. Often portfolio managers rely on buyside trading desks in order to implement their investment ideas. A trading desk adds value to their clients by supplying expertise in locating counterparties and formulating trading strategies. For example, a trading desk formulates a set of choices to meet its best execution obligation through the trading venues, order splitting strategies, broker choice and timing of the trades. We conjecture that the execution strategy of trading desks is one of the determinants of the intraday predictability of institutional trades and return reversals.

To study the economic reasoning behind this price pressures predictability, we investigate if the periodity is indeed driven by suboptimal trading desk execution. We first show that trading volume exhibits similar intraday pattern as price pressures. In addition, we relate the periodity of price pressures to trading desks' performance using a proprietary database of institutional investor equity transactions compiled by ANcerno Ltd. (formerly the Abel/Noser Corporation).

We find that execution quality is the worst at the end of the day yet institutional trading volume is surprisingly highest at the end of the day. Dividing brokers into good and bad performing, we find that poorer performing brokers trade more in the last hour of the day. Poorer performing brokers also have a higher execution cost at the end of the day and carry out less order splitting at the end of the day. We observe persistence in the performance of buy-side institutional desks and sell side brokers. Our findings suggest that intraday price pressure stems from execution strategies of under-performing trading desks end of the day clustering results in higher trading costs and poorer execution quality. To estimate the economic significance of these suboptimal trade execution, we set up a trading strategy to exploit these intraday predictability like a predatory anticipatory traders. Our trading strategy yields an economically and statistically significant monthly return of 16.11% . Our results have implications on the impact of broker selection and execution strategy on trading costs.

Chapter 2

The Price Effects of Liquidity Shocks: A Study of SEC's Tick-Size Experiment

2.1 Introduction

This paper investigates the stock price effects of the Tick Size Pilot Program, a two-year experiment launched on October 3, 2016 by the U.S. Securities and Exchange Commission (SEC) as mandated by the U.S. Congress to increase the tick size from 1 cent to 5 cents for a number of randomly chosen stocks. This field experiment provides a unique opportunity to study the effect of exogenous shocks to liquidity on stock prices and to estimate the liquidity premium. Stock prices may change as a result of changes in transactions costs *directly* through an effect on the present value of future trading costs as in Amihud and Mendelson (1986), Constantinides (1986), Vayanos (1998), Vayanos and Vila (1999) and others, as well as *indirectly* due to changes in expected returns caused by changes in liquidity risk as in Acharya and Pedersen (2005) or by changes in information risk as in Easley and O'Hara (2004) and O'Hara (2003). In this paper, we ask how large is the liquidity premium in response to the tick size change and what are its sources of variation. To the best of our knowledge, we are the first paper to study the impact of tick size on stock price. We also study several possible channels leading to the price change, including direct effects on stock prices holding expected returns constant, and indirect effects through expected returns.

The Tick Size Pilot Program consists of three pilot (treated) groups, each with about 400 stocks, and a control group with about 1,200 stocks. Stocks in groups 1 through 3 are all subject to an increase in the minimum *quote* increment from \$0.01 to \$0.05. Group 1 stocks are allowed to trade at their current price increment of \$0.01, whereas stocks in group 2 are required to *trade* in \$0.05 minimum increments, although with some exceptions. Stocks in group 3 adhere to the requirement of the second group, but are also subject to a "trade-at" requirement whereupon non-displayed orders can only trade at the bid or offer prices after all displayed liquidity in all lit venues has been filled at those prices. The trade-at requirement increases the cost of trading outside lit venues with potential consequences for liquidity, acquisition of information, and prices. Stocks in the control group continue quoting and trading at their current tick size increment of \$0.01. The pilot program was implemented on a staggered basis over the month of October 2016 starting with groups 1 and 2 and ending with group 3.

The main hypothesis of this paper is that the larger tick size leads to lower stock prices. To test this hypothesis, we estimate daily abnormal returns from September 1, 2016 to November 30, 2016 using a variety of return models. We study stocks with smaller, pre-experiment spreads separately from stocks with larger, pre-experiment spreads. Our results apply only to the former because the increase in tick size is more likely to be an active constraint for them. We find that stocks with small dollar quoted spread in groups 1 and 2 (group 3) experience a significant 1% (4%) value reduction compared to stocks in the control group after the tick change. These price changes imply a loss to investors of about \$7 billion. The decrease in stock prices occurs in the two weeks immediately after the pilot program implementation and appears to be permanent rather than transitory as we do not observe a subsequent reversal in stock returns. We do not find any significant price effect for stocks with a large quoted spread. These findings are consistent with Amihud and Mendelson (1986). The findings are not consistent with Vayanos (1998) who predicts that the price effect should be smaller for the more liquid stocks.

The experiment conducted by the SEC is unique because of the stratified random sampling procedure applied to the construction of the groups, the large size of the program, which involves about 1,200 test stocks and an equal amount of control stocks, and the limited duration of the program, which ends after two years. These characteristics create an ideal setting to study the stock price response to exogenous shocks to liquidity. First, the SEC's randomization creates a laboratory-like experiment in an actual financial market, eliminates any selection issue, and at the same time provides a control group of stocks built as part of the random assignment of securities to the pilot program, thus removing any discretion from the econometrician in the implementation of the difference-in-differences methodology. Second, the large size of the program gives greater power to detect price effects: when the NYSE lowered the minimum tick size from 1/16 of a dollar to 1 cent it also implemented a pilot program, but this program involved only 79 common stocks (Chakravarty, Wood, Van Ness, 2004).[1] Third, the limited duration of the program means that the price is unlikely to change due to policies that firms might undertake to reverse some of the unintended consequences from the tick size program such as by engaging in reverse stock split programs (Angel, 1997, but also Weld, Michaely, Thaler, and Benartzi, 2009).

The rest of the paper studies sources of variation, direct and indirect, that can explain the observed stock price changes. In Amihud and Mendelson (1986) and others, transactions costs have a *direct effect* on stock prices, holding expected returns (net of transactions costs) constant. We therefore analyze the effect of the tick size change on stock spreads, and liquidity more generally. We find that liquidity decreases for stocks in groups 1 and 2 as proxied by a variety of measures: quoted spreads, effective spreads and price impact increase and trading volume decreases as compared to stocks in the control group after the increase in tick size. For example, the effective spread, arguably the most relevant of these measures regarding trade

[1] In addition, in this earlier experiment the control goup were all the other firms in the NYSE and these firms were known to have to move also to the lower tick size.

execution costs (Bessembinder, 2003) is higher by an average of 0.15 (0.17 and 0.09) for group 1 stocks (groups 2 and 3), representing an amount equal to roughly 28% (39% and 15%) of the mean effective spread. The change in quoted spread is about twice as large. The qualitative nature of the spread results was largely expected in the design of the program. We also find that the response of group 2 stocks is very similar to that of group 1 stocks, suggesting that the main binding constraint in group 2 stocks is the requirement to quote in 5 cent increments. There is a marked difference in response of liquidity measures to the tick size change for group 3 stocks. These stocks experience a statistically significant increase in quoted spread, but not on the effective spread and only significant at 5% on price impact, and they do not experience a statistically significant decrease in trading volume. The evidence for group 3 stocks is consistent with the trade-at rule having countervailing liquidity effects to the change in tick size. Finally, market depth increases for all groups, particularly for group 3 stocks though we argue that this is largely a mechanical effect.

Amihud and Mendelson (1986) argue that stocks with higher transactions costs attract a clientele of investors with longer investor horizons, thus slowing the impact of trading costs on stock prices. We test this additional prediction using 13F data on turnover of institutional investors' portfolios to construct a proxy for investment horizon (see Gaspar, Massa and Matos, 2005, and Cella, Ellul and Giannetti, 2013). We find some evidence in support of Amihud and Mendelson's model: the investment horizon of institutional investors increases by 3% (5%) for the small quoted spread stocks in groups 1 and 2 (group 3) relative to the control group after the tick size increased.

Using a back of the envelope calculation à la Amihud and Mendelson (1988) and Foucault et al. (2013), the present value of the increase in transactions costs is responsible for about 22% of the observed change in prices for groups 1 and 2 stocks, and 3.25% for group 3 stocks, holding the expected return (net of transactions cost) constant. While these are arguably very rough estimates of the direct effect of transactions costs on prices, their small size suggests that a significant portion of the observed change in prices should come from an *indirect effect* of transactions costs on expected returns (net of transactions costs), either through priced liquidity risk (Acharya and Pedersen, 2005) or through priced information risk (Easley and O'Hara, 2004, and O'Hara, 2003).

Following Acharya and Pedersen (2005) we construct several firm betas that capture liquidity risk including a beta describing how firm liquidity co-moves with aggregate liquidity. We find a statistically insignificant decrease in liquidity risk for all test stocks. The sign of the point estimate suggests that the price level change attributable to changes in spreads is larger than the estimated price drop.

In Easley and O'Hara (2004) and O'Hara (2003), the presence of more uninformed investors or lower precision of private information decrease information quality and increase information risk and expected returns. We then ask if the increase in tick size caused changes in proxies related to price efficiency and speed of market response to news as a way to capture changes in the quality of information. We find that the treated stocks experience higher return autocorrelation and higher pricing error relative to the control stocks, suggesting a relative decrease in price efficiency. In addition, we trace the market response to news using RavenPack, a high-frequency news database, and find slower market response speeds to company-related news in all treated groups. We repeat the exercise using only macro news, as the content and frequency of company news itself may have changed after the program started, obtaining similar results. Our evidence is consistent with Hou and Moskowitz (2005) that show that firms with higher price delay in response to news have higher expected returns, and with Easley, Hvidkjaer, and O'Hara (2002) and Albuquerque, de Francisco and Marques (2008) who show that proxies for private information correlate with stock returns.

We conclude by calculating a point estimate for the liquidity premium. The liquidity premium is equal to the ratio between the change in the expected return and the change in spreads. For a stock with expected rate of return of 5%, the liquidity premium measured with respect to the *effective spread* change is equal to 0.31 (2.2) for groups 1 and 2 (group 3) stocks. As argued by Huang (2003), many asset pricing models with transactions costs (Constantinides, 1986, Aiyagari and Gertler, 1991, Heaton and Lucas, 1996, Vayanos, 1998, and ayanos and Vila, 1999) predict liquidity premia substantially lower than 0.2 under reasonable calibrations (see also Buss, Uppal, and Vilkov, 2011). There are however models that generate large liquidity premia. For example, in Garleanu and Pedersen (2004) bid-ask spreads do not impact prices when agents are symmetric, but can have large effects otherwise, in Huang (2003) borrowing constraints can lead to large liquidity premia, and in Lo, Mamaysky, and Wang (2004) transactions costs hinder risk sharing and lead to lower prices. In a partial equilibrium setting, Balduzzi and Lynch (1999) show that transactions costs can have large utility costs for investors that behave myopically.

The rest of the paper is organized as follows. Section 2.2 describes the institutional details of the Tick Size Pilot Program. Section 2.3 describes the data, gives the variable definitions, and presents some descriptive statistics. Section 4 presents the main result on price effects. Section 5 investigates sources of changes in prices, including direct costs of trading, and indirect costs through changes in expected returns. Section 6 discusses related literature, and Section 7 concludes.

2.2 Institutional Background

The Jumpstart Our Business Startups Act ("JOBS Act") signed in April of 2012 directs the SEC to conduct a study on how decimalization affects the number of IPOs and market quality of small cap stocks.[2] In July of 2012, the SEC reports back to Congress without reaching a firm conclusion on the question. Following this study, Congress mandates the SEC to implement a pilot program which would generate data to investigate the impact of increasing the tick size. In June of 2014, the SEC directs the Financial Industry Regulatory Authority and the National Securities Exchange to develop a tick size pilot program to widen the minimum tick size increment for a selection of small cap stocks. On May 6, 2015, the SEC approves the proposed plan.

The Tick Size Pilot Program consists of a control group and three pilot (test or treat-

[2]In the U.S., tick size (i.e., the minimum quoting and trading increment) is regulated under the Securities and Exchange Commission (SEC) rule 612 of Regulation National Market System (Reg NMS). This rule prohibits market participants from displaying, ranking, or accepting quotations, orders, or indications of interest in any NMS stock priced in an increment smaller than \$0.01, unless the stock is priced less than \$1.00 per share.

ment) groups. The control group contains approximately 1,200 stocks that continue quoting and trading at the current tick size increment. Each of the test groups contains approximately 400 stocks. Stocks in test group 1 are required to quote in $0.05 minimum increments, but are allowed to trade at their current price increment. For example, Retail Price Improving orders are qualified stock orders that offer price improvement over the current best bid and offer. These orders can still be entered and executed in $0.01 increments. Negotiated Trades, common in OTC, may also trade in increments less than $0.05. Stocks in test group 2 are required to both quote and trade in $0.05 minimum increments, but allow certain exemptions for midpoint executions, retail investors executions and negotiated trades. Stocks in test group 3 adhere to the requirement of the second test group, but are also subject to a "trade-at" requirement. The trade-at rule grants execution priority to lit orders, unless a dark order can provide a meaningful price improvement over the lit order and as such group 3 stocks are imposed an additional cost on trading outside lit venues with potential consequences for liquidity, acquisition of information, and prices. Certain exemptions to the rule apply. For example, trading centers are permitted to execute an order for a pilot security at a price equal to a protected bid or protected offer using both displayed and non-displayed liquidity if the order is of Block Size, that is of at least 5,000 shares and market capitalization of $\$100,000$.

The pilot program was implemented on a staggered basis. On September 6, 2016, the final list of 2,398 stocks to be included in the tick size pilot program is announced. Disclosure of which group a stock would belong to happens in October coinciding with the stock's activation date. On October 3, 2016, 5 stocks were activated in each of the test groups 1 and 2. On October 10, 2016, 100 stocks were activated in each of the test groups 1 and 2. On October 17, 2016, all remaining stocks in test groups 1 and 2 were activated. On October 17, 2016, 5 stocks were activated in test group 3. On October 24, 2016, 100 stocks were activated in test group 3, with the rest of the stocks in group 3 activated on October 31, 2016.

An important feature of the SEC's pilot program is the use of a stratified random sampling procedure in determining the stocks to be allocated to each group. The stratification is over three variables: share price, market capitalization, and trading volume and yields 27 possible categories (e.g., low price, medium market capitalization and high volume). The pilot securities were randomly selected from the 27 categories to form three test groups with the remaining securities forming the control group.

Supporters of the Tick Size Pilot Program argue that increasing tick size motivates market makers to provide more liquidity to small cap stocks and thus making these stocks more attractive to investors (Grant Thornton, 2014). In fact, the pilot program was lobbied by some investment banks and former stock exchange officials (Wall Street Journal, 2016). Opponents argue that increasing tick size increases investors' execution costs, and the complexity of this pilot reduces the efficiency of order execution. Additionally, they argue that a wider tick size leads to wealth transfer from liquidity takers to liquidity suppliers (e.g., Wall Street Journal, 2016). Surprisingly, neither supporters nor opponents of the tick size program commented on the potential price and cost of capital effects of the program, which could hurt the very firms that the program wished to help (one exception is Bessembinder et al., 2015). Below, we present evidence on stock price changes following the implementation of the program, and on liquidity changes as well as changes on liquidity risk and information risk.

2.3 Data Description

Our sample consists of all stocks in the Tick Size Pilot Program in the period from January 2016 to May 2017. We drop from the sample stocks that are delisted or experience a merger and acquisition during the sample period, stocks that are removed from the test group and added to the control group by the SEC due to a price decline below $1, stocks that are not common-ordinary stocks (i.e., keeping stocks with CRSP share codes of 10 or 11), and stocks without daily TAQ data.[3] The first two filters trigger the SEC to move stocks out of their treatment groups. These filters are consistent with those used in Rindi and Werner (2017) and Lin et al. (2017). We also drop firm-day observations when the average daily price for that firm and day is below $2. Otherwise, we follow Holden and Jacobsen (2014) in cleaning the daily TAQ data set.

We obtain the intraday quote and price data from the daily Trade and Quote (DTAQ), stock market data from the Center for Research in Security Prices (CRSP), Fama-French and momentum factors data from the Kenneth R. French data library, institutional investor holdings from Factset, and high frequency news data from RavenPack News Analytics (RavenPack) database. RavenPack covers all articles published on the Dow Jones Newswires providing a millisecond time stamp of release of the article. According to Beschwitz, Keim and Massa (2015), the latency between Dow Jones Newswires releasing an article and releasing it to RavenPack is approximately 300 milliseconds. We collect news that is most related to our companies (i.e., RavenPack's maximum "relevance score" of 100) and that are reported for the first time (i.e., RavenPack's maximum "freshness score" of 100). The mean number of news per company is 32.5 and the median is 19. In addition, we collect from RavenPack U.S. macroeconomic news published on DowJones Newswire. We keep news that are first reported and with a relevance score of at least 90. There are 1,693 macro news in our sample. Table 2.1 reports the mean of key variables for all three pilot groups for the whole sample.

[Table 2.1 about here.]

For each test group, we report results for two subsamples, stocks with small dollar quoted spread (below median spread), and stocks with large dollar quoted spread (above median spread). We also split the stocks in the control group between small versus large dollar quoted spread. The reason for doing so is that the increased tick size requirement may not be binding for all stocks, especially those that are less liquid and already have large bid-ask spreads. To split each group into two samples, we use pre-experiment data, measuring the median spread

[3] Dropping firms that are delisted or that experience a merger and acquisition during our sample period yields 1,139 stocks in the control group, a drop from 398 to 383 stocks (396 to 384, and 395 to 382) in group 1 (2, and 3, respectively). Dropping firms that are removed from the test group and added to the control group by the SEC due to a price decline below $1, group 1 (2 and 3, respectively) stocks decrease to 377 stocks (375 and 374, respectively). Keeping only common equity stocks leaves 979, 330, 323, and 315 stocks in our sample in the control, group 1, group 2 and 3, respectively. Finally, after dropping stocks without daily TAQ data, we obtain our final sample of 954, 323, 316, and 310 stocks in the control, group 1, group 2 and 3, respectively.

with daily data from January 1, 2016 to September 30, 2016.[4] We first split all stocks, treated plus control, into small and large dollar quoted spread. This procedure ensures similar pre-experiment average dollar quoted spread in each of the subsamples across all three groups, but may create unbalanced panels if the experiment is not well randomized. As it turns out, the size of each sample is quite homogeneous across groups.[5] Panel A of Table 2.2 shows that there are 159 (164) small (large) spread stocks in group 1; 156 (160) small (large) spread stocks in group 2; 152 (158) small (large) spread stocks in group 3; and, there are 484 (470) small (large) spread stocks in the control group. Table 2.2 also shows that the average pre-experiment dollar quoted spread for the small (large) quoted spread stocks in group 1 is \$0.0374 (\$0.2506); the average dollar quoted spread for the small (large) quoted spread stocks in group 2 is \$0.0392 (\$0.2413); the average dollar quoted spread for the small (large) quoted spread stocks in group 3 is \$0.0380 (\$0.2624); and, the average dollar quoted spread for the small (large) quoted spread stocks in the control group is \$0.0392 (\$0.2734). We discuss in the paper but do not tabulate results for each group as a whole. We note in advance that almost all of our results apply only to the more liquid stocks in each group, those with small quoted spreads. Thus, the results that use each group as a whole are generally economically and statistically weaker.

Panel A of Table 2.2 reports the mean of several key variables for all three pilot groups in the pre-implementation period.[6] The mean market capitalization in each of the groups for small spread stocks is close to \$800 million, indicating that the stocks in our sample are small cap stocks (the maximum market capitalization to participate in the pilot program is \$5 billion), but that these stocks are larger than those in the sample of large pre-experiment quoted spreads. In Panel B, we report the differences of key variables between each pilot group and the control group, and test whether such differences are statistically different from zero. We find that stocks in each of the pilot groups and in the control group exhibit similar total assets, market capitalization, book-to-market ratio, and liquidity (measured by *QuotedSprd* and *Volatility*). These results validate the randomization of the pilot program and ensure that stocks in the pilot groups and in the control group are similar over many dimensions.

[Table 2.2 about here.]

2.4 Impact of Tick Size on Stock Prices

This section presents results of the impact of a larger tick size on stock prices using a difference-in-differences technique. In this section, we group test stocks in groups 1 and 2 together. We do this for three reasons. First, we will show below that the various effects we study are quite

[4]By using pre-experiment data to construct the subsamples we also do not induce any selection bias since firms and investors did not know who would be in the program.

[5]Griffith and Roseman (2017) and Rindi and Werner (2017) separate the treated stocks into two groups based on whether the quoted spread is larger than or equal to \$0.05. Lin et al. (2017) also use the \$0.05 cut-off to identify the most constrained stocks (they use three subsamples). Our cutoff is equivalent to splitting firms at \$0.07 spread.

[6]We winsorize the quoted spread, effective spread, price impact and volatility at 1 and 99 percent. For these variables, the difference between the 99th percentile and the mean in the unwinsorized sample is more than 5 times the standard deviation of the respective winsorized series.

similar for both groups. Second, the stocks in the two groups are activated concurrently. Third, to increase the power of the test by increasing the size of both the treated and control groups.

Following Amihud, Mendelson, and Lauterbach (1997), and a large event study literature, we use abnormal stock returns to measure the impact of widening the tick size on the stock price. We calculate abnormal returns using three models: the CAPM, the Carhart (1997) four factor model that extends the Fama-French three factors to include the momentum factor, and the Fama-French 5-factor model. As an example, the Carhart model is

$$R_{it} - R_{ft} = \alpha_i + \beta_i \left(R_{mt} - R_{ft}\right) + \beta_{is} SMB_t + \beta_{ih} HML_t + \beta_{io} MOM_t + \varepsilon_{it}, \tag{2.1}$$

where $R_{i,t}$ is the return on stock i on day t, R_{f_t} and R_{m_t} represent the risk free rate and market return on day t, SMB_t is the difference between the return on portfolio of small stocks and the return on a portfolio of large stocks, HML_t is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks, and MOM_t is the momentum factor. We estimate the model parameters using pre-sample data (i.e., using 2015 data). We then calculate the abnormal return from September 1, 2016 to November 30, 2016 as

$$AR_{it} = R_{it} - R_{ft} - \left(\hat{\beta}_i \left(R_{mt} - R_{ft}\right) + \hat{\beta}_{is} SMB_t + \hat{\beta}_{ih} HML_t + \hat{\beta}_{io} MOM_t\right), \tag{2.2}$$

where $AR_{i,t}$ is the abnormal return for stock i on day t, and $\hat{\beta}_i$, $\hat{\beta}_{is}$, $\hat{\beta}_{ih}$ and $\hat{\beta}_{io}$ are the coefficients that we estimate for each firm using the pre-sample data.

Our main result is depicted in Figure 2.1. The figure plots the equally-weighted cumulative abnormal return for the combined groups 1 and 2 versus control (top panel) and group 3 versus control (bottom panel) from one month before full implementation of the program for each group to one month following full implementation (full implementation for groups 1 and 2 is October 17 and for group 3 is November 1). The cumulative abnormal return for each group is set to zero at the full implementation date in each case. The average abnormal return on each test group experienced a decline in price relative to the control group following the full implementation of the tick size program that occurred on Monday, October 17, 2016 for groups 1 and 2 and on Monday, October 31 for group 3. This decline appears permanent. Note that even though the list of firms was announced in early September, they were not assigned to the test groups until they were activated and we do not expect any differential anticipatory effect on treated versus control stocks.

[Figure 2.1 about here.]

To obtain point estimates and standard errors of the impact of the larger tick size on stock returns controlling for firm characteristics, we estimate the following OLS regression that accounts for the staggered implementation of the program,

$$\begin{aligned} AR_{i,t} =& \alpha + \gamma_1 Week1_t + \gamma_2 Week2_t + \gamma_3 Post_t + \gamma_4 Pilot_i \times Week1_t \\ &+ \gamma_5 Pilot_i \times Week2_t + \gamma_6 Pilot_i \times Post_t + \delta' X_{it} + \epsilon_{i,t}, \end{aligned} \tag{2.3}$$

where we denote by $Pilot_i$ a dummy variable that equals 1 if a stock belongs to the test group $i = 1\&2, 3$ and 0 otherwise, and where for groups 1 and 2 $Week1_t$ is a dummy variable equal to 1 for days between October 17 and October 21, and 0 otherwise, and $Week2_t$ is a dummy variable equal to 1 for dates between October 24 to October 28, and 0 otherwise, and for group 3, $Week1_t$ is a dummy variable equal to 1 for days between October 31 and November 4, and 0 otherwise, and $Week2_t$ is a dummy variable equal to 1 for dates between November 7 and November 11, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2$, and 0 otherwise, and thus depends on the treated group being considered. For example, for groups 1 and 2, $Post_t$ equals 1 after October 31. We also include all interaction terms of each date dummy and $Pilot$. We include in X_{it} a set of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and the lowest daily trading price, as well as month fixed effects and stock fixed effects that control for invariant differences in stocks such as the exchange where they trade. We use robust standard errors clustered at the firm level. We winsorize the bottom 0.5% and top 99.5% abnormal return observations (the winsorized value is larger than the winsorized mean by 3.4 times the standard deviation of the winsorized return distribution).

[Table 2.3 about here.]

Table 2.3 reports the regression results. Panel A (B) contains the results for pilot groups 1 and 2 (3). In each panel, Columns (1) and (2) present the results for the CAPM model, Columns (3) and (4) present the results for the Carhart model, and Columns (5) and (6) present the results for the Fama-French 5 factor model. We are interested in the coefficient associated with $Pilot_i \times Week1_t$ to detect the effect of the tick size program and perhaps also with the coefficient associated with $Pilot_i \times Week2_t$ if there is some learning by the market. We do not expect that the learning will continue past $Week2_t$. The results are largely invariant to the risk adjustment used. For groups 1 & 2, the coefficient associated with $Pilot_i \times Week1_t$ is -0.002 significant at the 5% level or better, which translates into a drop in risk-adjusted prices of $0.002 \times 5 = 1\%$, compared to the control group (note that the dummy $Week1_t$ is activated over 5 days). The effect on groups 1 and 2 appears permanent as the coefficients on $Pilot_i \times Week2_t$ and $Pilot_i \times Post_t$ are not significant.

As for test group 3, the sum of the coefficients associated with $Pilot_i \times Week1_t$ and $Pilot_i \times Week2_t$ is -0.008 in the Carhart model and -0.007 in the Fama French 5 factor model, with p-values below 1% (untabulated). These returns translates into a drop in risk-adjusted prices of about $0.008 \times 5 = 4\%$ if using the Carhart model, compared to the control group. The effect on group 3 also appears permanent as the coefficient on $Pilot_i \times Post_t$ is not significant. There is no price effect for stocks with large dollar quoted spread, i.e., the more illiquid stocks, in any of the test groups. The result of no effect for the more illiquid stocks is consistent with Amihud and Mendelson (1986), but not with Vayanos (1998) who predicts that the price effect should be smaller for the more liquid stocks. Bessembinder et al. (2015) predict that IPO stock prices will be lower with the increased tick size in the pilot program, consistent with our findings. In untabulated results we find no price drop when estimating the model above using the whole sample of stocks (small and large spread stocks) in each test group.

This drop in prices is a liquidity premium that we are able to identify given the construction of the program. Using the Carhart model, this premium represents a \$7 billion loss to investors (using the average market capitalization values from Table 2.2, panel A, the loss to groups 1 and 2 stocks is $0.01 \times (788 \times 159 + 792 \times 156)$ and the loss to group 3 stocks is $0.04 \times 746 \times 152$).

2.5 Sources of Price Variation

This section studies three potential sources of price variation that can explain the results above. A direct channel through which transactions costs increase prices, and indirect channels through changes in expected returns, liquidity risk changes, and information risk changes.

2.5.1 Changes in Transactions Costs

We consider several measures of transactions costs, and more generally of liquidity. We shall consider groups 1, 2 and 3 separately. From now on we drop observations in October 2016 to avoid potential contaminating factors associated with the staggered implementation of the pilot study through the implementation month and use the full sample from January 2016 to May 2017. We denote by $Post_t$ a dummy variable that equals 1 for dates on or after November 1, 2016, and 0 otherwise.[7] $Pilot_i$ is a dummy variable that equals 1 if a stock belongs to the test group $i = 1, 2, 3$ and 0 otherwise. We estimate the model

$$Liquidity_{it} = \alpha + \gamma_1 Post_t + \gamma_2 Pilot_i + \gamma_3 Post_t \times Pilot_i + \delta' X_{it} + \varepsilon_{it}, \tag{2.4}$$

separately for each test group using ordinary least squares. $Liquidity_{it}$ is a measure of liquidity for stock i on day t, and X_{it} is the same vector of control variables as before including among other variables month fixed effects and stock fixed effects. We report robust standard errors, clustered by firm. We are interested on the sign and size of the coefficient associated with $Post_t \times Pilot_i$ that captures the impact of widening the tick size on liquidity after the implementation of the Tick Size Pilot Program.

[Table 2.4 about here.]

Table 2.4 presents the results with group 1 (2 and 3) stocks in Panel A (B and C, respectively). Consider first the effect of the tick size change on spreads and price impact. *QuotedSprd* increases by about 0.31 for group 1 small dollar quoted spread stocks, and by 0.27 for groups 2 and 3 stocks, compared to the respective control groups. The changes are statistically significant at 1% level and represent 73% (62% and 66%) of the mean quoted spread for group 1 (groups 2 and 3, respectively). Statistically significant changes in the *EffectiveSprd* occur only for groups 1 and 2, but with smaller magnitude relative to the *QuotedSprd* change, and in the *PriceImpact* for all groups, with groups 1 and 2 with a magnitude that is about one

[7] This is a conservative approach for groups 1 and 2 as some of the change in market quality variables may have already occurred. Griffith and Roseman (2017) and Rindi and Werner (2017) also exclude the month of October.

fourth that of the *QuotedSprd* change. There are no statistically significant effects on spreads for stocks with large dollar quoted spread. In untabulated results we find that the realized spread, a proxy for liquidity suppliers' market-making profit, changes by about the same magnitude as the price impact. Also, we find that the results when using the full sample within each group are qualitatively the same, but economically and statistically weaker.

The results so far suggest that the tick size program induced a wealth transfer from liquidity takers to liquidity providers, especially for group 1 and 2 stocks.[8] These results are generally consistent with those expected by the proponents of the Pilot Program. The results are also consistent with Harris (1996) and others that argue that an increase in tick size is followed by reduced competition among market makers with a consequent increase in transactions costs for small market order traders that usually get executed at the NBBO (Harris, 1997). It is also possible that the tick size program causes some liquidity takers to switch to become liquidity providers, in which case the increase in effective spread is an upper bound to the increase in transactions costs of liquidity takers. The results are inconsistent with models where a larger tick size improves liquidity by reducing negotiation costs (Harris, 1991), or where a larger tick size encourages liquidity provision for illiquid stocks if investors switch from market to limit orders (Werner et al., 2015).

Recall that stocks in pilot group 3 are required both to quote and to trade with a $0.05 price increment, just like stocks in group 2. In addition, stocks in test group 3 are subject to the trade-at rule, which requires execution priority to be given to lit orders, unless dark orders can provide a meaningful price improvement over the lit orders. This additional requirement is costly for traders in dark exchanges. Theory (Zhu, 2014) and empirical evidence (Comerton-Forde and Putnis, 2015) suggest that orders executed in the dark are predominantly uninformed. Hence, increasing dark trading costs may force uninformed investors to the lit markets and decrease market markers' adverse selection costs. As a result, market makers reduce bid-ask spreads.

We now turn to market depth, which can be a more relevant measure for liquidity for large traders when they build or liquidate their position and try to minimize their price impact. We find that market depth increases for all test groups, particularly for group 3 stocks. For smaller dollar quoted spread stocks the increase is of $\$25,145$ ($\$28,882$ and $\$36,657$) for group 1 stocks (2 and 3, respectively), compared to the control group, which represents an increase of 242% (281% and 365%) of the mean dollar-depth for test group 1 (2 and 3, respectively). These results are consistent with the notion that a wider tick size makes it more expensive for liquidity providers to obtain price priority by submitting more aggressive limit orders. A wider tick size impedes price competition and forces the liquidity providers to queue at the same quoted price, which results in an increase in dollar-depth (see Harris, 1994, 1997, and Bessembinder, 2003, O'Hara, Saar, and Zhong 2015, and Yao and Ye 2017). A stronger effect for group 3 stocks is consistent with an almost mechanical effect that increased costs in dark pools attract more trades to lit pools and increase market depth. There is an effect also for the more illiquid stocks, with larger dollar quoted spreads, but the effect is economically much smaller contrary to predicted by Werner et al. (2015).

[Figure 2.2 about here.]

[8]We use the effective spread as a measure of liquidity providers' profit.

Trading volume declines by a statistically significant $4,865,800$ shares in group 1 and $5,521,000$ shares in group 2, representing 14% and 15% of the respective group means. There is no statistically significant change in volume for group 3 stocks and for the large dollar quoted spread stocks. This evidence is consistent with Harris (1997) and Goettler, Parlour and Rajan (2005) who argue that volume decreases in response to the increase in trading costs that investors face with the larger tick size. Finally, we find almost no change in volatility across all test groups. The results for depth, volume and volatility are qualitatively similar to those when we estimate the models for the each of the test groups as a whole.

Figure 2.2 summarizes these results by plotting the time series of average effective spreads, volume and market depth for each of the test groups and the control group, skipping the month of October 2016. The changes in spreads are easy to detect as are the changes in depth. There does not appear to be a spillover effect of the tick size change to the control group in terms of spreads, volume or depth. Volatility of market depth appears to have increased significantly for the treated stocks; there is also an increased volatility of market depth towards the end of the sample period for the control stocks, but it appears significantly smaller.

Liquidity Premium

We now provide a point estimate to the liquidity premium, i.e., the ratio between the change in the expected return and the change in spreads. Assume that the percent change in prices equals the negative of the change in the expected rate of return divided by the expected rate of return (as would be the case if the stock is a perpetuity with no growth). If the expected rate of return is 5%, then the groups 1 and 2 (3) stocks experience an increase in expected returns equal to $0.05\% = 0.01 \times 0.05$ ($0.20\% = 0.04 \times 0.05$). The liquidity premium measured with respect to the percent *quoted spread* change is thus equal to $0.16 = 0.05/0.31$ ($0.19 = 0.05/0.27$, and $0.74 = 0.20/0.27$) for group 1 (2 and 3, respectively) stocks. The liquidity premium measured with respect to the percent *effective spread* change is about $0.31 = 0.05/0.16$ ($2.2 = 0.20/0.09$) for group 1 and 2 (3) stocks.

The significantly larger liquidity premium for group 3 stocks suggests a multiplicative effect from the "trade-at" requirement given that the effect of the tick size change on quoted spreads was close in magnitude for group 1 and 2 stocks versus group 3 stocks. However, recall that for group 3 stocks there was no statistically significant difference in effective spreads before and after the Tick Size Program started and only a modest increase in price impact–hence the liquidity premium relative to the effective spread may not be well defined. This points to the possibility that the driver of the price decline for group 3 stocks has less to do with a liquidity premium and more to do with the costs associated with the "trade-at" requirement and its consequences in terms of the distribution of informed versus uninformed investors across lit versus dark venues. As discussed in the introduction, a liquidity premium of $0.16 - 0.31$ for groups 1 and 2 is large relative to calibrated values in many asset pricing models with transactions costs. In these models investors reduce their trading of illiquid assets with high transactions costs and require a low liquidity premium (see the papers cited above including Amihud and Mendelson, 1986, and Constantinides, 1986). Hence, the liquidity premium represents a second order effect on prices even if transactions costs have a first order impact over spreads and trading volume.

To convert the drop in prices into elasticities, note that the Tick Size Program entailed a 400% change in tick size. Therefore, the stock price elasticity to tick size equals -0.25% for the stocks in groups 1 and 2, and about -1% for the stocks in group 3, though recall group 3 stocks were additionally subject to a "trade-at" requirement. The stock price elasticity to the *QuotedSpread* is $-0.01/0.31 = -3.3\%$ for the stocks in group 1, it is $-0.01/0.27 = -3.7\%$ for the stocks in group 2, and $-0.04/0.27 = -15\%$ for the stocks in group 3.

Changes in Investor Horizon

Amihud and Mendelson (1986) predict that in the face of higher transactions costs a clientele effect arises where only the investors with longer investment horizons choose to trade. Here, we test this additional prediction.

[Table 2.5 about here.]

Table 2.5 presents the results for *ChurnRatio*, our proxy for (the inverse of) investor horizon. Without loss, we estimate the specification in the regression model (2.4) for groups 1 & 2, and group 3, with respective control groups, using the same control variables but with *ChurnRatio* as dependent variable. The models are estimated using ordinary least squares and we report robust standard errors clustered by firm. Because we are using quarterly data, we do not drop October 2016 data. We winsorize the dependent variable at 1% and 99%.

We find that small spread stocks experience a decrease in investor churn, or an increase in investor horizon, after the implementation of the tick size program compared to the control group. We find no effect for large spread stocks. To interpret the size of the coefficient estimates, note that the average small spread stock's churn ratio is 0.105, implying an average holding period of 4.76 years $(1/(0.105 \times 2))$. The churn ratio for stocks in groups 1 & 2 is reduced by 0.003 (see column (1)) to 0.102. So, the holding period becomes 4.9 years. This is equivalent to a 3% increase. The churn ratio for small spread stocks from group 3 decreases by 0.005 (see column (2)). So the average churn ratio becomes 0.104 and the holding period increases to 4.81 years $(1/(0.104 \times 2))$. This change is equivalent to a 5% increase in holding period. Recalling that effective spreads do not appear to have changed significantly for group 3 stocks, this change in investor horizon is likely to have been induced by specific restrictions imposed on group 3 stocks.

Note that many asset pricing models with transactions costs predict that holding periods increase with higher transactions costs, for a given investor (e.g., Constantinides, 1986, and Vayanos, 1998). Our measure captures a different dimension that is more in spirit with Amihud and Mendelson's model. Our turnover ratio holds constant the investor's horizon and asks instead how much more of the holdings of each stock are now in the hands of short- versus long-term institutional investors.

A Back of the Envelope Calculation

We use a back of the envelope present value calculation as in Amihud and Mendelson (1988) and Foucault et al. (2013) to translate the change in spreads into a direct price effect. First note that the pilot program is active only for two years, so we look for a price effect from higher spreads over a two year period. Second, we use the investor horizon of institutional investors as a benchmark. The institutional investors holding the treated stocks have an average holding period of about 5 years (in group 1 the average holding period is 4.7 years, and in groups 2 and 3 it is 4.6 years). Thus, assuming that investors churn their portfolio continuously over time, after 2 years they will have churned 2/5 or 40% of their portfolio and they will have paid 40% of the transactions costs involved in turning over their portfolio. Taking transactions costs as measured by quoted spreads, a change in quoted spreads of 0.31 cents for a \$1 stock, has a present value (ignoring discounting) of about $0.31 + 0.4 \times 0.31 = 0.43$ cents for group 1 stocks. For a \$1 stock, the observed change in returns for group 1 stocks of 1% equals 1 cent, meaning that the change in transactions costs represents 43% of the change in returns. Taking transactions costs as being measured by effective spreads, a change in effective spreads of 0.16 (0.09) for groups 1 and 2 (group 3) has a present value (ignoring discounting) of about 0.22 cents (0.13 cents) of \$1. For groups 1&2 (group 3), whose stock price changes by 1% (4%) or 1 (4) cent of a \$1 stock, these present value changes represent 22% (3.25%) of the change in returns. These rough calculations suggests that there may be a substantial portion of the observed change in prices across all groups that is due to the indirect effect that transactions costs have on prices via expected returns (net of transactions costs).

2.5.2 Changes in Liquidity Risk

In this subsection we ask whether the change in tick size may have induced a change in liquidity risk that induced the observed price decline. Acharya and Pedersen (2005) build on work by Chordia et al. (2000) and Huberman and Halka (2001) and others to construct a liquidity-adjusted capital asset pricing model where the required return on a stock depends on the covariances of its own return and liquidity with the market return and liquidity.

Following Acharya and Pedersen (2005), we calculate the liquidity beta for stock i at day t as a combination of four different betas. We use thirty-minute stock and market returns, r_{is} and r_{Ms}, and liquidity, c_{is} and c_{Ms}, to get

$$\beta_{i1t} = \frac{cov\left(r_{is}, r_{Ms} - E_{s-1}\left(r_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)},$$
$$\beta_{i2t} = \frac{cov\left(c_{is} - E_{s-1}\left(c_{is}\right), c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)},$$
$$\beta_{i3t} = \frac{cov\left(r_{is}, c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)},$$
$$\beta_{i4t} = \frac{cov\left(c_{is} - E_{s-1}\left(c_{is}\right), r_{Ms} - E_{s-1}\left(r_{Ms}\right)\right)}{var\left(r_{Ms} - E_{s-1}\left(r_{Ms}\right) - \left(c_{Ms} - E_{s-1}\left(c_{Ms}\right)\right)\right)}.$$

We use the proportional quoted spread as a measure of liquidity for stock i at the thirty-minute interval s, c_{is}. We use the equally-weighted average of c_{is} for all stocks in the market as a measure of market liquidity, c_{Ms}. Similarly, we compute the market return as the equally-weighted average of all r_{is} in the market.[9] We use thirty-minute intervals because these stocks

[9] This market return series has correlation of 0.8 with the daily stock return of the S&P 500.

may not trade often during the day (see Rindi and Werner, 2017). We model the conditional expectations of all variables using the mean of five lagged values observed during the same thirty-minute interval in previous days. Acharya and Pedersen's net beta is defined as

$$\beta_{it} = \beta_{i1t} + \beta_{i2t} - \beta_{i3t} - \beta_{i4t}.$$

β_1 is similar to the CAPM beta, β_2 prices co-movement in liquidity, and β_3 captures the possibility that the stock can be a hedge against aggregate liquidity shocks, and β_4 captures the possibility that the stock is liquid when the market is doing poorly.

Table 2.6 presents the results of running the difference-in-differences specification in model (2.4) for groups 1& 2, and group 3, with respective control groups, using the same control variables but with net beta as the dependent variable. We also run the same regressions for β_{1t} and for the beta that captures liquidity components $\beta_{i2t} - \beta_{i3t} - \beta_{i4t}$ (panels B and C). We find that for stocks with small quoted spread, net-beta falls by 0.072 (0.076) after the start of the pilot program for the treated stocks in groups 1 and 2 (group 3) relative to the control group (see columns (1) and (2) of panel A). Moreover, most of the decline in net-beta comes from a decline in β_1 (see panel B). Finally, panel C shows that there does not appear to be a change in $\beta_{i2t} - \beta_{i3t} - \beta_{i4t}$. While the point estimate of the change in $\beta_{i2t} - \beta_{i3t} - \beta_{i4t}$ is negative, indicating a *lower* liquidity risk premium after the start of the Pilot program, this estimate is not statistically significant.[10]

[Table 2.6 about here.]

2.5.3 Changes in Price Efficiency

Information risk can contribute to changes in stock prices through the quality of information in the marketplace. To assess this possibility, in this subsection we use measures of price efficiency and of the speed of market response to news as proxies for quality of information. We estimate the specification in the regression model (2.4) for each group, with the respective control groups, using the same control variables but with price efficiency variables as dependent variables. Our price efficiency proxies are *AR10*, *PrcError*, and the speed of market response to news variables *PriceResponse*, *VolumeResponse*, *QuoteResponse1*, and *QuoteResponse2*. We again are able to separate groups 1 and 2 due to the larger number of observations.

[Table 2.7 about here.]

The results for the absolute value of return autocorrelation (*AR10*) and Hasbrouck's (1993) pricing error (*PrcError*) are displayed in Table 2.7. The models are estimated using ordinary least squares and we report robust standard errors clustered by firm. Starting with Panel A for small dollar quoted spread stocks, we note the robust evidence indicating a worsening in price efficiency. For example, return autocorrelation increases by 0.101 as shown in column (1) (0.090 and 0.082, as shown in columns (2) and (3)) for test group 1 stocks (2 and 3, respectively), compared to the control group, representing an increase of 36% (32% and 30%)

[10] Results using Amihud's measure as a proxy for c_{is} are similar.

for test group 1 stocks (2 and 3, respectively) relative to their mean. This evidence is consistent with Chordia et al. (2008) that study price efficiency with decimalization. Measured using *PrcError*, the changes in price efficiency are somewhat smaller percentage wise relative to those for *AR10*. For large dollar quoted spread stocks, there is only an increase in *PrcError* for group 1 and 2 stocks and a decrease in return autocorrelation for group 3 stocks, but the effects are significantly smaller relative to the effect on the small dollar quoted spread stocks of the respective groups. The online appendix shows that the results when we estimate the model for both *AR10* and *PrcError* for each group as a whole shows economic magnitudes smaller by about 40%.

[Table 2.8 about here.]

[Table 2.9 about here.]

Table 2.8 presents the results for the market response speed to company-specific news and Table 2.9 for macro news. We use the two-limit Tobit model to account for the fact that the variables *PriceResponse*, *VolumeResponse*, *QuoteResponse1*, and *QuoteResponse2* are bounded between 0 and 1. We are not able to estimate these models using stock fixed effects and instead use stock primary listed exchange fixed effects.

By and large our evidence regarding company-specific news is consistent with that of Table 2.7, with small dollar quoted spread stocks in test groups 1 and 2 having a greater reduction in response speed than those in test group 3, compared to the control group (coefficients −0.233 and −0.244 versus −0.207 for groups 1 through 3 reported in column (1) of panels A through C). Volume and quote response speed change by less in test groups 1 and 2, whereas in group 3 their change loses significance. There is some evidence of slower speed of market response also for the large dollar quoted spread stocks, but it is weaker both in economic magnitude and statistical significance. The evidence for the changing speed of market response due to a changing tick size is stronger for macro news as documented in Table 2.9 and shows up in both small and large dollar quoted spreads. This stronger evidence could be caused by the greater statistical power of the tests coming from the significantly larger number of observations.[11]

Overall, the results from both tables suggest a decrease in price efficiency following the adoption of a larger tick size for all three test groups, though only for the small dollar quoted spread stocks.[12] Our empirical results for groups 1 and 2 stocks are consistent with the prediction of Anshuman and Kalay (1998) that a wider tick size reduces informed investors' likelihood of trading. Anshuman and Kalay's (1998) model suggests that informed traders invest more to acquire accurate signals under continuous pricing than under discrete tick size trading and larger bid-ask spreads. Therefore, a larger tick size can lead to less price efficiency and lower quality of information. Likewise, in Goettler, Parlour and Rajan (2005), a larger tick size makes liquidity traders less aggressive and reduces price efficiency.[13]

[11] We have more observations than in the regressions with company specific news, because we can measure a market response to a piece of macro news for every firm in our sample.

[12] The results are consistent with Kerr, Sadka and Sadka (2017) who study the effect of liquidity on the predictability of earnings growth using prices where the shock to liquidity is the1997 reduction in tick size from one eighth to one sixteenth.

[13] Our results are inconsistent with Zhao and Chung's (2006) proposed alternative that a larger tick size may

For group 3 stocks, recall that we do not find a significant change in effective spreads or in price impact measures. So, it is unlikely that the price drop in group 3 is a consequence of an increase in transactions costs and thus a consequence of less information acquisition as in Anshuman and Kalay (1998). Instead, it is possible that the trade-at requirement that group 3 stocks are subject to caused a shift of uninformed investors from dark pools to lit exchanges that kept spreads low (see Zhu, 2014, and Comerton-Forde and Putnis, 2015).

The decrease in price efficiency and the slower price discovery are consistent with an increase in information risk. In the models of Easley and O'Hara (2004) and O'Hara (2003) information risk, the risk that exists of trading in assets with privately informed investors, increases with a decrease in information quality, either through an increase in uninformed traders or a decrease in the precision of private information because prices end up revealing less information to the uninformed traders in equilibrium. Thus we conjecture that information risk may have increased for all groups, at least partly explaining the stock price response.

2.6 Related Literature

Several papers have tried to detect the effect of shocks to bid-ask spreads on stock prices. Barclay, Kandel and Marx (1998) study this question within the context of stocks that move from Nasdaq to the NYSE or Amex and stocks that move from Amex to the NYSE. While they observe changes in spreads for stocks moving to and from Nasdaq consistent with our findings, they find no significant relation between changes in bid-ask spreads and changes in stock prices. Our field experiment has the advantage of eliminating the selection issue–arising because the choice of exchange venue is not exogenous–that can impact causal inference of stock price effects. Elyasiani, Hauser and Lauterbach (2000) also study stocks that move from Nasdaq to the NYSE and attribute some of the listing excess return to liquidity changes in those stocks. The studies that are closest to ours, in the sense of using a laboratory-like experiment in actual financial markets, are Bessembinder (2003) and Chakravarty, Wood, Van Ness (2004) who investigate the effects of decimalization on a sample of NYSE common stock initially trading in decimals.[14] Because the NYSE changed the trading requirements via a phased pilot program, they are able to form a sample of unaffected stocks that controls for other contemporaneous events. Both papers find that quoted spreads declined after decimalization and Chakravarty et al. also finds that stock return volatilities decline over the long term. Neither paper reports on stock price effects. Muscarella and Piwowar (2001) find a price increase for frequently traded stocks in the Paris Bourse that move from call trading to continuous trading, but theirs is not a randomized sample like ours, nor do they study expected return effects. Relative to this literature we also innovate by finding supportive evidence that microstructure shocks, such as a tick size change, can have consequences for firms' cost of capital.

We conjecture that the lack of clear causal evidence of changes in the tick size on stock prices in the literature and the many theoretical arguments pointing to a second order effect of

improve price efficiency by making it more expensive to front-runners to step in front of existing orders and to receive execution precedence. Reducing front-running risk increases the profit for informed traders, which motivates them to gather more information.

[14]Fang, Noe and Tice (2009) study the effect of decimalization on the change in market to book value of assets from one year prior to decimalization to one year after decimalization.

transactions costs on stock prices may explain the absence of a discussion of price effects from either proponents and opponents of the tick size program. However, our evidence suggests that the program may have hurt the very firms that the study wished to help.

There is a long empirical literature starting with Amihud and Mendelson (1986, 1991) and Brennan and Subrahmanyam (1996) that shows that risk-adjusted stock and bond returns correlate positively with liquidity measures (see, in addition, Pastor and Stambaugh, 2003, Amihud, 2002, Sadka, 2010, Beber, Driessen, and Tuijp, 2012, and Foucault, Pagano and Roell, 2013). The findings in this literature may be confounded by the fact that liquidity is affected by and affects firm policies (e.g., Chen, Goldstein, and Jiang, 2006, Ellul and Pagano, 2006, and Sadka, 2011) and that liquidity may also proxy for other risk factors. Moreover, the lack of more direct evidence to date on the link between exogenous measures of transactions costs and prices raises a concern that these confounding aspects may be of first order. Our paper suggests otherwise as it is the first paper that shows that exogenous shocks to transactions costs have price effects.

The JOBS Act envisioned the study conducted by the SEC in order to collect information to better assess how tick size may impact liquidity and price efficiency. The scant literature studying how stock prices are affected by bid-ask spreads contrasts with the large body of literature studying the impact of tick size on liquidity.[15] See for example Harris (1994, 1997), Ahn, Charles and Choe (1996), Goldstein and Kavajecz (2000), Jones and Lipson (2001), and Bessembinder (2003), among others. More recently, Griffith and Roseman (2017) and Hansen et al. (2017), Lin et al. (2017), and Rindi and Werner (2017) also make use of the SEC's Tick Size Pilot Program to study the effect of bid-ask spreads on liquidity, including spreads, price impact, volume and depth.[16] These papers all conclude, like we do, that increasing tick size increases spreads, price impact and depth especially for the more constrained stocks. The effect of a larger tick size on trading volume is less clear. Though the literature generally documents a negative relationship between trading volume and bid-ask spreads, Porter and Weaver (1997) and Rindi and Werner (2017) find no effect of tick size on volume. We find that trading volume experiences a significant decline for pilot groups 1 and 2 stocks and no change for group 3 stocks. Griffith and Roseman (2017), Hansen et al. (2017) and Lin et al. (2017) also find a significant drop in consolidated volume for treated firms after the tick size pilot program.

Our paper is the first to show price efficiency changes using the tick size pilot program, which are consistent with changes in information risk. We provide empirical evidence on the

[15]Theoretical studies have been developed to examine the effect of tick size changes in different market structures. Foucault, Kadan and Kandel (2005) investigate a dynamic limit order book populated by strategic liquidity traders of varying impatience, and predict that a reduction in tick size can result in higher spread by impairing market resiliency and enabling traders to trade less aggressively. By modeling the competition between a specialist with market power and a competitive limit order book, Seppi (1997) shows that larger tick size is more favorable for large traders than for small traders. Werner et al. (2015) model order submission strategies of rational trades and show that tick size reduction improves market quality for liquid stocks, but deteriorates market quality for illiquid stocks. Kadan (2006) studies the welfare effects of a change in tick size in a dealer marker and argues that an increase in tick size benefits dealers while hurting investors when the number of dealers is large, and vice versa when the number of dealers is small. The JOBS Act specifically acknowledged the possibility that increasing the tick size encourages market participants to provide more liquidity, and analysts to cover these firms, thereby attracting more investors to invest in small cap stocks.

[16]Comerton-Forde, Gregoire and Zhong (2017) uses the tick size pilot program as an exogenous shock to the market share of inverted exchanges to study market quality of inverted fee models, and Lin, Swan and Mollica (2017) study the allocation of investors across exchanges.

causal effect of a reduction in price efficiency due to an increase in tick size. Anshuman and Kalay's (1998) model suggests that a larger tick size reduces the value of private information, thus decreasing price efficiency. In their model, informed traders invest more to acquire accurate signals under continuous pricing, while a wider tick size would discourage investors from acquiring accurate information about stock value. Zhao and Chung (2006) find evidence supporting the Anshulan and Kalay (1998) model, though they consider an alternative hypothesis where a larger tick size may improve price efficiency by reducing the likelihood of front-running, which increases the profit for informed traders and motivates them to gather more information. Likewise, Cordella and Foucault (1999) argue that the larger tick size creates a bigger gap between the competitive price and the expected asset value and prompts dealers to adjust prices more quickly. We find that after widening the tick size, market reaction speed to news decreases, suggesting that it takes longer for stock price to incorporate information, thus a decrease in price efficiency.

2.7 Conclusion

We provide empirical evidence of a causal negative impact of a larger tick size on stock prices and calculate the liquidity premium implied by the change in tick size. The sources of stock price variation appear different across the various treated stocks in the program. We show that the decline in stock prices is associated with an increase in spreads and in price impact, and with a reduction in volume for groups 1 and 2 stocks. For these stocks, we show that there is an increase in investor horizon consistent with the view that transactions costs have a direct effect over stock prices holding expected returns constant, as in Amihud and Mendelson (1986). However, for group 3 stocks, we show that there is a change in quoted spreads but no change in effective spreads or in trading volume.

We also study the indirect effect on stock prices through expected returns (net of transactions costs) of the change in tick size. We show that there is no statistically significant change in liquidity risk across all test groups. However, we show that all stocks experience a decline in price efficiency suggesting that information risk and thus expected returns increased for the treated stocks. This evidence is consistent with firm's cost of capital being affected by market microstructure features.

The experiment conducted by the SEC was mandated by the 2012 JOBS Act. The main motivation for the experiment was to study how different tick size trading requirements affect the liquidity of emerging stocks to perhaps encourage more of these firms to go public. Given the large theoretical literature arguing that liquidity has second order effects on prices, and given an existing sizeable empirical literature arguing similarly as discussed above, it is reasonable to assume that the regulator did not expect that the very companies the JOBS Act meant to help would lose value through the experiment.

2.8 Appendix: Data definitions

Stock Liquidity Variables Following Holden and Jacobsen (2014), we use daily TAQ data to construct several liquidity measures. Percent quoted spread is the difference between the national best ask and the national best bid (NBBO) at any time interval divided by the midpoint of the two. The daily percent quoted spread (*QuotedSprd*) is the weighted average percent quoted spread computed over all time intervals, where each weight is the length of the time interval for which the percent quoted spread is available.

The quoted spread is calculated by taking the daily average of all quotes every time the NBBO is updated. It does not require any trade to take place. Arguably, the information contained in updates of the NBBO is more relevant in the study of the speed of market response to news, than in describing execution costs since traders may choose to execute orders when bid-ask spreads are narrower (Bessembinder, 2003). We therefore, consider an alternative measure of spreads that is calculated "conditional on" trade executions. The daily percent effective spread (*EffectiveSprd*) is the dollar-volume-weighted average of the percent effective spread computed over all trades in the day. The percent effective spread for each trade is twice the signed difference ('+' for buyer initiated and '-' for seller initiated) between the price of the trade and the midpoint between the national best ask and the national best bid at the time of the trade, divided by the midpoint at the time of the trade. We use the Lee and Ready (1991) algorithm to determine whether a trade is buyer- or seller-initiated. The daily price impact (*PriceImpact*) is the dollar-volume-weighted average of percent price impact computed over all trades during the day. For a given stock, the percent price impact on each trade is twice the signed difference between the midpoint available five minutes after the trade and the midpoint at the time of the trade, divided by the midpoint at the time of the trade.[17] For ease of reading the results, we measure *QuotedSprd*, *EffectiveSprd*, and *PriceImpact* in percent.

In addition, we study market depth (*MarketDepth*) defined as the average of displayed dollar-depth at the NBBO and measures the number of shares (in hundreds) that must be traded before the stock price moves, daily volume (*Volume*) (in hundreds of shares) (results are similar if using the number of trades during the day), and realized variance (*Volatility*) is the sum of squared intraday five-minute returns. We winsorize the bottom 1% and top 1% of quoted spread, effective spread, price impact and volatility. For these variables, the difference between the 99th percentile and the mean in the unwinsorized samples is more than 5 times the standard deviation of the respective winsorized series.

Investor Horizon Our proxy for investor horizon is the (inverse of the) $ChurnRatio$ borrowed from Gaspar, Massa and Matos (2005) and Cella, Ellul and Giannetti (2013). We use institutional investor data from Factset for the sample period Q1:2015–Q2:2017. Turnover for each institution is pre-determined in the sense that we use 2015 turnover data (pre-pilot program data) to calculate it. Therefore, our results are not tainted by changes in volume during implementation. For each quarter, the $ChurnRatio$ of any stock is measured as the weighted average of the portfolio turnover ratios. The weight is the proportion of shares held

[17] We also study the realized spread that equals the effective spread minus price impact. The results are consistent with both the effective spread and price impact variables.

by an investor to total shares outstanding in the quarter. Cella et al. suggest that this weighting gives a more precise estimate of the selling pressure experienced by each stock as compared to the proportion of shares held by an investor to total institutional investor shares in the quarter. An increase in this weighted average signals a relatively greater presence of short-term investors, which churn their portfolios more frequently (see Cella et al., 2013, for details). Investor horizon (in years) can be calculated as $1/(2 \times ChurnRatio)$.

Price Efficiency Variables $AR10$ is the absolute value of the ten-second midpoint return autocorrelation for each stock on each day (Boehmer and Kelley, 2009). We retain only the firm-day observations for which there are at least 100 trades. A high value of $AR10$ is indicative of inefficiency under the assumption that with efficient prices, the high-frequency return should follow a random walk. Both positive and negative autocorrelation indicates predictability in returns.

Our second price efficiency measure is from Hasbrouck (1993) and Boehmer and Kelley (2009). This measure assumes that the transaction price can be decomposed into an informational component that represents the expected value of the stock, or efficient price, and a non-informational component that captures transitory deviations from the efficient price, such as tick size or inventory effects. The variability (measured by the standard deviation) of the non-informational component as a percentage of the variability of transaction prices is a measure of the information (in)efficiency in prices (see the appendix in Boehmer and Wu, 2013, for details). We denote this measure by pricing error (*PrcError*).

Our other measures of price efficiency capture the speed with which stock prices respond to news (see Beschwitz, Keim and Massa, 2015). We calculate stock price response to company-specific news and to macroeconomic news. The reasons to look at macro news are that firms may be heterogeneous in the volume and significance of company-specific news and this may affect our inference, and that the flow and content of firm specific news may also have changed as a consequence of the tick size program. None of these concerns affect our inference when we use macro news. We define stock price response speed as $PriceResponse = \frac{|return_{t-1,t+10}|}{|return_{t-1,t+10}|+|return_{t+10,t+120}|}$. $|return_{t-1,t+10}|$ is the absolute value of the stock return over an 11-second time horizon from $t-1$ to $t+10$, t is the second that the news is released, $|return_{t+10,t+120}|$ is the absolute value of the stock return over an 110-second time horizon from $t+10$ to $t+120$. *PriceResponse* gives the amount of two minute return adjustment that takes place in the first 10 seconds after the release of the news. Volume response speed (*VolumeResponse*) is defined similarly to *PriceResponse*, but uses volume instead of the absolute return, and captures the amount of two-minute volume adjustments that take place in the first 10 seconds after the news announcement. The third and fourth measures are based on quote adjustment. *QuoteResponse1* is the proportion of quotes adjusted in the first 10 seconds over a two-minute interval after the news announcement. The variable is calculated as the number of NBBO price updates and NBBO depth updates in the first 10 second over those that are updated in the first two-minutes. Finally, *QuoteResponse2* is defined analogously to *QuoteResponse1*, but it only counts the number of NBBO price updates.

For both company news and macroeconomic news, RavenPack provides two measures of sentiment on each article: the Composite Sentiment Score (CSS) and the Event Sentiment

Score (ESS). Both measures range from 0 to 100, with 0 (100) representing the most negative (positive) news and 50 representing neutral news. We define the absolute value of the sentiment score as the absolute value of ($ESS - 50$) if ESS is non-missing or if CSS is equal to 50, or the absolute value of ($CSS - 50$) otherwise. Following Beschwitz, Keim, and Massa (2015), we use the absolute value of the sentiment score in the news response speed regressions as a control.

Table 2.1: **Summary Statistics for Key Variables**

The table presents descriptive statistics for each test group from January 01, 2016 to May 31, 2017. Panel A reports summary statistics for the control group. Panels B to D report summary statistics for test groups 1 to 3, respectively. $QuotedSprd$ is the time-weighted average of percent quoted spread, $EffectiveSprd$ is the dollar-volume-weighted average of percent effective spread, $PriceImpact$ is the dollar-volume-weighted average of percent price impact, $MarketDepth$ is the average displayed dollar depth at the NBBO, $Volume$ is the daily volume, $Volatility$ is the realized variance, $AR10$ and $PrcError$ are price efficiency measures. $ChurnRatio$ is measured as the weighted average of the total portfolio turnover ratios of stock i's investors in quarter t. All spread measures are multiplied by 100 for ease of reading. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. We report the summary statistics for small and large dollar quoted spread stocks separately.

Panel A: Control Group

	SMALL QUOTED SPREAD STOCKS						LARGE QUOTED SPREAD STOCKS					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd	90144	0.412	0.474	0.275	0.073	8.111	87288	1.613	1.882	0.818	0.073	8.111
EffectiveSprd	90135	0.556	1.509	0.213	0.044	12.834	85170	1.291	2.137	0.514	0.044	12.834
PriceImpact	90135	0.338	0.889	0.142	-0.609	7.418	85137	0.519	1.152	0.181	-0.609	7.418
Market Depth	90143	9806	8083	8052	515	423462	87269	15163	31707	10405	420	2023329
Volume	90138	303684	439069	194231	2	23292925	85465	88586	211302	28523	1	16489984
Volatility	90144	0.151	1.118	0.000	0.000	9.292	86863	0.146	1.119	0.000	0.000	9.292
AR10	84017	0.280	0.140	0.267	0.000	0.914	47936	0.338	0.145	0.330	0.000	0.940
PrcError	75021	0.176	0.162	0.138	0.011	1.090	33314	0.186	0.145	0.154	0.022	1.093
ChurnRatio	1417	0.103	0.043	0.107	0.001	0.291	1382	0.072	0.049	0.066	0.000	0.255

Panel B: Pilot Group 1

	SMALL QUOTED SPREAD STOCKS						LARGE QUOTED SPREAD STOCKS					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd	29487	0.415	0.477	0.272	0.073	8.111	30334	1.380	1.671	0.677	0.073	8.111
EffectiveSprd	29487	0.520	1.418	0.206	0.044	12.834	29888	1.016	1.634	0.421	0.044	12.834
PriceImpact	29487	0.291	0.737	0.135	-0.609	7.418	29878	0.420	0.915	0.164	-0.609	7.418
Market Depth	29487	10425	10566	8482	646	551854	30334	14553	17935	10982	443	1022462
Volume	29487	340705	547945	199923	102	30938197	29951	90862	202521	35810	1	14585454
Volatility	29487	0.070	0.785	0.000	0.000	9.292	30206	0.030	0.379	0.000	0.000	9.292
AR10	27142	0.278	0.138	0.264	0.000	0.897	18104	0.337	0.145	0.329	0.000	0.893
PrcError	23932	0.168	0.150	0.134	0.008	1.088	12826	0.182	0.133	0.155	0.022	1.087
ChurnRatio	469	0.105	0.046	0.101	0.003	0.245	478	0.080	0.048	0.081	0.001	0.229

Panel C: Pilot Group 2

	SMALL QUOTED SPREAD STOCKS						LARGE QUOTED SPREAD STOCKS					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd	28915	0.400	0.477	0.234	0.073	7.694	29700	1.607	1.863	0.819	0.073	8.111
EffectiveSprd	28915	0.412	0.869	0.185	0.044	12.834	29034	1.273	2.021	0.515	0.044	12.834
PriceImpact	28915	0.264	0.578	0.130	-0.609	7.418	29031	0.525	1.156	0.186	-0.609	7.418
Market Depth	28915	10411	8716	8935	605	348372	29694	13482	15820	10022	573	1203311
Volume	28915	317339	432827	200700	4	23503988	29096	92051	202002	29437	1	6686550
Volatility	28915	0.014	0.256	0.000	0.000	9.292	29591	0.126	0.996	0.000	0.000	9.292
AR10	26689	0.280	0.141	0.264	0.000	0.890	16706	0.337	0.145	0.332	0.000	0.949
PrcError	23688	0.162	0.131	0.135	0.019	1.086	11279	0.194	0.173	0.153	0.017	1.087
ChurnRatio	458	0.109	0.047	0.113	0.001	0.223	464	0.068	0.047	0.067	0.000	0.210

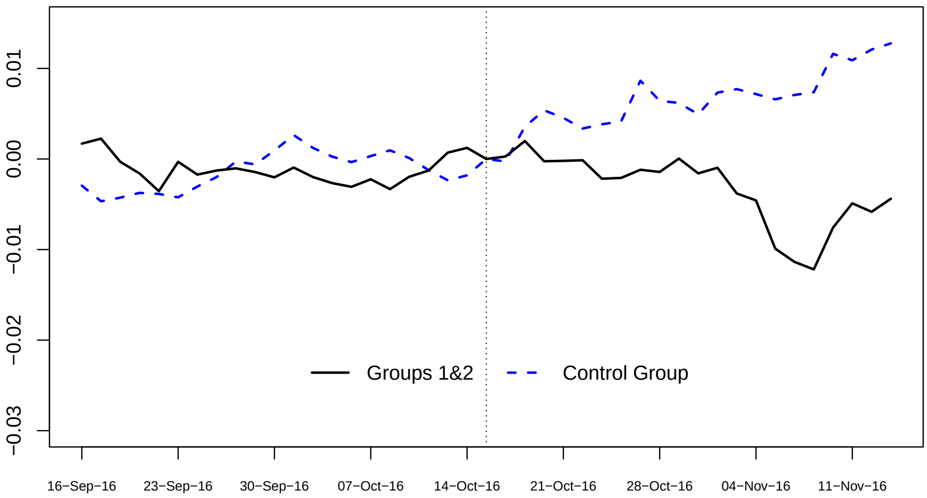
Panel D: Pilot Group 3

	SMALL QUOTED SPREAD STOCKS						LARGE QUOTED SPREAD STOCKS					
	N	Mean	Stdev	Median	Min	Max	N	Mean	Stdev	Median	Min	Max
QuotedSprd	28115	0.397	0.523	0.238	0.073	8.111	29435	1.439875	1.652	0.776	0.073	8.111
EffectiveSprd	28114	0.561	1.556	0.186	0.044	12.834	28933	1.35141	2.392	0.518	0.044	12.834
PriceImpact	28114	0.325	0.871	0.129	-0.609	7.418	28917	0.596208	1.355	0.178	-0.609	7.418
Market Depth	28115	10116	7621	8557	627	223357	29428	15848.39	21797	10727	484	530352
Volume	28114	337537	453780	224742	2	15910008	28998	88358.86	194878	30199	1	8356901
Volatility	28115	0.123	0.903	0.000	0.000	9.292	29322	0.317104	1.658	0.000	0.000	9.292
AR10	26536	0.277	0.139	0.263	0.000	0.916	16624	0.344387	0.146	0.338	0.000	0.931
PrcError	23919	0.172	0.158	0.135	0.012	1.089	11306	0.235118	0.235	0.165	0.009	1.090
ChurnRatio	445	0.109	0.045	0.114	0.001	0.220	466	0.073	0.046	0.064	0.001	0.235

Figure 2.1: **Cumulative Abnormal Return**

The figure plots the daily cumulative abnormal return of treated groups and control group from September 01, 2016 to November 30, 2016. The top panel plots the cumulative abnormalreturn of test stocks in groups 1 and 2 versus the control group (test stocks in groups 1 and 2 are activated fully into the program on October 17, 2016). The bottom panel plots the cumulative abnormal return of test stocks in group 3 versus the control group (test stocks in group 3 are activated fully into the program on November 1, 2016).

Cumulative Abnormal Returns Groups 1&2 v. Control Group



Cumulative Abnormal Returns Group 3 v. Control Group

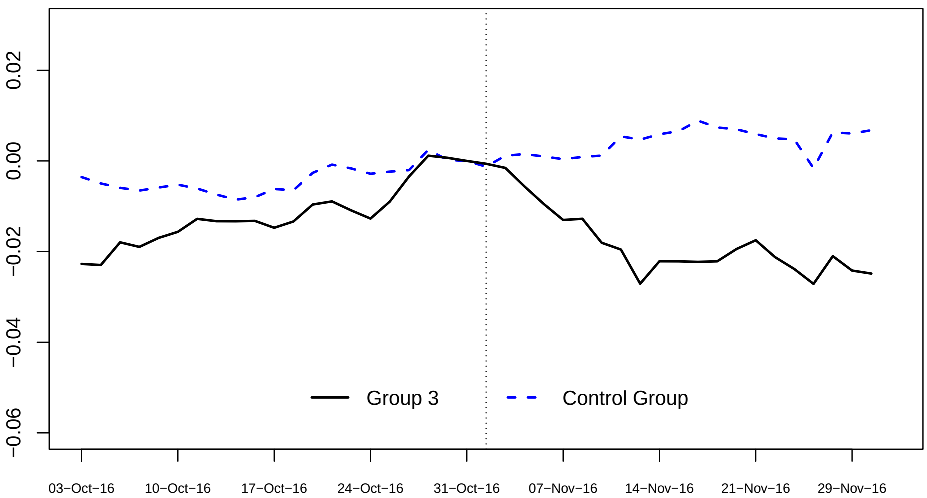


Figure 2.2: **Market Liquidity**

The figure plots the daily percent effective spread (top panel), trading volume (mid panel), and dollar market depth (bottom panel) for stocks in test groups 1 to 3 versus the control group. The month of October 2016 is the implementation month and is dropped.

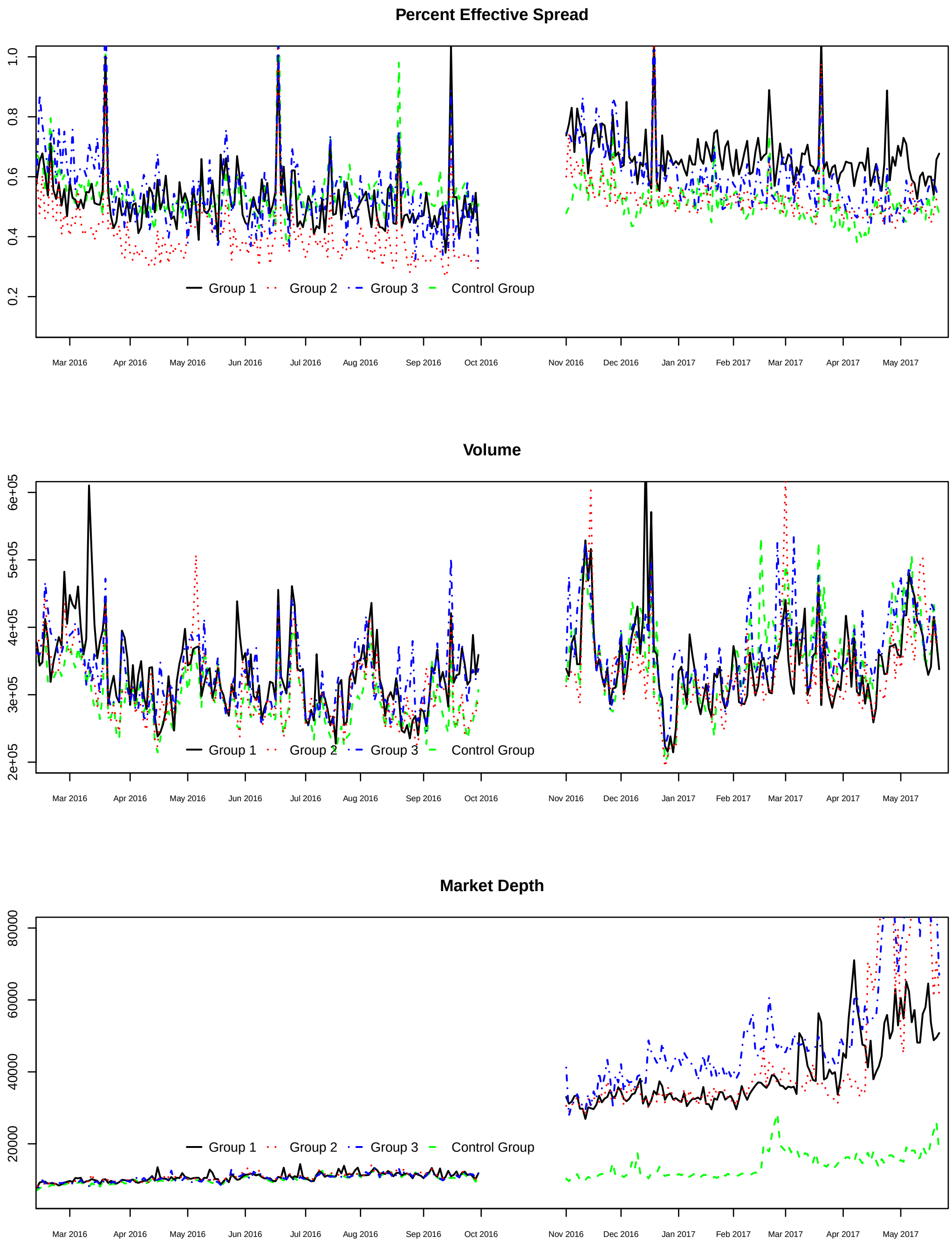


Table 2.2: **Pre-implementation Characteristics of Treated and Control Firms**

The table presents descriptive statistics of treated stocks ('G1' - 'G3') and control stocks ('C') from January 01, 2016 to September 30, 2016. Panel A reports average firm characteristics for each group. Panel B reports the differences between the treatment and the control group. Total asset (*Asset*), Market Capitalization (*Size*), and market-to-book ratio (*MB*) are measured on December 2015. Daily trading volume (*Volume*), dollar quoted spread (*QuotedSprd*), and realized volatility (*Volatility*) are based on data from January 1 to September 30, 2016. *Asset* and *Size* are measured in millions of dollars. *QuotedSprd* is measured in cents. The first (second) row of each variable in Panel B reports the difference (t-statistics for the difference) between Control and Treatment Group. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. We report summary statistics for small and large dollar quoted spread stocks separately. ***, **, and * indicate significance at the 1%, 5%, and 10% levels using two-tailed tests.

Panel A: Sample Mean for Treatment and Control Groups

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	C	G1	G2	G3	C	G1	G2	G3
Number of Stocks	484	159	156	152	470	164	160	158
Asset	1664	1390	1828	1366	1033	1188	912	1189
Size	770	788	792	746	574	640	532	560
MB	6.06	3.59	3.52	4.67	3.37	8.16	2.61	3.14
Volume	303023	338862	316710	334715	86479	88824	89491	86561
QuotedSprd ($c)	3.92	3.74	3.92	3.80	27.34	25.06	24.13	26.24
Volatility	0.15	0.07	0.01	0.13	0.19	0.03	0.15	0.33
inverse of the share price	0.12	0.13	0.12	0.12	0.09	0.08	0.09	0.08
High_m_Low	0.52	0.50	0.52	0.54	0.91	0.92	0.83	0.96
Share Turnover	8.25	7.66	7.85	8.27	4.46	4.84	5.32	4.41

Panel B: Difference between Treatment and Control Group

Difference (Control - Test)		G1	G2	G3		G1	G2	G3
Asset		275	-164	365		-154	121	-156
		(0.78)	(-0.43)	(0.82)		(-0.71)	(0.56)	(-0.71)
Size		-18	-22	25		-66	42	15
		(-0.25)	(-0.31)	(0.35)		(-0.95)	(0.61)	(0.21)
MB		2	3	1		-5	1	0
		(1.06)	(1.07)	(0.54)		(-1.51)	(1.22)	(0.36)
Volume		-35838	-13686	-31692		-2345	-3012	-82
		(-1.59)	(-0.63)	(-1.45)		(-0.20)	(-0.24)	(-0.01)
QuotedSprd ($c)		0.18	-0.01	0.12		2.28	3.20	1.10
		(1.18)	(-0.04)	(0.77)		(0.83)	(1.20)	(0.39)
Volatility		0.09	0.14*	0.02		0.16*	0.04	-0.14
		(1.03)	(1.73)	(0.26)		(1.82)	(0.44)	(-1.22)
inverse of the share price		-0.01	-0.00	-0.00		0.01	0.00	0.01
		(-0.70)	(-0.32)	(-0.04)		(1.23)	(-0.34)	(1.06)
High_m_Low		0.02	0.00	-0.02		0.00	0.08	-0.05
		(0.89)	(-0.13)	(-0.61)		(-0.02)	(0.98)	(-0.49)
Share Turnover		0.59	0.40	-0.01		-0.38	-0.86	0.05
		(0.70)	(0.47)	(-0.02)		(-0.87)	(-1.61)	(0.11)

Table 2.3: **Abnormal Returns**

The table reports OLS regression results of the following model: $AR_{i,t} = \alpha + \gamma_1 Week1 + \gamma_2 Week2 + \gamma_3 Post_t + \gamma_4 Pilot_i \times Week1 + \gamma_5 Pilot_i \times Week2 + \gamma_6 Pilot_i \times Post_t + \delta^{'} X_{i,t} + \epsilon_{i,t}$, where $AR_{i,t}$ is the abnormal return for stock i on day t. Panel A (B) contains the results for pilot groups 1&2 (3). $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. For groups 1 and 2, $Week1$ is a dummy variable equal to 1 for dates between October 17 and October 21, and 0 otherwise, and $Week2$ is a dummy variable equal to 1 for dates between October 24 to October 28, and 0 otherwise, and for group 3, $Week1$ is a dummy variable equal to 1 for dates between October 31 and November 4, and 0 otherwise, and $Week2$ is a dummy variable equal to 1 for dates between November 7 and November 11, and 0 otherwise. $Post_t$ is a dummy variable that equals 1 for dates following $Week2$; and 0 otherwise, and thus depends on the treated group being considered. We also include all interaction terms of each date dummy and $Pilot_i$. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and time and stock fixed effects. Columns (1) and (2) present the results using the CAPM model. Columns (3) and (4) present the results using the Carhart model. Columns (5) and (6) present the results using the Fama French 5 Factor model. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. Odd (even) number columns report results for small (large) spread stocks. We cluster the standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Groups 1&2

	CAPM		Carhart		Fama French 5 Factor	
	Small Spread	Large Spread	Small Spread	Large Spread	Small Spread	Large Spread
	(1)	(2)	(3)	(4)	(5)	(6)
Week1	0.004***	0.000	0.002***	-0.001	0.002***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week2	-0.001*	-0.000	0.001**	0.001**	0.002***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post	0.003***	0.002***	0.001**	0.001	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pilot1&2 x Week1	-0.002**	0.000	-0.002**	0.000	-0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot1&2 x Week2	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot1&2 x Post	-0.000	-0.001*	-0.000	-0.001*	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	48,060	47,847	48,049	47,797	48,049	47,797
R-squared	0.042	0.046	0.026	0.043	0.023	0.040
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 3

Week1	0.000	-0.001	0.002***	-0.000	0.001**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week2	0.015***	0.011***	0.002*	0.002**	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post	-0.001	0.000	0.000	0.000	-0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot3 x Week1	-0.003**	0.001	-0.003**	0.001	-0.003*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pilot3 x Week2	-0.004**	-0.001	-0.005**	-0.001	-0.004**	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pilot3x Post	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	38,207	37,469	38,133	37,313	38,133	37,313
R-squared	0.059	0.061	0.027	0.047	0.023	0.041

Table 2.4: **Market Liquidity**

The table reports OLS regression results of the following model: $Liquidity_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $Liquidity_{i,t}$ is a measure of liquidity for stock i on day t, identified at the top of each column. Columns (1) to (6) report results using percent quoted spread, percent effective spread, percent price impact, dollar-depth, total daily trading volume, and volatility as measures of liquidity. Panels A and B give results for group 1 stocks, Panels C and D give results for group 2 stocks, and Panels E and F give results for group 3 stocks. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. We drop observations in October 2016. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and time and stock fixed effects. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Small Quoted Spread Stocks from Pilot Group 1

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.029***	0.015	-0.011	1.422	39.699**	0.057*
	(0.011)	(0.048)	(0.024)	(1.686)	(16.139)	(0.031)
Pilot1 x Post	0.311***	0.154**	0.082***	25.145***	-48.658***	-0.041
	(0.024)	(0.071)	(0.025)	(4.703)	(14.857)	(0.039)
Observations	205,432	205,419	205,419	205,432	205,422	205,432
Adjusted R-squared	0.582	0.635	0.408	0.157	0.466	0.716

Panel B: Large Quoted Spread Stocks from Pilot Group 1

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.258***	-0.267***	-0.171***	4.147***	9.990	0.020
	(0.043)	(0.041)	(0.023)	(0.586)	(6.523)	(0.020)
Pilot1 x Post	-0.042	0.064	0.031	8.797***	-4.514	0.002
	(0.057)	(0.063)	(0.024)	(1.253)	(3.561)	(0.013)
Observations	202,204	198,288	198,203	202,204	198,697	201,514
Adjusted R-squared	0.669	0.561	0.252	0.440	0.743	0.763
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Small Quoted Spread Stocks from Pilot Group 2

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.027**	-0.010	-0.025	0.408	30.292**	0.041
	(0.011)	(0.045)	(0.024)	(2.882)	(15.089)	(0.029)
Pilot2 x Post	0.267***	0.173***	0.088**	28.882***	-55.210***	-0.005
	(0.025)	(0.064)	(0.035)	(9.070)	(16.807)	(0.047)
Observations	204,011	203,998	203,998	204,011	204,001	204,011
Adjusted R-squared	0.576	0.618	0.406	0.105	0.455	0.718
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Large Quoted Spread Stocks from Pilot Group 2

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.291***	-0.285***	-0.156***	4.426***	9.604	0.009
	(0.044)	(0.046)	(0.026)	(0.551)	(6.993)	(0.025)
Pilot2 x Post	-0.008	0.036	0.013	7.673***	-0.104	0.021
	(0.054)	(0.068)	(0.028)	(0.807)	(4.722)	(0.051)
Observations	201,096	196,860	196,788	201,096	197,277	200,424
Adjusted R-squared	0.672	0.562	0.270	0.489	0.720	0.752
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Small Quoted Spread Stocks from Pilot Group 3

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.029***	-0.006	-0.017	0.635	33.297**	0.048
	(0.011)	(0.045)	(0.024)	(1.458)	(15.939)	(0.030)
Pilot3 x Post	0.272***	0.090	0.067**	36.657***	-22.172	-0.068*
	(0.025)	(0.073)	(0.028)	(7.753)	(18.202)	(0.039)
Observations	202,723	202,709	202,709	202,723	202,712	202,723
Adjusted R-squared	0.589	0.627	0.417	0.173	0.455	0.712
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel F: Large Quoted Spread Stocks from Pilot Group 3

	QuotedSprd	EffectiveSprd	PriceImpact	MarketDepth	Volume	Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.302***	-0.286***	-0.161***	4.322***	6.545	0.027
	(0.043)	(0.044)	(0.026)	(0.542)	(6.330)	(0.027)
Pilot3 x Post	-0.006	-0.066	-0.013	8.718***	3.012	-0.103
	(0.051)	(0.075)	(0.041)	(0.948)	(3.670)	(0.075)
Observations	200,379	196,388	196,307	200,379	196,799	199,718
Adjusted R-squared	0.663	0.587	0.299	0.510	0.794	0.729
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.5: **Investment Horizon**

The table reports OLS regression results of the following model: $ChurnRatio_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $ChurnRatio_{i,t}$ is measured as the weighted average of the total portfolio turnover ratios of stock i's investors in quarter t. Columns (1) and (2) report regression results for stocks with smallest dollar quoted spread, and Columns (3) and (4) report regression results for stock with largest dollar quoted spread. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. $Post_t$ is a dummy variable equal to 1 for dates in or after Quarter 4, 2016, and 0 otherwise. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and time and stock fixed effects. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. We cluster the standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
	(1)	(2)	(3)	(4)
Post	-0.105***	-0.106***	-0.079***	-0.077***
	(0.002)	(0.002)	(0.002)	(0.002)
Pilot1&2 x Post	-0.003*		0.000	
	(0.002)		(0.001)	
Pilot3 x Post		-0.005**		0.001
		(0.002)		(0.002)
Observations	4,566	3,630	4,493	3,575
Adjusted R-squared	0.873	0.876	0.861	0.854
Controls	Yes	Yes	Yes	Yes

Table 2.6: **Liquidity Risk**

The table reports OLS regression results of the following model: $\beta_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot + \delta' X_{i,t} + \epsilon_{i,t}$, where $\beta_{i,t}$ is a measure of liquidity risk for stock i on day t. Panel A (B and C) reports results using β_i (β_{1i} and $\beta_{liq,i}$) as measures of liquidity risk. These are defined as:

$\beta_{1i} = \frac{cov(r_{is}, r_{Ms} - E_{s-1}(r_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_{2i} = \frac{cov(c_{is} - E_{s-1}(c_{is}), c_{Ms} - E_{s-1}(c_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_{3i} = \frac{cov(r_{is}, c_{Ms} - E_{s-1}(c_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_{4i} = \frac{cov(c_{is} - E_{t-1}(c_{is}), r_{Ms} - E_{s-1}(r_{Ms}))}{var(r_{Ms} - E_{s-1}(r_{Ms}) - [c_{Ms} - E_{s-1}(c_{Ms})])}$

$\beta_i = \beta_{1i} + \beta_{2i} - \beta_{3i} - \beta_{4i}$

$\beta_{liq,i} = \beta_{2i} - \beta_{3i} - \beta_{4i}$

We use the proportional quoted spread (c_{is}) as a measure of liquidity for stock i at thirty-minute s. c_{Ms} is the equally-weighted average of c_{is} for all common stocks traded in the US. r_{is} is stock i's thirty-minute return in interval s, and r_{Ms} is the equally-weighted average of r_{is} for all common stocks traded in the US. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and time and stock fixed effects. Columns (1) and (2) report regression results for stocks with smallest dollar quoted spread, and Columns (3) and (4) report regression results for stock with largest dollar quoted spread. We cluster the standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Impact of Widening Tick Size on β_i

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
	(1)	(2)	(3)	(4)
Post	-0.498***	-0.494***	-0.053	-0.040
	(0.024)	(0.027)	(0.036)	(0.039)
Pilot1&2 x Post	-0.072***		-0.058**	
	(0.021)		(0.029)	
Pilot3 x Post		-0.076***		-0.086
		(0.026)		(0.055)
Observations	252,680	200,558	241,905	190,884
Adjusted R-squared	0.044	0.042	0.044	0.051
Controls	Yes	Yes	Yes	Yes

Panel B: Impact of Widening Tick Size on β_{1i}

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
Post	-0.569***	-0.567***	-0.381***	-0.378***
	(0.023)	(0.026)	(0.028)	(0.031)
Pilot1&2 x Post	-0.052**		-0.004	
	(0.021)		(0.022)	
Pilot3 x Post		-0.074***		0.001
		(0.024)		(0.039)
Observations	252,680	200,558	241,905	190,884
Adjusted R-squared	0.048	0.046	0.053	0.059
Controls	Yes	Yes	Yes	Yes

Panel C: Impact of Widening Tick Size on $\beta_{liq,i}$

	SMALL QUOTED SPREAD STOCKS		LARGE QUOTED SPREAD STOCKS	
Post	0.071***	0.073***	0.329***	0.338***
	(0.013)	(0.016)	(0.026)	(0.029)
Pilot1&2 x Post	-0.020		-0.054***	
	(0.013)		(0.019)	
Pilot3 x Post		-0.002		-0.088***
		(0.019)		(0.031)
Observations	252,680	200,558	241,905	190,884
Adjusted R-squared	0.028	0.031	0.020	0.022
Controls	Yes	Yes	Yes	Yes

Table 2.7: **Price Efficiency**

The table reports OLS regression results of the following model: $PriceEfficiency_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Post_t \times Pilot_i + \delta' X_{i,t} + \epsilon_{i,t}$, where $PriceEfficiency_{i,t}$ is a measure of price efficiency, $AR10$ and $PrcError$, for stock i on day t. Panel A (B) reports regression results for stocks with smallest (largest) dollar quoted spread. Columns (1) to (3) use return autocorrelation as a measure of price efficiency. Columns (4) to (6) use pricing error as measure of price efficiency. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to the test group (i = 1, 2, 3), and 0 otherwise. $Post$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. We drop observations in October 2016. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, and time and stock fixed effects. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Small Dollar Quoted Spread Stocks

	AR10			PrcError		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.047***	0.047***	0.046***	0.003	0.004	0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Pilot1 x Post	0.101***			0.021***		
	(0.005)			(0.005)		
Pilot2 x Post		0.090***			0.024***	
		(0.005)			(0.004)	
Pilot3 x Post			0.082***			0.027***
			(0.005)			(0.005)
Observations	191,619	190,920	190,622	170,981	170,922	171,187
Adjusted R-squared	0.184	0.170	0.174	0.744	0.754	0.755
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Large Dollar Quoted Spread Stocks

	AR10			PrcError		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.035***	0.037***	0.036***	-0.007**	-0.004	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Pilot1 x Post	0.003			0.012*		
	(0.004)			(0.006)		
Pilot2 x Post		0.005			0.016***	
		(0.004)			(0.005)	
Pilot3 x Post			-0.015***			-0.004
			(0.004)			(0.009)
Observations	117,985	115,368	115,526	82,044	79,434	79,408
Adjusted R-squared	0.093	0.096	0.095	0.686	0.718	0.725
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.8: **Trade Response Speed to Firm Specific News**

This table reports tobit regression results of the following model: $Response_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Pilot_i + \gamma_3 Post_t \times Pilot_i + \delta^{'} X_{i,t} + \epsilon_{i,t}$, where $Response_{i,t}$ measures how fast trade reacts to firm specific news for stock i on day t. $PriceResponse$ shows the amount of two minute return adjustment that takes place in the first 10 seconds after the release of the news. $VolumeResponse$ captures the amount of two-minute volume adjusted in the first 10 seconds after the news announcement. $QuoteResponse1$ is calculated as the proportion of quote adjusted (including both NBBO changes and depth at NBBO changes) in the first 10 seconds after the news announcement ($QuoteResponse1$). $QuoteResponse2$ only counts the number of NBBO changes and ignores depth at NBBO changes. In Panels A, B and C, we report results for groups 1, 2 and 3, respectively. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. Columns (1) to (4) report regression results for stocks with smallest dollar quoted spread, and Columns (5) and (8) report regression results for stock with largest dollar quoted spread. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. We drop observations in October 2016. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, sentiment score of the news, and time and stock primary listed exchange fixed effects. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.110*	0.021	-0.011	-0.037	-0.113*	0.045	-0.044	-0.068*
	(0.043)	(0.029)	(0.012)	(0.027)	(0.048)	(0.064)	(0.023)	(0.031)
Pilot1	0.011	0.012	0.002	0.001	-0.012	0.036	-0.009	-0.008
	(0.022)	(0.017)	(0.006)	(0.012)	(0.031)	(0.036)	(0.015)	(0.020)
Pilot1 x Post	-0.233***	-0.057*	-0.022*	-0.129***	-0.160***	-0.044	-0.013	-0.048
	(0.052)	(0.022)	(0.010)	(0.029)	(0.042)	(0.049)	(0.018)	(0.026)
Observations	12517	15403	16768	13237	9685	8621	11555	10140
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 2

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.063	0.009	-0.005	-0.023	-0.106*	0.064	-0.059*	-0.063
	(0.043)	(0.030)	(0.012)	(0.027)	(0.051)	(0.064)	(0.024)	(0.033)
Pilot2	-0.012	0.009	0.006	0.000	-0.021	0.073	0.002	-0.008
	(0.024)	(0.017)	(0.007)	(0.015)	(0.033)	(0.043)	(0.017)	(0.021)
Pilot2 x Post	-0.244***	-0.066*	-0.031***	-0.143***	-0.176**	-0.103	-0.030	-0.078*
	(0.067)	(0.027)	(0.009)	(0.037)	(0.057)	(0.062)	(0.020)	(0.037)
Observations	12265	15107	16535	12962	9037	8056	10720	9461
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Pilot Group 3

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.085*	0.036	-0.015	-0.039	-0.129**	0.011	-0.050*	-0.073*
	(0.042)	(0.029)	(0.012)	(0.026)	(0.048)	(0.070)	(0.024)	(0.032)
Pilot3	0.018	0.008	0.010	0.011	-0.034	0.050	-0.003	-0.018
	(0.025)	(0.018)	(0.006)	(0.014)	(0.026)	(0.037)	(0.014)	(0.018)
Pilot3 x Post	-0.207***	-0.030	-0.016	-0.102**	-0.132**	-0.073	-0.024	-0.054
	(0.051)	(0.027)	(0.010)	(0.032)	(0.047)	(0.052)	(0.019)	(0.032)
Observations	12426	15125	16469	13119	9372	8367	11267	9835
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.9: **Trade Response Speed to Macro News**

This table reports tobit regression results of the following model: $Response_{i,t} = \alpha + \gamma_1 Post_t + \gamma_2 Pilot_i + \gamma_3 Post_t \times Pilot_i + \delta^{'} X_{i,t} + \epsilon_{i,t}$, where $Response_{i,t}$ measures how fast trade reacts to macro news for stock i on day t. $PriceResponse$ shows the amount of two minute return adjustment that takes place in the first 10 seconds after the release of the news. $VolumeResponse$ captures the amount of two-minute volume adjusted in the first 10 seconds after the news announcement. $QuoteResponse1$ is calculated as the proportion of quote adjusted (including both NBBO changes and depth at NBBO changes) in the first 10 seconds after the news announcement ($QuoteResponse1$). $QuoteResponse2$ only counts the number of NBBO changes and ignores depth at NBBO changes. In Panels A, B and C, we report results for groups 1, 2 and 3, respectively. We divide sample stocks into two groups based on their average quoted dollar spread before October 2016. Columns (1) to (4) report regression results for stocks with smallest dollar quoted spread, and Columns (5) and (8) report regression results for stock with largest dollar quoted spread. $Pilot_i$ is a dummy variable equal to 1 if a stock belongs to test group (i = 1, 2, 3), and 0 otherwise. We drop observations in October 2016. $Post_t$ is a dummy variable equal to 1 for dates on or after November 1, 2016, and 0 otherwise. X is a vector of control variables: share turnover, the inverse of the share price, the difference between the highest daily trading price and lowest daily trading price, sentiment score of the news, and time and stock primary listed exchange fixed effects. We cluster standard errors at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Pilot Group 1

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.052***	-0.006	-0.008***	-0.015***	-0.048***	0.009	-0.005*	-0.010**
	(0.005)	(0.005)	(0.002)	(0.003)	(0.006)	(0.009)	(0.002)	(0.003)
Pilot1	0.002	0.012	0.003	0.000	0.005	-0.004	0.002	0.001
	(0.006)	(0.007)	(0.003)	(0.003)	(0.006)	(0.013)	(0.003)	(0.003)
Pilot1 x Post	-0.226***	-0.031***	-0.009***	-0.110***	-0.176***	-0.034***	-0.039***	-0.097***
	(0.010)	(0.005)	(0.002)	(0.006)	(0.009)	(0.009)	(0.003)	(0.005)
Observations	1325399	1600058	1762163	1394940	1037394	882263	1293977	1101006
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Pilot Group 2

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.053***	-0.006	-0.009***	-0.014***	-0.054***	0.003	-0.009***	-0.015***
	(0.006)	(0.005)	(0.002)	(0.003)	(0.006)	(0.009)	(0.003)	(0.003)
Pilot2	0.004	0.003	0.002	-0.001	0.002	0.008	0.002	0.002
	(0.006)	(0.007)	(0.002)	(0.003)	(0.007)	(0.013)	(0.003)	(0.003)
Pilot2 x Post	-0.227***	-0.035***	-0.012***	-0.115***	-0.165***	-0.040***	-0.037***	-0.092***
	(0.012)	(0.005)	(0.002)	(0.006)	(0.010)	(0.009)	(0.003)	(0.005)
Observations	1334212	1595560	1764044	1404278	1014636	860891	1271277	1077517
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Pilot Group 3

	SMALL QUOTED SPREAD STOCKS				LARGE QUOTED SPREAD STOCKS			
	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2	PriceResponse	VolumeResponse	QuoteResponse1	QuoteResponse2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.058***	-0.007	-0.011***	-0.019***	-0.049***	-0.003	-0.006*	-0.010**
	(0.005)	(0.005)	(0.002)	(0.003)	(0.006)	(0.010)	(0.003)	(0.003)
Pilot3	-0.008	0.005	0.001	-0.004	0.000	-0.005	0.000	-0.002
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.014)	(0.003)	(0.003)
Pilot3 x Post	-0.187***	-0.022***	-0.004*	-0.099***	-0.171***	-0.037***	-0.034***	-0.091***
	(0.009)	(0.005)	(0.002)	(0.005)	(0.009)	(0.009)	(0.003)	(0.005)
Observations	1330619	1596422	1755728	1401470	1012806	860969	1270894	1077969
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 3

Multimarket High-Frequency Trading and Commonality in Liquidity

3.1 Introduction

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

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

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

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

In this paper, we examine the effect of multimarket HFT activity on systematic liquidity co-movements of stocks across different markets. Following Chordia, Roll, and Subrahmanyam (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. High-frequency traders share similar algorithms (Chaboud et al. 2014, Benos et al. 2015), which can lead to excess co-movements in their demand and supply, and consequently, to commonality in liquidity across stocks even within the same market. For example, 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. However, HFTs often engage in trading across multiple markets, which essentially connects these markets in a single network and might facilitate cross-market liquidity spillovers.[2] Specifically, we hypothesize that multimarket HFT activity induces stronger commonality in liquidity for stocks traded within the aggregate network of markets, even after controlling for their liquidity co-movements within their home market.

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

We use the staggered entrance of Chi-X, an alternative platform for trading European equities, as an instrument for an increase in multimarket high-frequency trading activity. Two main competitive advantages of Chi-X at the time of its introduction, compared to national stock exchanges, are its lower execution fees, and its 22 to 84 times faster speed of order processing. Both of these features should arguably attract high-frequency traders. Jovanovic and Menkveld (2016) and Menkveld (2013) indeed find that one large HFT takes part in 70-80% of Chi-X trades for Dutch and Belgian index stocks, and almost 10% of all trades for these stocks on their home market, Euronext. Essentially, it is acting as a multimarket liquidity provider, with 4 in 5 of its trades being passive in both markets. Importantly, Menkveld (2013) also shows that Chi-X market shares jump above 10% with the entry of this HFT, and drop almost to zero on days when it is absent from the market.

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

Since trading of European major index stocks on Chi-X was introduced in several phases, it allows us to clearly identify the causal effect of multimarket HFT activity on the systematic liquidity co-variations of stocks across European equity markets. Variation in Chi-X entry times into 11 different markets in our sample should alleviate valid concerns about general time trends in commonality in liquidity, or any potential effects of the financial crisis. Further, for the staggered introduction of Chi-X to be a valid instrument, it must satisfy the exclusion restriction, i.e. its entry dates must not be related to contemporaneous changes in systematic stock liquidity co-movements other than through the effect of HFT activity. However, such a relation is rather unlikely, since it would mean that Chi-X was able to accurately predict changes in systematic liquidity co-movements of stocks traded across 11 European markets. Importantly, the introduction of Chi-X makes it easier to simultaneously engage in fast trading of all major European equities on a single trading platform, hitherto not possible at a comparable speed. Even though Chi-X might be a primary trading platform for HFTs, multimarket HFT trading activity between Chi-X and home markets makes the liquidity of multiple European markets interconnected, potentially inducing stronger liquidity co-movements within the aggregate network of European markets.[3]

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

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

Understanding liquidity risks arising from multimarket HFT trading activity is important for policymakers, institutional investors, firms and virtually all market participants. Stronger co-variations in aggregate European liquidity make propagation of liquidity shocks easier across markets, increasing the risk of contagion and threatening the stability of global financial markets. Negative liquidity shocks are of special concern during crisis periods, because they imply higher

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

transaction costs and the inability to trade assets quickly without large impact on their prices.

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

In the next step, we examine EU liquidity betas, by adding fluctuations in liquidity of the FTSE Eurofirst 100, a pan-European index, to the model.[4] Consistent with our first prediction, EU liquidity betas significantly increase by almost 40%, relative to their mean level in the pre-Chi-X period. We use Scandinavian stocks that are not part of Eurofirst 100 as our control group, and in line with expectations, we do not find any evidence of significantly higher EU liquidity betas for these stocks. After we control for liquidity co-movements with the aggregate European market, an increase in home liquidity betas drops by almost half and is overall lower, as compared to an increase in EU liquidity betas. For a group of major European countries, including the UK, Germany and France, home liquidity betas actually drop in the post-Chi-X period. Overall, our findings suggest that European-wide liquidity co-variations have become stronger than co-variations within the home market following an increase in multimarket high-frequency trading activity. Additionally, subperiod splits show that liquidity co-variations with the aggregate European market are especially high in down markets, implying that multimarket HFT activity makes European equity markets more susceptible to the transmission of liquidity shocks during crisis periods.

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

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

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

to the daily level.

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

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

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

3.2 Institutional Background and Identification Strategy

3.2.1 Introduction of Chi-X

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

The first and the largest of the European MTFs is Chi-X, introduced by Instinet six months ahead of MiFID in April 2007. Similar to many national stock exchanges, it is organized as an electronic limit order book with a price-time priority rule. Two main competitive advantages of Chi-X are its lower execution fees and faster speed of order processing, or low latency.[5] 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.[6] 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.[7]

Chi-X is also the first pan-European trading platform, enabling simultaneous trading of all major European equities on a single venue. Figure 3.1 demonstrates how Chi-X serves as a connection link for individual European markets on an example of LSE and Euronext Paris. Importantly, the entry of Chi-X into European equity markets was staggered in several phases. German (DAX30) and Dutch (AEX) large-cap index stocks first started trading on its platform in April 2007. UK (FTSE100) and French (CAC40) stocks followed in July 2007 and October 2007, respectively. By the end of 2008, Chi-X expanded further into Belgian (BEL20), Scandinavian (OMXS30, OMXH25, OMXC20 and OBX), Spanish (IBEX35) and Italian (FTMIB) stocks. Figure 3.2 shows the timeline of Chi-X entrance into European equity markets and Appendix A lists Chi-X introduction dates for each country in our sample.

[Insert Figures 3.1 and 3.2 approximately here]

Chi-X market shares were initially low, but had increased to levels above 10% for the UK, France, Germany and the Netherlands by the end of 2008. By the beginning of 2010, they were already above 20% for these countries and started crossing the 10%-threshold for later entrants, such as Belgium, Sweden and Finland. Figure 3.3 and Table 3.1 present quarterly averages of Chi-X market shares by country. In 2011, Chi-X was taken over by BATS, a competitor MTF, resulting in its name change to BATS Chi-X Europe. However, the company still operates two separate limit order books: BATS CXE (Chi-X) and BATS BXE (BATS), which mainly differ in their fee structures.

[Insert Figure 3.3 and Table 3.1 approximately here]

By the end of 2014, Chi-X (BATS CXE) captured around 25% of trades for British, French, German, Dutch, Belgian, Finnish and Swedish stocks, and more than 15% of trades for remaining countries. Its market shares by far dominate the market shares of BATS and Turquoise, another MTF who entered the European market in fall 2008. In 2014, the Turquoise share was below 10% and the BATS BXE share below 5% for all major European stock indices.[8]

[5]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.

[6]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.

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

[8]Data on market fragmentation for all major European indices are provided by Fidessa on

3.2.2 Identification Strategy

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

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

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

Lastly, for the staggered introduction of Chi-X to be a valid instrument, it must satisfy the exclusion restriction, i.e., it should not be correlated with the error term in the explanatory equation. In other words, Chi-X entry dates must not be related to contemporaneous changes in systematic stock liquidity co-movements other than through the effect of HFT activity. We argue that such correlation with the error term is rather unlikely, since it would mean that Chi-

http://fragmentation.fidessa.com/europe.

X chooses its entry dates strategically and is able to accurately predict an increase in systematic liquidity co-movements across different countries. Further, we do not find any significant deviations of systematic stock liquidity co-movements from their unconditional means in the quarter preceding the introduction of Chi-X, which provides additional support for the exogeneity of our instrument.

3.3 Data and Sample Construction

3.3.1 Sample Construction

We download the composition of main European stock indices over the period January 2004 - December 2014 from the Thomson Reuters Tick History (TRTH) database. Countries covered in this paper are Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, and the United Kingdom. Table 3.2 lists the corresponding index for each country. Our initial sample consists of all stocks that constitute these indices during our sample period. If the composition of an index changes, we keep both old and new index constituents for the entire sample period to keep the number of firms in our sample constant.

We concentrate our analysis on the main European stock indices for two reasons. First, at the time of the introduction of Chi-X to each country, it is possible to trade only this country's main index constituents, with mid-cap and other stocks starting their trading only later on the Chi-X platform. Second, constituents of main indices represent the largest and the most liquid stocks in each country, which should encourage the active participation of high-frequency traders. Panel A of Table 3.2 reports the number of distinct firms and Panel B the number of firm-month observations for each country.

[Insert Table 3.2 approximately here]

The initial sample consists of 539 firms. In the first step, we filter out Reuters Instrument Codes (RICs) that appear to be erroneously reported as an index constituent by TRTH (Filter 1).[9] Appendix B provides details of our data cleaning procedure. We further require the stock price to be greater than 2 at the end of the previous trading day for UK stocks, and greater than 2 for other European stocks (Filter 2).[10] Lastly, we require the stock to be traded for at least 1,000 different 5-minute intervals in a given month. Excluding the stocks that do not satisfy the criteria above leaves 445 firms and 50,278 firm-months in our final sample.

3.3.2 Measuring Liquidity

Given that high frequency traders have relatively short trading horizons, we opt for the 5-minute quoted relative spread as the benchmark measure in our analysis.[11] Formally, we calculate the quoted relative spread, *qspread*, as

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

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

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

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

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

Following Chordia, Roll, and Subrahmanyam (2000), we calculate first differences of the relative quoted spread, $\triangle qspread$, to capture fluctuations in intraday liquidity.[12] 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.[13] Specifically, for stock i and interval t, $\triangle qspread_{i,t}$ is standardized by the monthly mean and standard deviation of $\triangle qspread$ estimated for stock i in the corresponding hour h across all days.

Arguably, liquidity co-variations on a daily basis might be more important for lower-frequency traders, such as institutional and retail investors. With short trading horizons of high frequency traders, it is *ex ante* not clear whether stronger intraday liquidity co-variations also aggregate to the daily level. Therefore, we also present results for daily closing bid-ask spreads and the Amihud measure of liquidity in our section with robustness checks.[14] 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.[15] Importantly, we find even stronger liquidity co-variations on the daily level in the post-Chi-X period, which suggests that intraday liquidity co-variations indeed aggregate to the daily level.

3.3.3 Summary statistics

Table 3.3 presents summary statistics of market capitalization (Panel A) and the relative quoted spread (Panel B) across all sample stocks separately for each country. Our main data source for prices, volume traded and bid-ask spreads is TRTH. Data on market capitalization, *firm size* (in millions of euros), are from Datastream. Appendix C provides a detailed description of variable definitions.

[Insert Table 3.3 approximately here]

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

[13]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.

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

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

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

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

3.4 HFT Activity and Liquidity Co-variations

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

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

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

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

$\Delta qspread_{Home,t,d}$, for all 5-minute intervals t and all trading days d in a given month:

$$\Delta qspread_{i,t,d} = \alpha + \beta_{i,Home} \Delta qspread_{Home,t,d} + \varepsilon_{i,t,d}. \tag{3.1}$$

As in Kamara, Lou, and Sadka (2008) and Koch, Ruenzi, and Starks (2016), we calculate $\Delta qspread_{Home,t,d}$ as the cross-sectional value-weighted average of $\Delta qspread_{j,t,d}$ for all stocks in the home country index (e.g., FTSE100 for UK stocks) with $j \neq i$.[16] Our main coefficient of interest is $\beta_{i,Home}$, which captures the sensitivity of the stock's liquidity to the aggregate home market liquidity, or its systematic liquidity co-movement with the home market. In the following, we refer to $\beta_{i,Home}$ as home liquidity beta.

[Insert Figure 3.4 approximately here]

Figure 3.4 displays three-month moving averages of home liquidity betas, aggregated across all stocks in our sample. It depicts a significant overall increase in systematic liquidity co-movements of stocks over time, starting with the average liquidity beta of around 0.13 at the beginning of 2005, rising up first to 0.28 by 2009 and further to 0.47 by the end of 2014. These general time trends in liquidity betas can potentially be explained by the financial crisis of 2008-2009, turmoil on European financial markets in 2010-2011 due to the debt crisis in Greece, and subsequent market stabilization in 2012. Even though all these factors undoubtedly contribute to variation in liquidity betas, our aim is to separate the effect of multimarket HFT activity from other concurrent events. To this end, we use the staggered entry of Chi-X into European financial markets as our instrument for an exogenous increase in HFT activity, and compare home liquidity betas in the pre- and post-Chi-X periods in the next step.

Home liquidity co-variations: Pre- vs Post-Chi-X. We first start with the univariate analysis of the pre- and post-Chi-X home liquidity betas. For each country, Table 3.4 reports the averages of liquidity betas across all stocks and months in our sample, separately in the pre- and post-Chi-X periods. We further report the difference in liquidity betas between the two periods, $Diff$, and test whether it is significantly different from zero.

[Insert Table 3.4 approximately here]

Our benchmark definition of the post-Chi-X period is based on the month, when the average Chi-X market share for a given country index reaches 10%. Our reasons for choosing the 10% cutoff as our benchmark are twofold. First, we would like to ensure that there is a substantial amount of trading in the index constituents on the Chi-X platform. Indeed, Table 3.1 shows that when Chi-X is initially introduced in a country, its market share is usually at most 1%. It takes around one year for most of the countries to reach a market share of 10%, with Norway, Denmark and Spain taking exceptionally long - around three years after the initial introduction of the Chi-X platform. Our second reason for choosing the 10% cutoff point is based on empirical evidence from Menkveld (2013), who finds that the Chi-X market share for Dutch stocks jumps above 10% only with the entry of a multimarket high-frequency trader. We provide further robustness checks of our definition of the post-Chi-X period in Section 5.

[16]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.

From Table 3.4, we observe that the average post-Chi-X home liquidity beta increases by 0.27, from 0.19 to 0.46, and this increase is statistically significant at the 1% level. This finding provides the first empirical evidence consistent with our hypothesis that HFT activity induces stronger liquidity co-movements in the home market. Importantly, we observe a significant increase in home liquidity betas for all countries in our sample. Home liquidity betas in the UK, Germany and France increase by 0.28-0.30. The highest increase of 0.38 is observed for Swedish stocks and the lowest increase of 0.07-0.08 for Norwegian and Danish stocks, which can potentially be explained by the prolonged time period that Norway and Denmark take before their Chi-X market shares reach a significant level of 10%.

In the next step, we test our prediction in the multivariate setup, controlling for stock characteristics, time- and country-fixed effects. Specifically, we run a panel OLS regression of β_{Home}, estimated for each stock i in month m, on the dummy variable, $Post$, which equals 1 for all months after the country's Chi-X market share reaches 10%, and is zero otherwise. The vector of standardized control variables includes the log of market capitalization at the end of the previous month, $ln(firm\,size)_{i,m-1}$; the average 5-minute quoted spread, calculated over the previous month, $qspread_{i,m-1}$; the year-fixed, YFE, and country-fixed effects, CFE.[17] We allow standard errors to cluster at the firm level in order to account for cross-sectional dependence. Our specification is as follows:

$$\beta_{Home,i,m} = \alpha + \gamma_1 Post_{i,m} + \gamma_2 ln(firm\,size)_{i,m-1} + \gamma_3 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}. \quad (3.2)$$

The inclusion of year-fixed effects eliminates shocks to the systematic liquidity co-movements that are common to all countries, whereas country-fixed effects control for general levels of home liquidity betas within each country. Therefore, given the year- and country-fixed effects, our identification stems from cross-country variation in the $Post$ dummy: we compare systematic liquidity co-movements for index stocks that have already started their trading on the Chi-X platform (and have reached a 10% market share) to those that are not traded yet, and thus represent the control group in the current month. For unrelated shocks to affect our results, they would have to be correlated with Chi-X entry dates across all countries in our sample, which, in our view, is rather unlikely.[18]

[Insert Table 3.5 approximately here]

Model (1) of Table 3.5 reports results for the total sample. Consistent with our expectations, home liquidity betas significantly increase on average by 0.07 after the introduction of Chi-X, which represents a 37% increase relative to their mean of 0.19 in the pre-Chi-X period. This 37% increase is both statistically and economically significant. Our control variables also

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

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

display expected signs: larger stocks and stocks that are more liquid exhibit in general stronger systematic co-movements with aggregate home market liquidity, consistent with prior findings of Kamara, Lou, and Sadka (2008) and Koch, Ruenzi, and Starks (2016).

Models (2) to (4) present results for subsample splits across different countries. To conserve space, we pool 11 individual countries into three country groups, based on their Chi-X entry times. Model (2) reports our findings for the first group of major European countries, the indices of which started trading on Chi-X soon after its entry in 2007: the UK, France, Germany, the Netherlands and Belgium.[19] Surprisingly, we do not observe any significant increases in home liquidity betas for this country group, after we control for size, liquidity, year- and country-fixed effects. In contrast, we find a significant increase of 0.05 in home liquidity betas of four Scandinavian countries, which started trading on Chi-X in the first two quarters of 2008 (our second country group). Given their average pre-Chi-X home liquidity betas of 0.04-0.06, an increase of 0.05 suggests that liquidity co-movements with the home market have doubled for Scandinavian stocks. Model (4) shows an even more significant increase of 0.14 in home liquidity betas for our third group, consisting of Italy and Spain, which start trading on Chi-X in the last two quarters of 2008.

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

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

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

$$\Delta qspread_{i,t,d}, = \alpha + \beta_{i,HomeExclEU} \Delta qspread_{Home,t,d} + \beta_{i,EU} \Delta qspread_{EU,t,d} + \varepsilon_{i,t,d}. \tag{3.3}$$

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

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

We refer to $\beta_{i,EU}$ as EU liquidity beta.

We choose FTSE Eurofirst 100 as our proxy for the aggregate European market, because it is a pan-European index, which consists of the 60 largest European companies ranked by market capitalization, and 40 additional companies chosen on the basis of their size and sector representation by the FTSE Group. Table 3.6 presents the composition of FTSE Eurofirst 100 during our sample period.

[Insert Table 3.6 approximately here]

We aggregate all statistics on the country level and report country codes in the first column. The second column shows the number of distinct companies in each country that represent a part of the index. As with home country indices, if the composition of Eurofirst 100 changes, we keep both old and new index constituents for the entire sample period to avoid any biases, such that the total number of companies in the index increases to 127 over 2004-2014. We report the average daily number of shares (in thousands) and euro volume (in millions) of index constituents traded in each country in the third and fourth columns, respectively. The last column displays the daily euro volume of index constituents for each country as a percentage of the total daily Eurofirst volume.[20]

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

[Insert Figure 3.5 approximately here]

Figure 3.5 displays the development of EU and home liquidity betas, estimated from equation (3), over our sample period. The solid line shows the three-month moving average EU liquidity betas, β_{EU}, and the dashed line the corresponding values for home liquidity betas, $\beta_{HomeExclEU}$, over 2005-2014. Importantly, both EU and home liquidity betas increase significantly over the decade. However, EU liquidity betas start dominating home liquidity betas in early 2008 and reach their peak level of 0.38 in 2011. By contrast, the level of home liquidity betas practically never exceeds 0.30. These findings suggest that liquidity co-variations with the aggregate European market have become more important in recent years, as compared to the co-variations with the home market.

European-wide liquidity co-variations: Pre- vs Post-Chi-X. To examine the effect of multimarket HFT activity on European-wide liquidity co-variations, we first compute the difference between average pre- and post-Chi-X EU liquidity betas. Our univariate tests

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

show that the average post-Chi-X EU liquidity betas increase by 0.18, from 0.15 to 0.33, and this increase is statistically significant at the 1% level. We do not report these results, but they are available upon request.

In the next step, we re-estimate our specification from equation (2) with $\beta_{i,EU}$ as the dependent variable, again controlling for firm size, average relative spread, year- and country-fixed effects. Panel A of Table 3.7 reports the results. It has the same layout as Table 3.5, presenting results first for the total sample, followed by subsample splits for three country groups and for subperiods of down and up markets.

[Insert Table 3.7 approximately here]

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

Panel B shows the corresponding results for home liquidity betas, estimated after additionally controlling for EU liquidity betas from equation (3), $\beta_{i,HomeExclEU}$. For brevity, we report coefficients only on our main variable of interest, *Post*, but all regressions also include controls, year- and country-fixed effects. The coefficient on *Post* for home liquidity betas drops by more than half, from 0.07 to 0.033, after controlling for EU liquidity betas. This result suggests that liquidity co-variations with the home market become actually less important in the post-Chi-X period, after we control for liquidity co-movements with the aggregate European market. For our first country group (GB, FR, DE, NL, BE), liquidity co-variations with the home market even drop significantly in the post-Chi-X period (Model 2). The insignificant coefficient on *Post* from Table 3.5 for these countries can thus be decomposed into significant increase in EU liquidity betas and a simultaneous decrease in home liquidity betas. For Scandinavian countries, representing our control group, home liquidity betas are still significantly higher in the post-Chi-X period, consistent with our previous results from Table 3.5. Interestingly, for Italy and Spain, home liquidity betas also increase in the post-Chi-X period, which suggests that both EU and home liquidity co-variations become stronger for these countries in recent years.

The last two columns of both panels present results for subperiods of down and up markets, correspondingly. EU liquidity betas are significantly higher both in down and up markets in the post-Chi-X period, with a higher coefficient of 0.071 for down markets. In contrast, home liquidity betas increase significantly only in up markets. These findings suggest that with a rise in multimarket HFT activity European-wide liquidity co-variations dominate co-variations with the home market during crisis periods. We observe similar results in Figure 3.5. Consistent with our multivariate analysis, EU liquidity betas increase during the financial crisis of 2008-2009, whereas home liquidity betas simultaneously drop over this period.

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

3.4.3 Intensity of HFT Trading Activity and Liquidity Co-variations

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

$$\begin{aligned} \beta_{EU,i,m} &= \alpha + \gamma_1 High\,HFT\,Activity_{i,m} \cdot Post_{i,m} + \gamma_2 Low\,HFT\,Activity_{i,m} \cdot Post_{i,m} + \\ &+ \gamma_3 ln(firm\,size)_{i,m-1} + \gamma_4 qspread_{i,m-1} + YFE + CFE + \varepsilon_{i,m}. \end{aligned} \tag{3.4}$$

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

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

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

$$\begin{aligned} \triangle Vol_{i,t}^{Home} &= \alpha_i^{Home} + \gamma_i^{Home} \triangle Vol_{i,t-1}^{Home} + \beta_i^{Chi-X} \triangle Vol_{i,t-1}^{Chi-X} + \delta_i ret_{i,t} + \varepsilon_{i,t}^{Home} \\ \triangle Vol_{i,t}^{Chi-X} &= \alpha_i^{Chi-X} + \gamma_i^{Chi-X} \triangle Vol_{i,t-1}^{Chi-X} + \beta_i^{Home} \triangle Vol_{i,t-1}^{Home} + \delta_i ret_{i,t} + \varepsilon_{i,t}^{Chi-X}, \end{aligned} \quad (3.5)$$

where $\triangle Vol_{i,t}$ is the change in the trading volume, calculated as the logarithm of the ratio of interval t to interval $t-1$ euro (pound) trading volume.[21] We also control for the firm's stock return in the home market, ret, to account for unexpected volume that might be related to trading on an information signal. *Multimarket Trading* for stock i in month m is calculated as the contemporaneous correlation between the unexpected trading volume in the home market, $\varepsilon_{i,t}^{Home}$, and on the Chi-X platform, $\varepsilon_{i,t}^{Chi-X}$. The higher the correlation in trading volume shocks between the two markets, the more intensive is the multimarket trading of this stock. Since trading across multiple markets requires costly technological investment and continuous monitoring, it is plausible to assume that multimarket trading between Chi-X and the home market is to a large extent driven by liquidity demanding high-frequency traders.

[Insert Table 3.8 approximately here]

Table 3.8 reports annual averages of the *Multimarket Trading* measure for each country since the introduction of Chi-X in 2007. On average, the correlation in unexpected trading volumes between Chi-X and the home market increases from 0.34 in 2007 to 0.68 in 2010, and continues to stay at this relatively high level until the end of our sample period. This considerable increase in the intensity of multimarket trading is also consistent with the rise in high-frequency trading over recent years.

We report our findings on the cross-sectional differences in liquidity co-movements in Table 3.9. The first three models use *Chi-X market share* and the last three models *Multimarket Trading* as our measure of HFT activity. For each of the two measures, we first present results for the total sample, followed by sample splits for down and up markets.

[Insert Table 3.9 approximately here]

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

Next, we split our total sample into subperiods of down and up markets, using the same definition as in the previous section. For *Chi-X market share*, we observe that γ_1 continues

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

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

3.5 Robustness checks

Daily liquidity measures. As our first robustness check, we repeat our analyses from Tables 3.5 and 3.7 with two daily liquidity measures: the daily relative spread and the Amihud measure, *illiq*.[22] *Ex ante,* it is not clear whether intraday liquidity co-variations also aggregate to the daily level.[23] However, daily liquidity co-variations might be of higher importance for institutional and retail investors, because they have longer trading horizons than high-frequency traders.

Since there is now only one observation per day for each liquidity measure, we can no longer estimate liquidity betas on the monthly basis and therefore re-estimate equations (1) and (3) to obtain β_{Home}, β_{EU} and $\beta_{HomeExclEU}$ for each stock and each quarter. Afterwards, we re-estimate our specification from equation (2) with each of the three betas as the dependent variable. *Post* now takes value of 1 starting in the quarter when the country's Chi-X market share reaches 10%, and is zero otherwise. We also include firm size and average liquidity over the previous quarter as control variables. Panel A of Table 3.10 presents results. To conserve space, we only report the coefficient on *Post* for each specification. The first three columns present results for the daily relative spread and the last three columns for the Amihud measure.

[Insert Table 3.10 approximately here]

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

Assessing benchmark treatment dates. In the next step, we conduct placebo tests to assess whether our treatment dates, based on the month when the average Chi-X market share for a given country index reaches 10%, provide reasonably sharp identification with respect to changes in systematic liquidity co-movements. In particular, we randomly assign our treatment dates between the first month of 2004 and the last month of 2014. Using 5,000 replications,

[22] Please refer to Section 3.3.2 for detailed definitions of both measures.

[23] 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.

we repeat our analyses from Tables 3.5 and 3.7 with 5-minute spreads and summarize the distributions of the coefficients and t-statistics on *Post* in Panel B of Table 3.10. We report the average, 5th and 95th percentiles across the 5,000 replications. We also report the percentiles of our actual estimates and t-statistics in the last row.

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

3.6 Conclusions

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

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

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

3.7 Appendix A: Chi-X Inclusion Date

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

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

3.8 Appendix B: Thomson Reuters Tick History (TRTH) Data Filtering

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

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

3.9 Appendix C: Variable Definitions

Variable	Description	Source
Chi-X Market Share	Chi-X market share, defined as the ratio of the daily volume traded on Chi-X relative to the total daily volume traded on both Chi-X and the home exchange.	TRTH
$firm\,size$	Market capitalization (in / million) at the end of each quarter t	Datastream
High HFT Activity	A dummy variable, which equals 1 for stocks with above median intensity of HFT activity in our sample, and is zero otherwise. We use either *Chi-X market share* or *Multimarket Trading* to measure intensity of HFT activity.	TRTH
illiq	The Amihud (2002) measure, calculated as the ratio of the absolute daily price change, $\lvert R_{i,d}\rvert$, to the daily euro (pound) volume traded (in millions) on the stock's primary exchange, $DVol_{i,d}$: $illiq_{i,d} = \frac{\lvert R_{i,d}\rvert}{DVol_{i,d}}$. We calculate $illiq(avg)$ as the quarterly average of the daily Amihud (2002) measure.	TRTH
Low HFT Activity	A dummy variable, which equals 1 for stocks with below median intensity of HFT activity in our sample, and is zero otherwise. We use either *Chi-X market share* or *Multimarket Trading* to measure intensity of HFT activity.	TRTH
Multimarket Trading	The *Multimarket Trading* measure of Halling, Moulton, and Panayides (2013)., estimated from the following VAR model: $\triangle Vol_{i,t}^{Home} = \alpha_i^{Home} + \gamma_i^{Home} \triangle Vol_{i,t-1}^{Home} + \beta_i^{ChiX} \triangle Vol_{i,t-1}^{ChiX} + ret_{i,t} + \varepsilon_{i,t}^{Home}$ $\triangle Vol_{i,t}^{ChiX} = \alpha_i^{ChiX} + \gamma_i^{ChiX} \triangle Vol_{i,t-1}^{ChiX} + \beta_i^{Home} \triangle Vol_{i,t-1}^{Home} + ret_{i,t} + \varepsilon_{i,t}^{ChiX}$ where $\triangle Vol_{i,t}$ is the change in the trading volume, calculated as the logarithm of the ratio of interval t to interval $t-1$ euro (pound) trading volume; and $ret_{i,t}$ is the firm's stock return in the home market. *Multimarket Trading* for stock i in month m is calculated as the contemporaneous correlation between $\varepsilon_{i,t}^{Home}$and $\varepsilon_{i,t}^{ChiX}$.	TRTH
POST	A dummy variable, which equals 1 for all months after the country's Chi-X market share reaches 10%, and is zero otherwise.	TRTH

Variable	Description	Source
qspread	The quoted relative spread, calculated as $qspread_{i,t} = \frac{A_{i,t}-B_{i,t}}{(A_{i,t}+B_{i,t})/2}$, where $A_{i,t}$ is the ask price and $B_{i,t}$ the bid price prevalent for stock i on its primary exchange at the end of the 5-minute interval t. We delete observations with negative spreads or spreads exceeding 20%, and winsorize the upper and lower 1% of the *qspread* distribution to avoid outliers.	TRTH
ret	The firm's stock return in the home market	TRTH

Figure 3.1: **Chi-X as a connection link for fragmented European markets**

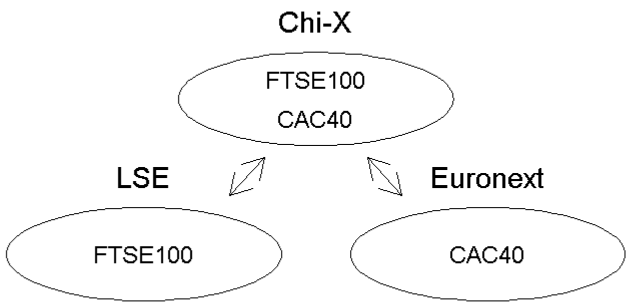


Figure 3.2: **Staggered entrance of Chi-X into European equity markets**

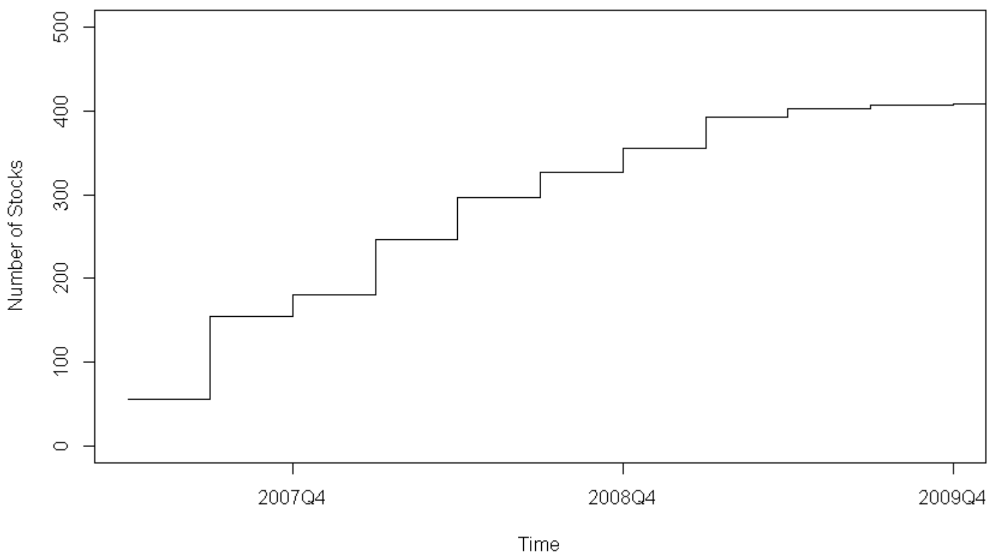


Figure 3.3: **Chi-X Market Share by Country.**

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

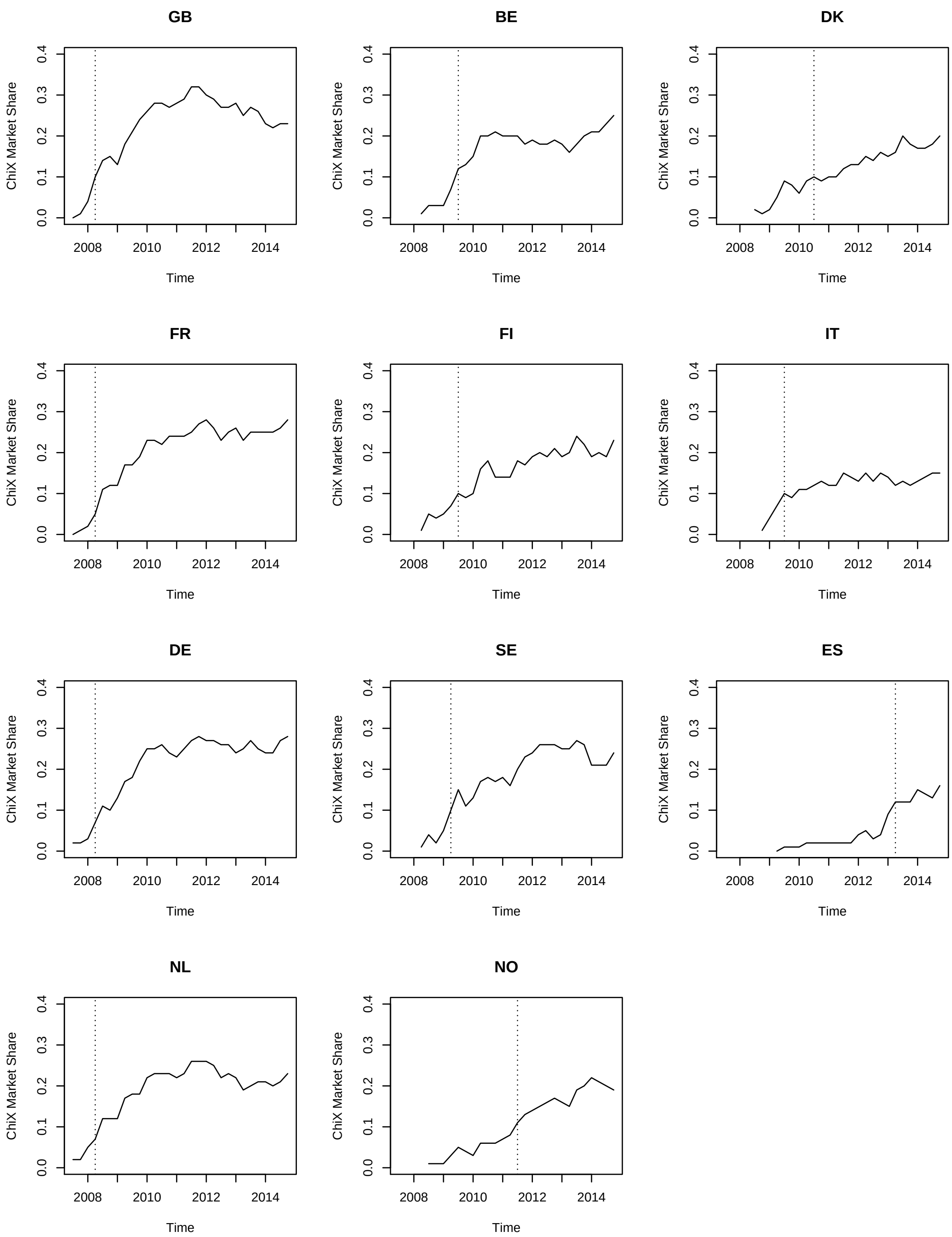


Figure 3.4: **Development of Aggregate Home Liquidity Betas over Time.**

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

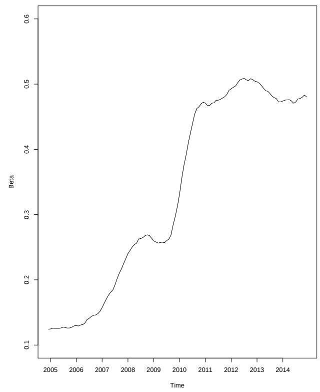


Figure 3.5: **Development of Aggregate EU and Home Liquidity Betas over Time.**

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

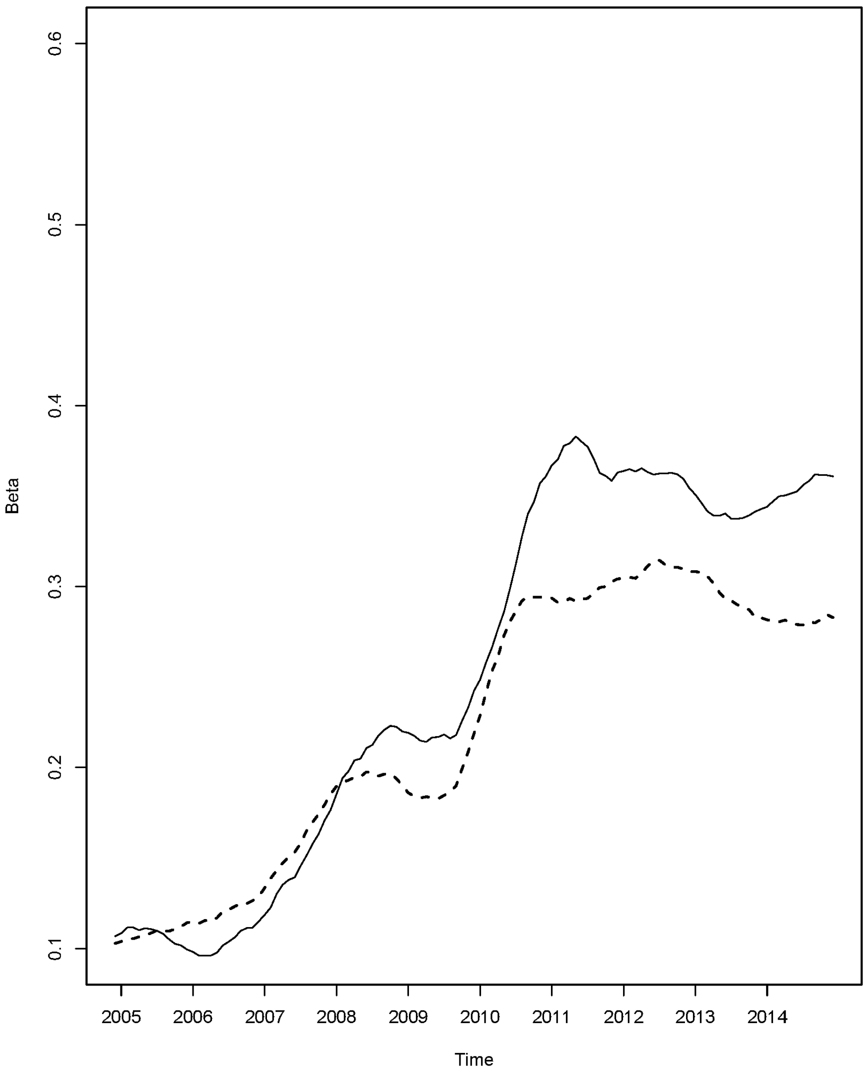


Table 3.1: **Chi-X Market Share by Country.**

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

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

Table 3.2: **Sample Construction.**

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

Panel A: Number of Distinct Firms

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

Panel B: Number of Firm-Month Observations

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

Table 3.3: **Summary Statistics.**

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

Panel A: Summary Statistics for *firm size*

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

Panel B: Summary Statistics for *qspread*

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

Table 3.4: **Liquidity Co-movements with the Home Market: Univariate Analysis.**

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

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

Table 3.5: **Liquidity Co-movements with the Home Market: Multivariate Analysis.**

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

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

Table 3.6: **Composition of FTSE Eurofirst 100.**

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

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

Table 3.7: **Liquidity Co-movements with the European market: Multivariate Analysis.**

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

Panel A: EU Beta

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

Panel B: Home Beta, after Controlling for EU Beta

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

Table 3.8: **Multimarket Trading by Country.**

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

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

Table 3.9: **Intensity of HFT Trading Activity and Liquidity Co-movements with the European market.**

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

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

Table 3.10: **Robustness checks.**

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

Panel A: Daily Liquidity Measures

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

Panel B: Placebo regressions

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

Chapter 4

Institutional Trading Costs and Intraday Returns

4.1 Introduction

Trading cost is an important determinant of institutional investors' performance as large trading cost can erode or eliminate the value added by portfolio managers. Keim and Madhavan (1995) provide evidence that arbitrageurs and investors, who try to follow a particular index are concerned about delay cost. This is also highlighted by Schwartz and Steil (2002) in a survey of chief investment officers (CIOs) of 72 major asset management firms in North America, Europe and Australia with an asset management of $2.1 trillion, show that large institutions rank execution cost and speed as important determinants of how they choose brokers. It is not surprising that fund managers devote significant efforts to developing their execution strategies and transaction cost analysis (TCA).

In this paper, we postulate that sub-optimal execution by trading desks leads to predictable patterns in trading volume and return predictability among common stocks. We divide the trading day into 13 half-hour trading intervals to study the nature of intraday return predictability. Consistent with the previous literature and Heston et al. (2010), we find the presence of negative autocorrelation in intraday stock return. Intraday negative autocorrelation in returns is often associated with temporary price pressure due to risk-averse intermediaries charging price impact for temporarily holding the position in the absence of a natural counterparty. For example, Kraus and Stoll (1972) shows the existence of price pressures by studying large institutional trades. These transitory price effects, intraday return reversal and their relation to intraday pattern of how trading desks work their trades are the focus of this study.

We find that temporary price pressure is larger and more prevalent at the beginning and the end of the trading day. This suggests the predictability of large uninformed institutional trades within a trading day. While Guercio and Tkac (2002), Frazzini and Lamont (2008), and Lou (2012) find evidence of persistent fund flows into and out of mutual funds that induces return predictability across days, it is unlikely that fund flows explains the intraday pattern of institutional trades. Often portfolio managers rely on buyside trading desks in order to implement their investment ideas. A trading desk adds value to their clients by supplying expertise in locating counterparties and formulating trading strategies. For example, a trading desk formulates a set of choices to meet its best execution obligation through the trading venues, order splitting strategies, broker choice and timing of the trades. We conjecture that the execution strategy of trading desks is one of the determinants of the intraday predictability of institutional trades and return reversals.

To study the economic reasoning behind this price pressures predictability, we investigate if the periodity is indeed driven by suboptimal trading desk execution. We first show that trading volume exhibits similar intraday pattern as price pressures. In addition, we relate the periodity of price pressures to trading desks' performance using a proprietary database of institutional investor equity transactions compiled by ANcerno Ltd. (formerly the Abel/Noser Corporation).

The data contain approximately around 20 million tickets involving $2 trillion dollars that are initiated by 136 institutional investors over the period from 2006-2010. The ANcerno database is distinctive in that it contains a detailed history of trading activity by each institution. Furthermore, the dataset provides information on tickets sent by an institution to a broker; each ticket typically results in more than one execution. The data for each ticket include stock identifiers that help in obtaining relevant data from other sources and, more importantly for this study, codes that identify the institution and the broker. The detailed transaction-level ANcerno dataset seems particularly well suited for studying the performance of trading desks and their relation to intraday return predictability.

We find that execution quality is the worst at the end of the day yet institutional trading volume is surprisingly highest at the end of the day. Dividing brokers into good and bad performing, we find that poorer performing brokers trade more in the last hour of the day. Poorer performing brokers also have a higher execution cost at the end of the day and carry out less order splitting at the end of the day. We observe persistence in the performance of buy-side institutional desks and sell side brokers. Our findings suggest that intraday price pressure stems from execution strategies of under-performing trading desks end of the day clustering results in higher trading costs and poorer execution quality. To estimate the economic significance of these suboptimal trade execution, we set up a trading strategy to exploit these intraday predictability like a predatory anticipatory traders. Our trading strategy yields an economically and statistically significant monthly return of 16.11%. Our results have implications on the impact of broker selection and execution strategy on trading costs.

Our paper is related to the literature on intraday asset prices and on heterogeneity in transaction costs across intermediaries. Existing studies, such as Chordia et al. (2011); Cprwin and Schultz (2012), focus on intraday trading activity and volatility. Heston et al.(2010) find a striking intraday pattern that returns on certain individual stocks tend to persist at the same half-hour intervals across trading days, and that this pattern can last for up to 40 trading days. Keim and Madhavan (1997) and Linnainmaa (2007) show dispersion in trading costs of institutions and mutual funds across retail and institutional broker types. Anand et al. (2012) examine persistence in trading performance of buy-side institutional desks and sell-side brokers. We complement these literature by focusing on short-term return reversal and intraday price pressure and relating these patterns to specific intermediaries.

4.2 Data and Variable description

Our analysis comprises two different samples: the U.S. sample and the European sample of stocks. Our U.S. sample of firms consists of all New York Stock Exchange (NYSE) listed firms from January 2006 through December 2010 that we are able to match with the NYSE Trade and Quotation (TAQ) database. We retain only assets whose CRSP share codes are 10 or 11, that is, we discard certificates, American Depositary Receipts, shares of beneficial interest, units, companies incorporated outside the United States, Trusts, closed-end funds, preferred stocks, and REITs. As a result our sample consisted of 1,715 firms. We use the TAQ database to calculate intraday stock returns.

The European dataset covers stocks traded in Austria, Belgium, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and United Kingdom, between January 2002 and December 2012. We obtain the intraday trade and quote price for each company from Thomson Reuters Tick History (TRTH) dataset. Figure 4.1 provide summary on the number of stocks per country in our sample. About 51% of our sample comes from Germany, following by the UK, France, Sweden and Switzerland. The stocks from the remaining countries constitute less than 5% each. Every country has at least 149 firms.

Insert Figure 4.1 about here

Institutional investor trading data comes from ANcerno database. Summary statistics for ANcerno's trade data are presented in Table 4.1. This database covers a total of 136 different mutual funds during our sample period. Institutions in the ANcerno database are responsible for approximately 20 million tickets involving more than $2 trillion in trading volume. The data contains a detailed history of trading activity by each institution, such as the CUSIP of the traded stock, direction and volume of trade, prices and time of the trade. It also contains information on tickets sent by an institution to a broker. The data for each ticket include stock identifiers, codes that identify the type of the institution and the broker.

Insert Table 4.1 about here

For each stock i we calculate log returns $ret_{i,t}$ over half-hour interval t. That is, for each trading day, we compute 13 intraday intervals from 9:30 a.m. to 4:00 p.m. excluding after-hour trading and overnight open-close price movements.

In addition to returns, we also measure trade imbalance $tib_{i,t}$ for stock i at time interval t as the overall dollar volume difference between buying initiated and seller intimated trades during time interval t. As the TAQ data does not contain trade direction, we sign trades using Lee and Ready (2011) signing algorithm.

In addition to market-wide trade imbalance we also compute institutional trade imbalance $itib_{i,t}$ for stock i as the dollar volume difference between buying initiated and seller intimated institutional trades during time interval t. Variable $itrvol_{i,t}$ denotes institutional trading volume in stock i at time t.

Finally, we consider execution shortfall as a measure of execution costs. Execution shortfall $shortfall_{b,t}$ is defined as the difference between the execution price of a ticket τ and the stock price when the trading desk sends the ticket to the broker:

$$shortfall_{b,\tau} = \frac{P_1(b,\tau) - P_0(b,\tau)}{P_0(b,\tau)} \times D(b,\tau), \tag{4.1}$$

where $P_1(b,\tau)$ is the value weighted execution price of ticket τ, $P_0(b,\tau)$ is the price at the time when the broker b receives the tickets, and $D(b,\tau)$ is a variable that equals to 1 for buy tickets and -1 for sell tickets. ANcerno database provides the execution prices for each trade across funds and stocks. It also reports time of the ticket reception which can be used along with a high-frequency database, like TAQ or Tick History Thomson Reuters to infer $P_0(b,\tau)$.

4.3 Empirical Results

We begin this study by measuring the intraday price pressure in the cross-section of U.S. stock returns for each half-hour interval. It is well known that short-term stock returns are negatively autocorrelated (e.g. Lehmann, 1990; Lo and MacKinlay, 1990). Although this phenomenon does not occur in the model of Glosten and Milgrom (1985), in which the spreads are due solely to adverse selection caused by informed traders, it appears in other models with bid-ask spreads (Glosten and Harris, 1988; Roll, 1984) or specialist inventory effects (Stoll, 1978). Here we study temporary price pressure or reversal of stock prices based on the pattern of autocorrelation over various horizons.

We analyze intraday stock returns using the cross-sectional methodology of Heston et al. (2010). We run cross-sectional regressions of half-hour stock returns on returns lagged by $j \in \{1, ..., 13\}$ half-hour intervals,

$$r_{i,t} = \alpha_t + \beta_{1,t} r_{i,t-1} + ... + \beta_{13,t} r_{i,t-13} + u_{i,t}, \tag{4.2}$$

where $r_{i,t}$ is the return on stock i in the half-hour interval t. The slope $\beta_{k,t}$ represent the response of returns at half-hour t to returns over interval lagged by k half-hour periods. We use all firms with returns available in intervals from t to $t-13$. We present unconditional return responses, averaging over different times of the day. We calculate the pattern of return effects by averaging return responses over time for half-hour lags k. Note that using cross-regression in this way is different from measuring the autocorrelation returns. In particular, the cross-sectional regression subtracts an overall market effect, which reduces variance and focuses on returns relative stocks.

Table 4.2 presents the average return responses across different lags for lags up to 13 half-hour intervals (see column *All*. Consistent with the previous literature, the first six lags of return responses are negative and statistically significant.

The largest impact is at the first half-hour lag. An increase in the previous half-hour return is associated with 0.14% decline of the following half-hour return. This means that stock returns experience a reversal period lasting on average three hours.

Insert Table 4.2 about here

To see further when the price reversals are the strongest, we compute the average past return responses for opening (see column *Open* of Table 4.2), closing (column *Close*) and the remaining middle of the day half-hour intervals (column *Middle*). The pattern is similar across all three categories. The strongest reversal effect is during the opening half-hour. Figures 4.2 and 4.3 illustrate these findings.

Insert Figures 4.2 and 4.3 about here

The effect indicates that there is a substantial and statistically significant price pressure occurring during the day with a pronounced U-shaped intraday pattern. This suggest a substantial amount of uninformed trading that happens systematically at the same time intervals.

To see if the intraday price pressure is purely the U.S. phenomenon or is it also present in international markets we perform similar analysis using the data from European market[1] We perform similar cross-sectional regression in the cross section of all European stocks. This allows us to identify return predictability that are common across countries.

Given that European markets open in total for 8.5 hours, we divide every trading day into 17 half-hour trading intervals. Similar to Heston et al. (2010), we analyze intraday stock returns using the cross sectional regression similar to Equation (4.2). That is, for each half-hour interval t, we run the cross sectional regression of half-hour stock return on returns lagged by 17 half-hour period and country fixed effects:

$$r_{i,t} = \alpha_t + \beta_{1,t} r_{i,t-1} + ... + \beta_{13,t} r_{i,t-17} + \sum_{j=1}^{12} \omega_{i,j,t} I_{i,j} + u_{i,t}, \tag{4.3}$$

where $r_{i,t}$ is the return on stock i in the half-hour interval t, $I_{i,j}$ is a dummy variable that equals to one if firm i belongs to country j, and zero otherwise. The slope $\beta_{k,t}$ represent the response of returns at half-hour t to returns over interval lagged by k half-hour periods.

Insert Table 4.3 about here

The estimation results are present in Table 4.3. There is again an intraday return predictability pattern that is similar to the one we found in the U.S. market. The largest impact is also at the first half-hour lag. The magnitude of the price reversals in the European markets is larger than in the U.S. An increase in the previous half-hour return is associated with 0.26% decline of the following half-hour return. When conditioning only on the opening half-hour interval (that is, the price pressures caused by trading during the closing half-hour of the previous day), this coefficient increases to 0.42%.

Our next step is to find out what is the role institutional trading plays in generating this pattern. To do so, we repeat our cross-sectional regressions by controlling for past institutional trade imbalance as well as total market trade imbalance. Specifically, we estimate

$$\begin{aligned} r_{i,t} &= \alpha_t + \beta_t^1 r_{i,t-1} + ... + \beta_t^{13} r_{i,t-13} + \gamma_t^1 itib_{i,t-1} + ... + \gamma_t^{13} itib_{i,t-13} \\ &+ \delta_t^1 tib_{i,t-1} + ... + \delta_t^{13} tib_{i,t-13} + u_{i,t}, \end{aligned} \tag{4.4}$$

where $tib_{i,t}$ denotes total trade imbalance in stock i and time t and $itib_{i,t}$ corresponds to institutional trade imbalance. Given that the U.S. sample of ANcerno database has the largest

[1]We focus on European markets in order to avoid biased results due to asynchronous trading hours. This allows us to run the cross sectional regression without clock synchronization problem.

coverage of institutional investors, we concentrate in the remainder of the paper on the U.S. data. Table 4.4 presents the estimation results.

Insert Table 4.4 about here

The price reversal pattern remains strong and statistically significant after inclusion of both trade imbalance variables. The magnitude of the reversals however decreases. The first lag of the institutional trade imbalance variable is negative and statistically significant. This indicates that institutional investors create significant price pressures and distort stock prices. Specifically, one million institutional trade order is associated with 65.2 bp return reversal within next half-hour interval.

Insert Table 4.5 about here

While the previous result demonstrates that institutional investors contribute to price pressures, there is a concern that *itib* variable is persistent and hence the result is spurious due to omission of the contemporaneous trade imbalance. To mitigate this concern, we also control for the contemporaneous variables. Table 4.5 presents the estimation results. The conclusion remain as before. Both *itib* and *tib* are highly statistically significant and have positive signs. This suggests that institutional investors indeed exploit price reversals and profit from it. However, despite this, the lagged *itib* variable is still negative and statistically significant. Moreover, the price reversal pattern remain in the data after controlling for the institutional trading. This means that large portion of existing price pressures is created by other market participants.

Having established pronounced pattern of intraday price reversals, we now turn to the question on optimality of institutional investors trading pattern.Figure 4.4 plots average trading volume by institutional investors broken down for different half-hour intervals. It shows that large of institutional orders, about 31% of overall institutional investors' dollar trading volume, has been executed during the last half-hour interval.

Insert Figure 4.4 about here

In order to shed light on optimality of such behaviour, we first compute price sensitivity to institutional trade imbalance. We regress half-hour returns on contemporaneous institutional trade imbalance and control for market trade imbalance in the cross-section for each half-hour interval:

$$r_{i,t} = \alpha_t + \lambda_t itib_{i,t} + \delta_t tib_{i,t} + u_{i,t}. \tag{4.5}$$

We average λ_t over different half-hour intervals to estimate the extent by which institutional trades move prices and hence suffer from price impact. Figure 4.5 plots intraday pattern of the estimated λ coefficient.

Insert Figure 4.5 about here

Price impacts are negative for most of the half-hour intervals. The only two exceptions are opening and closing intervals. During first half-hour interval institutional investors experience by far the largest sensitivity to their trades. A one billion trade just after the market opening tend to move price by about 75.5 basis point. Price sensitivity to institutional order just before market closure is also positive but substantially smaller. Specifically, a one billion trade tend to move price by about 5.4 basis point. The result suggest that institutional orders that are executed during non-opening and non-closing intervals are on average subject to smaller transaction costs. This could be due to the fact that there orders are executed against uninformed individual investor trades. However, the market typically adversely react to institutional orders executed during the first and the last half-hour of trading. By trading aggressively during those intervals institutional brokers inflict substantial costs on institutional investors.

This trading behaviour creates substantial price pressures and short-term reversals that can be exploited by other market participants. To gauge economic value of these costs we form a trading strategy designed to exploit intraday price reversals. Given our results in Table 4.2 that the largest price reversals occurs at lag 1 returns, our strategy will trade on the shortest half-hour horizon. Specifically, each half-hour interval we sort stocks by their previous half-hour return and form ten equally weighted portfolios for each past return decile. We buy portfolio with the lowest past return (P_1) and short sell portfolio with the highest past return (P_{10}). The results of the strategy performance is given in Table 4.6.

Insert Table 4.6 about here

Portfolio returns are monotonically decreasing form portfolio P_1 to P_{10}. The average half-hour return from $P_1 - P_{10}$ portfolio is 31.93 bp and it statistically significant. As expected given our previous finding, the highest performance of this strategy is during the opening hours (that is, exploiting price pressures created by trading in the previous day closing hour). If we condition the trading only on this interval, $P_1 - P_{10}$ portfolio generates returns of 73.22 bp (statistically significant at 1% level). This amounts on average 16.11% per month.

The previous results sow evidence that brokers executing institutional investors' orders occur substantial costs due to suboptimal execution strategies. In the remainder of this section we will study heterogeneity of trading desks execution quality. To do so, we compute execution shortfall for order submitted during each half-hour interval.

Insert Figure 4.6 about here

Figure 4.6 presents the average volume weighted shortfall figures broken down by interval. On average, execution shortfall does have a pronounced increasing pattern. To shed more light on factors determining execution shortfall, we classify orders that are subsequently split and not split by the corresponding broker.

An institutional desk typically breaks up a large order into smaller tickets and works the order over time. The timing and sequence of release of tickets to multiple brokers that span multiple periods is an important dynamic decision made by the trading desk. We implement an algorithm to 'link' seemingly related tickets in the database into a single multiperiod order. Specifically, we group all tickets from the same institution across brokers on the same side of the trade (buy or sell) in a given stock over adjacent periods into a linked ticket order. Tickets that are canceled with a broker, but replaced with another broker, are captured in the analysis; however, canceled tickets that are never replaced are lost. Through this procedure, we determine whether an order is split or not split by a broker.

Insert Figure 4.7 about here

As expected, the orders that have been split by the broker on average exhibit smaller execution shortfall. The only exception constitute orders that have been submitted by the investors within half-hour of market closure.

Insert Figure 4.8 about here

Figure 4.8 shows dollar volume of split and non-split orders. As we can see, the percentage of non-split orders increases towards the end of the day. During the last half-hour interval brokers do not split about 41.7% of orders while during the first part of the day this percentage is 29.4%.

Insert Figure 4.9 about here

Figure 4.9 shows the distribution of trading volume across day by well performing and poorly performing brokers. To identify well performing broker we focus on trading desks with total trading volume over 5 million dollars over the entire sample. We splits those brokers into two groups based on whether their execution shortfall is above or below the sample median. While both group of brokers exhibit pronounced intraday pattern with executing larger fraction of orders towards the end of the day, poorly performing trading desks leave larger fraction of their trading volume for the last closing half-hour interval.

Insert Figure 4.10 about here

We also check if the execution shortfall of well and poorly performing desks is distributed in a similar fashion as the aggregate execution shortfall. Figure 4.10 shows that while both groups suffer from large execution shortfall towards the end of the day, losses of poorly performing desks are considerable during the last interval.

Insert Figure 4.11 about here

Finally, we check if there is a substantial difference in the way brokers manage their orders. Figure 4.11 shows declining pattern of percentage of split orders throughout the day.

4.4 Conclusion

Execution costs represent a necessary expense that is associated with the implementation of portfolio managers' trading strategies. As a result, it is important that investment firms examine the execution quality given that it can affect the returns to any investment strategy. For example, Wermers (2000) estimates that execution costs reduce the average mutual fund's gross return by eighty basis points per year. We find that the execution of orders by brokers are predictable within a trading day and executions are clustered at the end of the day where trading costs is the highest.

We show that the execution strategy of high performing institutions outperform their peer brokers, who have a tendency to trade at the end of the day. Executions of trades by poor performing brokers coincides with periodic and predictably intraday price pressure. An important contribution our study makes to the literature is the empirical link between an broker's execution performance and intraday return predictability. The economically significant magnitude of the trading-alpha exploiting this intraday return predictability suggests that the current execution algorithm and strategy of most brokers are sub-optimal.

Figure 4.1: **Sample Construction: international data**

The figure plots number of stocks in the European sample. Sample goes from January 2002 to December 2012.

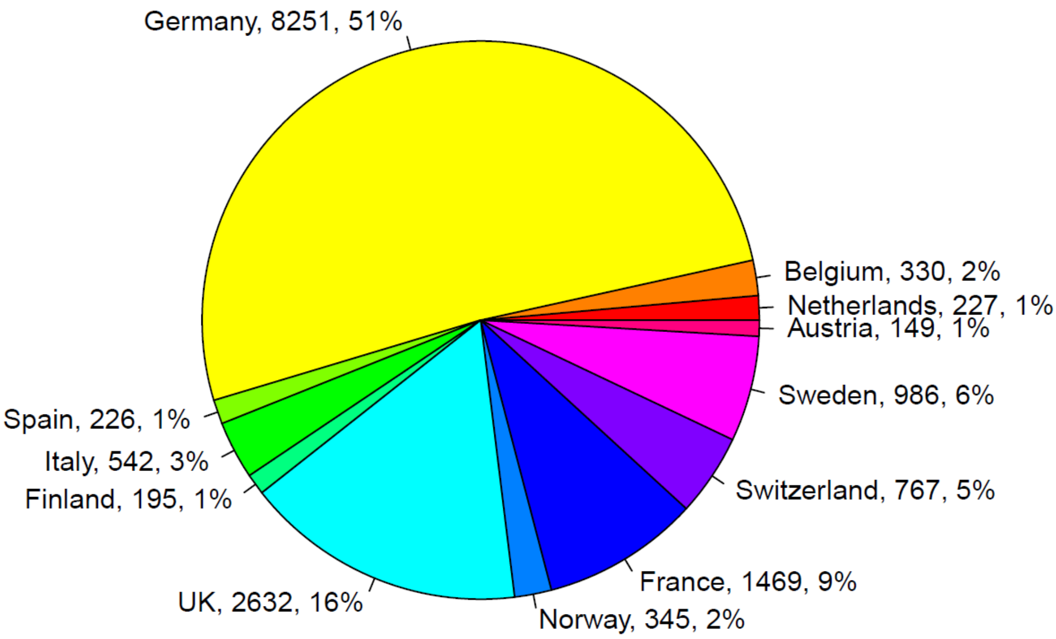


Figure 4.2: **Cross-sectional regressions of half-hour-interval returns.**

The figure presents the estimation results of the intraday return predictability pattern. We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \beta_{1,t} r_{i,t-1} + ... + \beta_{13,t} r_{i,t-13} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t. The cross-sectional regressions are estimated for each half-hour interval t, from January 2000 through December 2015. The upper panel plots time-series averages of $\beta_{k,t}$ in percentages across all half-hour intervals, where the lag variable k ranges from 1 to 13 (horizontal axis). The lower panel presents the corresponding t-statistics that are computed based on standard errors adjusted for autocorrelation.

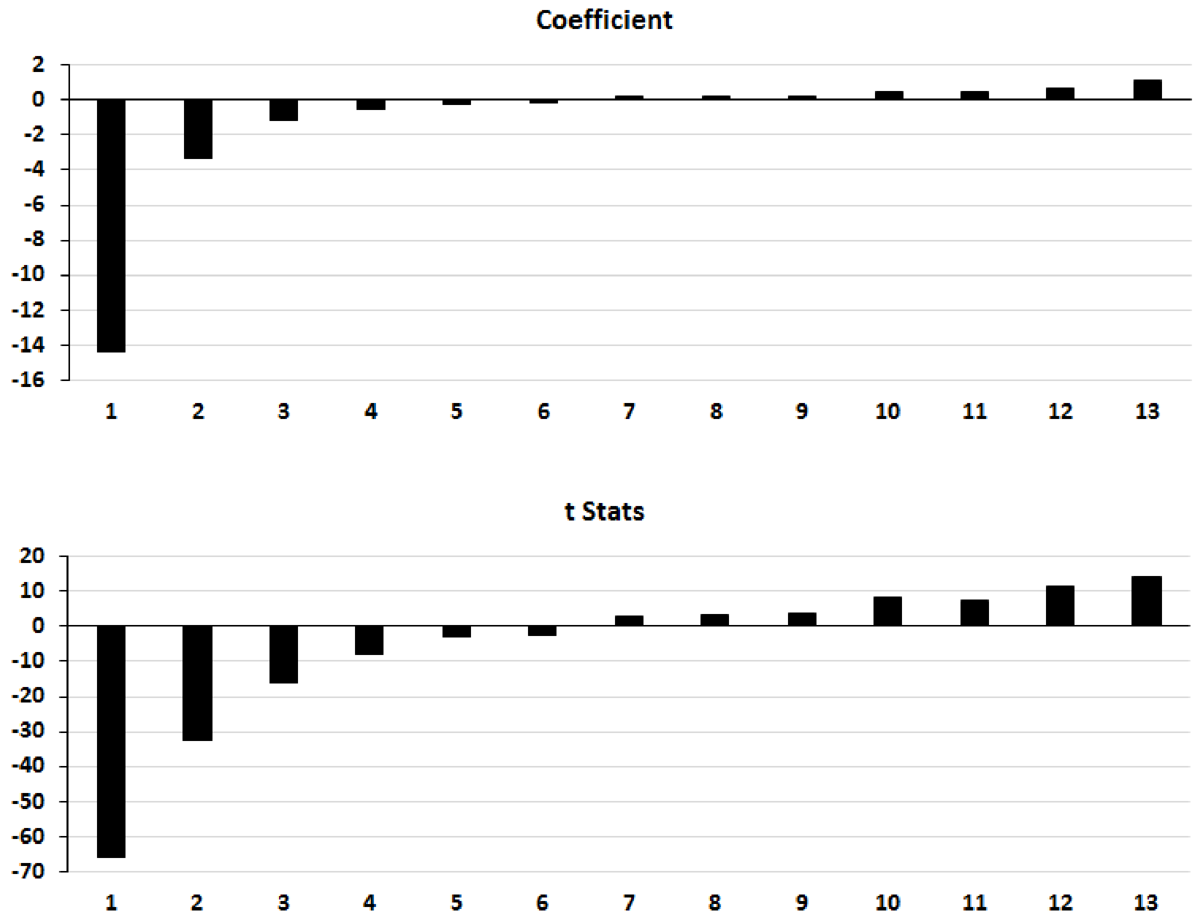
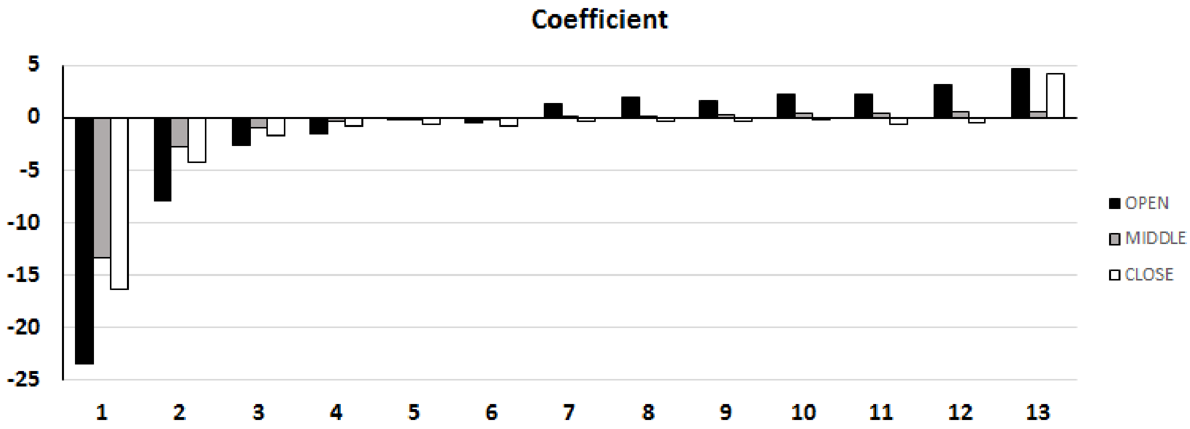


Figure 4.3: **Cross-sectional regressions of half-hour-interval returns: Opening and closing hours.**

The figure presents the estimation results of the intraday return predictability pattern. We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \beta_{1,t} r_{i,t-1} + ... + \beta_{13,t} r_{i,t-13} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t. The cross-sectional regressions are estimated for each half-hour interval t, from January 2006 through December 2010. The upper panel plots time-series averages of $\beta_{k,t}$ in percentages across opening half-hour intervals (bar *OPEN*), closing half-hour intervals (bar *CLOSE*) and all half-hour intervals except opening and closing ones (bar *MIDDLE*). The lower panel presents the corresponding t-statistics that are computed based on standard errors adjusted for autocorrelation.



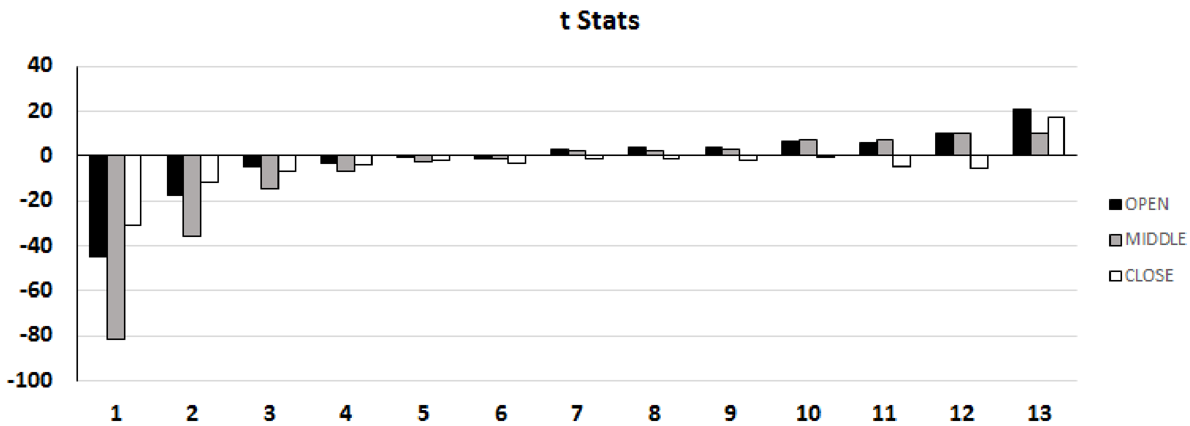


Figure 4.4: **Institutional trading volume**

The figure plots average institutional trading volume for each of 13 half-hour interval within trading days. Trading volume is in billions of dollars. Sample goes from January 2006 through December 2010.

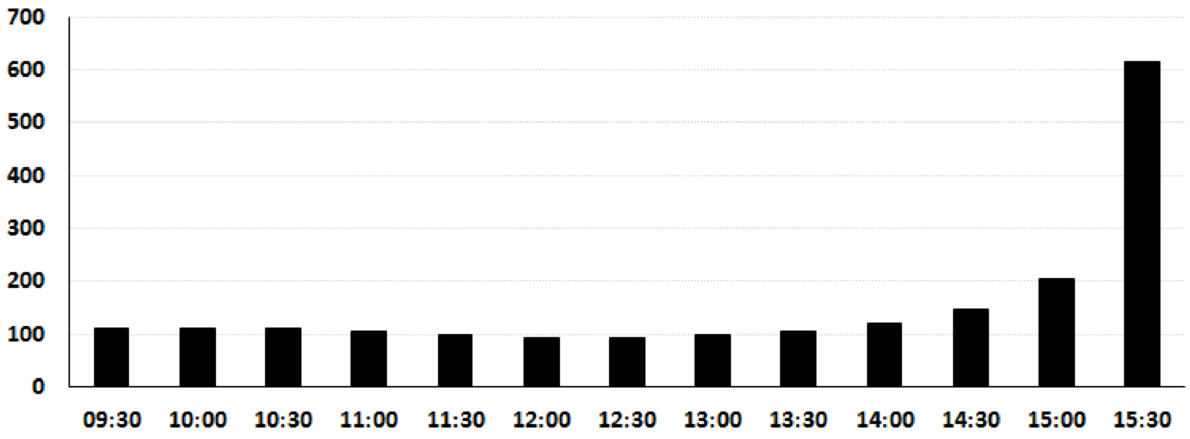


Figure 4.5: **Contemporaneous price impacts**

The figure presents the estimation results of the sensitivity of stock returns to the contemporaneous institutional trade imbalance in the cross-section. We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \lambda_t itib_{i,t} + \delta_t tib_{i,t} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t, $itib_{i,t}$ is institutional trade imbalance defined as buyer initiated minus sellers initiated institutional trading volume expressed in millions of trade, $tib_{i,t}$ is total market trade imbalance defined as buyer initiated minus sellers initiated total market trading volume expressed in millions of trade. The cross-sectional regressions are estimated for each half-hour interval t, from January 2006 through December 2010. The upper panel plots time-series averages of λ_t in percentages across all half-hour intervals, where the lag variable k ranges from 1 to 13 (horizontal axis). The lower panel presents the corresponding t-statistics that are computed based on standard errors adjusted for autocorrelation.

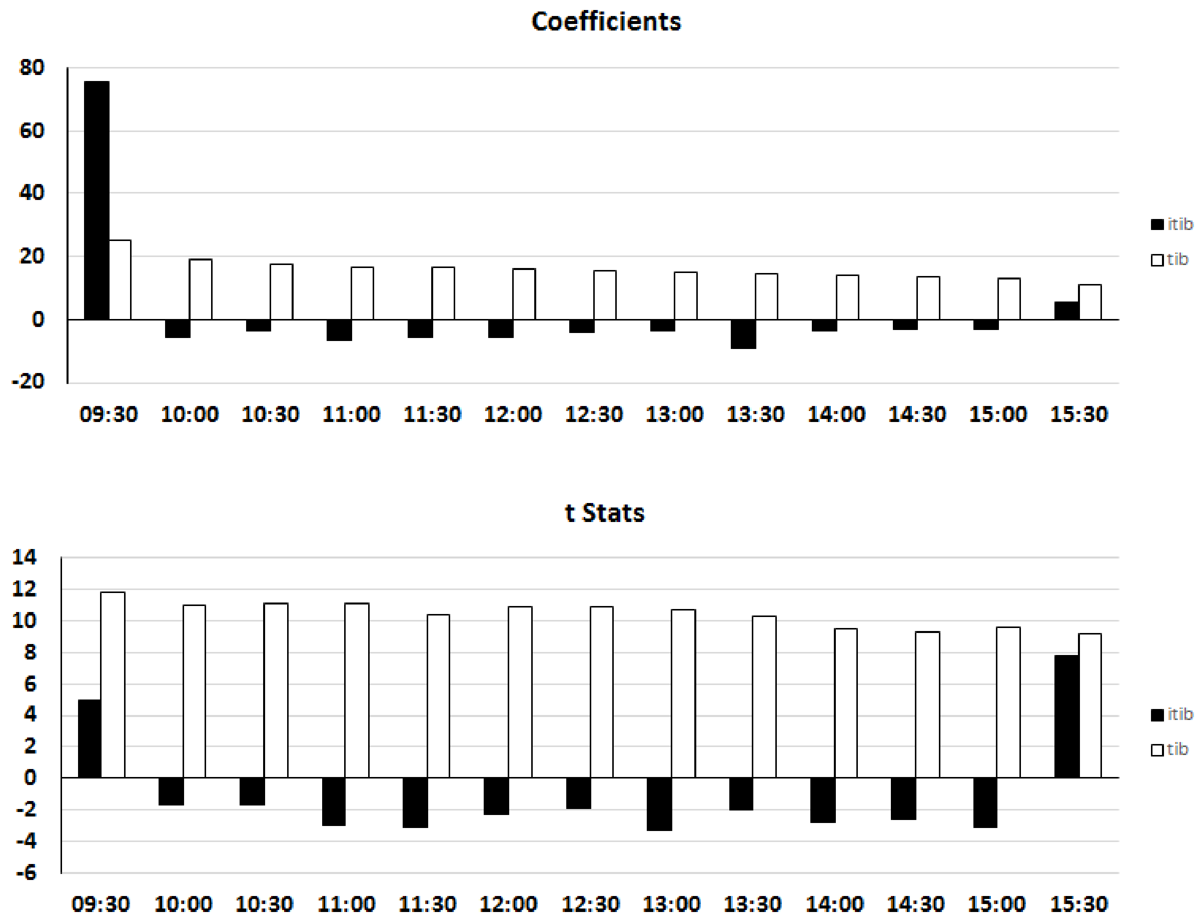


Figure 4.6: **Execution shortfall**

The figure presents average institutional execution shortfall for each of 13 half-hour interval within trading days. Execution short (in basis points) is defined as the difference between the execution price of a ticket τ and the stock price when the trading desk sends the ticket to the broker. Horizontal line indicates the half-hour interval. Sample goes from January 2006 through December 2010.

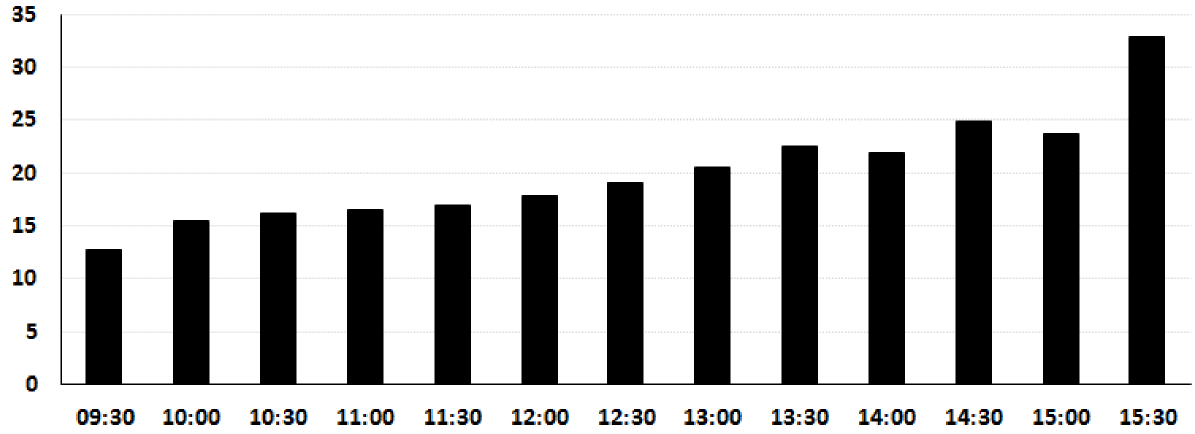


Figure 4.7: **Execution shortfall: Splitting orders**

The figure presents average institutional execution shortfall for each of 13 half-hour interval within trading days. Execution short (in basis points) is defined as the difference between the execution price of a ticket τ and the stock price when the trading desk sends the ticket to the broker. Horizontal line indicates the half-hour interval. We classify each broker into two categories: brokers that split the original order and brokers that do not split the orders. We compute average execution shortfall for all institutional investors for each broker category. Sample goes from January 2006 through December 2010.

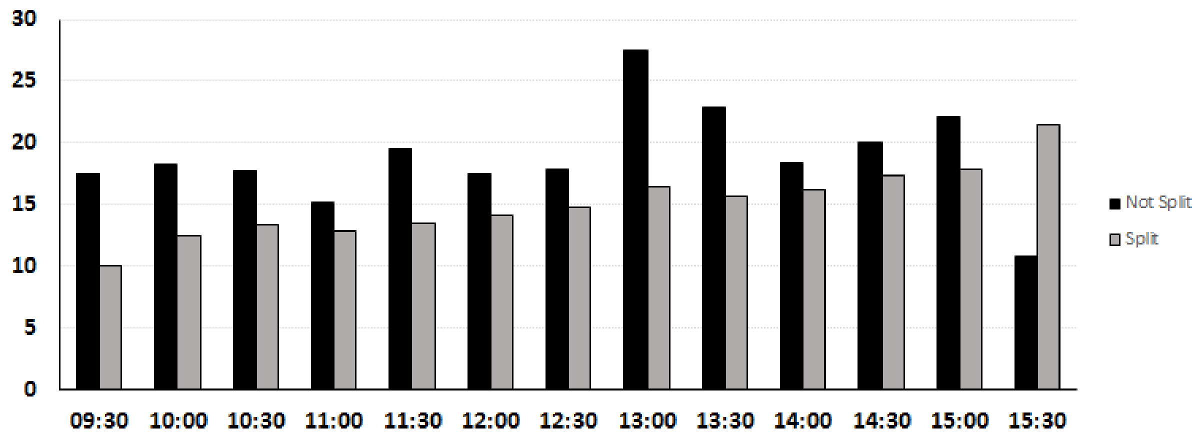


Figure 4.8: **Institutional trading volume: Splitting orders**

The figure plots percentage of institutional trading volume for split, randomly split and non-randomly split orders for each of 13 half-hour interval within trading days. Horizontal line indicates the half-hour interval. We classify each broker into two categories: brokers that split the original order and brokers that do not split the orders. Furthermore, we classify brokers that split their orders into those who split them randomly and those who does not randomize the orders. We do this by calculating the Herfindahl index of each broker's trades and assign brokers that have their Herfindahl index above median as non-random, while those below median as random. We compute trading volume as average for each half-hour interval across all trading days for all institutional investors for each broker category. Sample goes from January 2006 through December 2010.

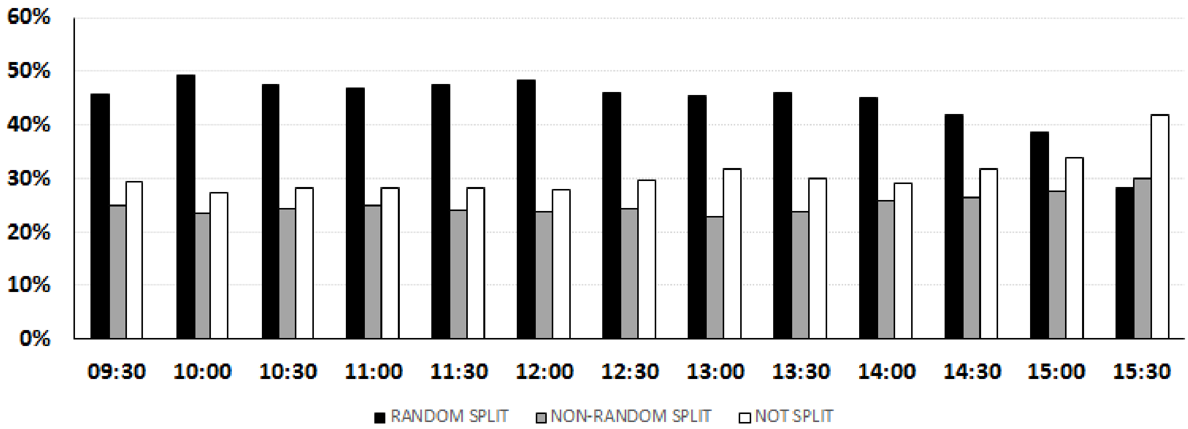


Figure 4.9: **Distribution of trading volume of well and poorly performing brokers across day**

The figure plots distribution of total trading volume of well and poorly performing brokers for each of 13 half-hour interval within trading days. Horizontal line indicates the half-hour interval. We classify each broker into two categories: well performing and poorly performing brokers depending on whether their total trading volume across sample is above or below the sample median. We consider only brokers with total trading volume over 5 million dollars. Sample goes from January 2006 through December 2010.

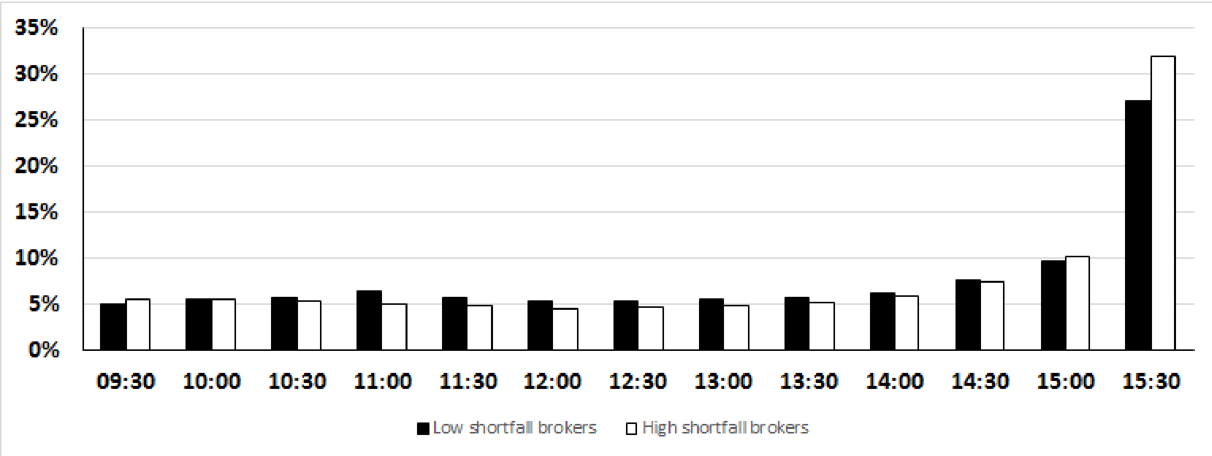


Figure 4.10: **Distribution of execution shortfall of well and poorly performing brokers across day**

The figure plots distribution of execution shortfall of well and poorly performing brokers for each of 13 half-hour interval within trading days. Horizontal line indicates the half-hour interval. We classify each broker into two categories: well performing and poorly performing brokers depending on whether their total trading volume across sample is above or below the sample median. We consider only brokers with total trading volume over 5 million dollars. Sample goes from January 2006 through December 2010.

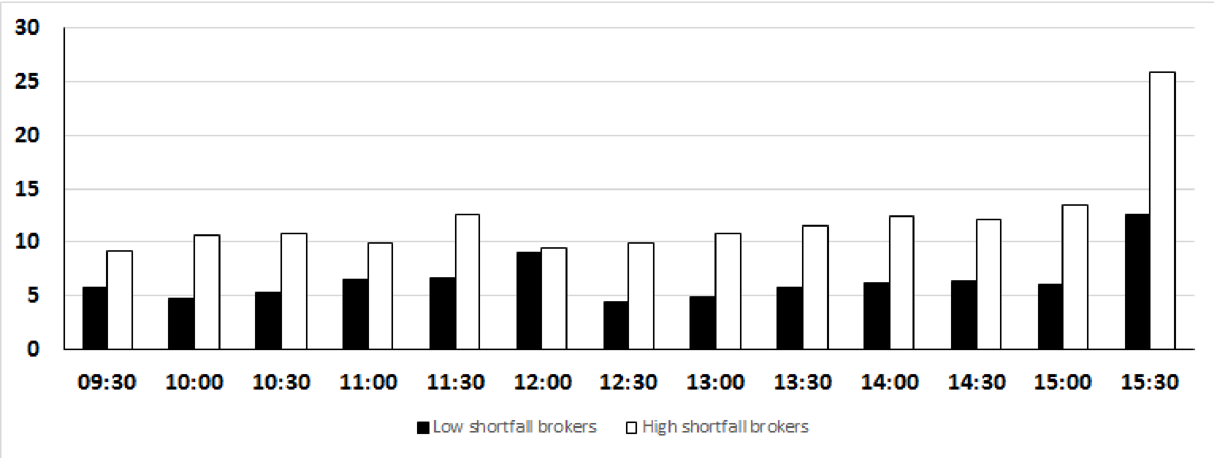


Figure 4.11: **Percentage of order slitting by well and poorly performing brokers across day**

The figure plots percentage of order splitting by well and poorly performing brokers for each of 13 half-hour interval within trading days. Horizontal line indicates the half-hour interval. We classify each broker into two categories: well performing and poorly performing brokers depending on whether their total trading volume across sample is above or below the sample median. For each broker type and each half-hour interval we compute fraction of split orders. We consider only brokers with total trading volume over 5 million dollars. Sample goes from January 2006 through December 2010.

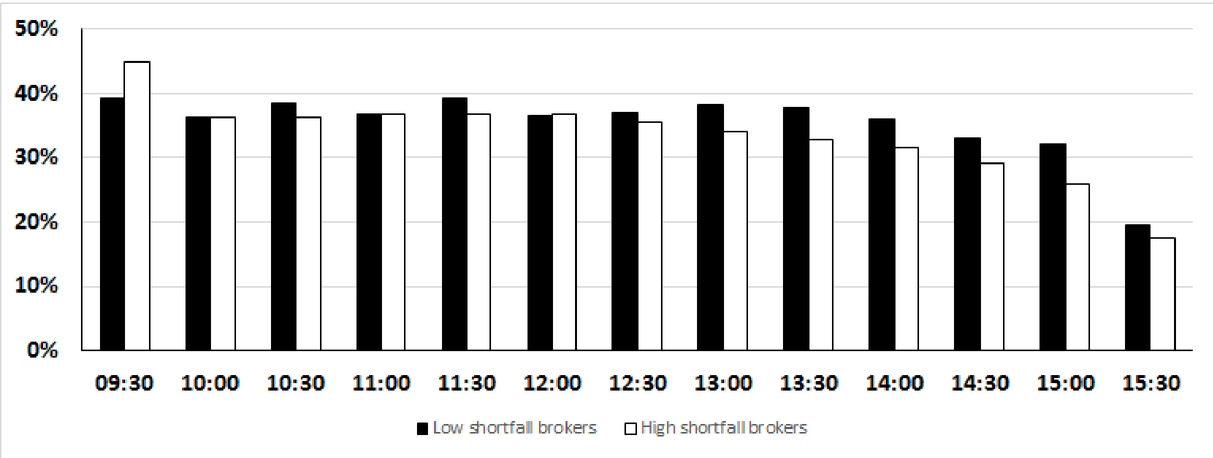


Table 4.1: **Summary Statistics**

This table reports the descriptive statistics for our sample of institutional trades from Ancerno Ltd. for the period from January, 2006 to December 2010. The analysis is conducted by using institutional tickets, which could be executed through multiple trades. We restrict the sample to tickets, where the broker handling the ticket can be identified, the execution shortfall is less than or equal to 10%, the executed ticket volume is less than or equal to the total daily trading volume reported in CRSP, and the ticket is for a common stock that has data available in the CRSP and TAQ databases. We present descriptive statistics for the full sample, as well as by disaggregating the sample based on year. Execution shortfall is measured for buy tickets as the execution price minus the market price at the time of ticket placement divided by the market price at ticket placement and is reported in basis points. Trading volume in in billions of dollars.

	No of brokers	No of institutions	No of stocks	No of tickets	Ticket size	Trading volume	No of executions per ticket	Execution shortfall
Full Sample	10,572	136	3,069	20,361,428	67,749.46	1955.063	4.30	15.37
2006	5,345	79	2,220	4,690,147	60,847.78	540.774	4.62	11.58
2007	4,955	75	2,289	5,239,688	61,064.65	544.243	4.38	12.27
2008	4,286	69	2,235	4,352,275	65,165.83	458.059	3.87	19.81
2009	3,570	60	2,106	3,330,552	81,870.21	232.951	4.07	21.01
2010	2,882	52	2,107	2,748,766	79,249.54	179.035	4.69	13.93

Table 4.2: **Cross-sectional regressions of half-hour returns**

This table presents the estimation results of the intraday return predictability pattern. We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \beta_{1,t} r_{i,t-1} + ... + \beta_{13,t} r_{i,t-13} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t. The cross-sectional regressions are estimated for each half-hour interval t, from January 2006 through December 2010. The data reports time-series averages of $\beta_{k,t}$ in percentages across all half-hour intervals (Column *All hours*), opening half-hour intervals (column *Open*), closing half-hour intervals (column *Close*) and all half-hour intervals except opening and closing ones (column *Middle*). t-statistics in parentheses are computed based on standard errors adjusted for autocorrelation.

Variable	All hours	Open	Middle	Close
ret_{t-1}	-14.37 (-66.0)	-23.44 (-45.2)	-13.36 (-81.4)	-16.35 (-30.9)
ret_{t-2}	-3.35 (-32.7)	-7.89 (-17.3)	-2.86 (-35.6)	-4.24 (-11.8)
ret_{t-3}	-1.13 (-16.2)	-2.56 (-4.99)	-0.96 (-15.0)	-1.66 (-7.11)
ret_{t-4}	-0.51 (-7.99)	-1.50 (-3.23)	-0.39 (-6.80)	-0.81 (-4.26)
ret_{t-5}	-0.20 (-2.83)	-0.27 (-0.51)	-0.15 (-2.64)	-0.66 (-2.29)
ret_{t-6}	-0.15 (-2.36)	-0.46 (-1.00)	-0.06 (-1.04)	-0.87 (-3.47)
ret_{t-7}	0.19 (2.97)	1.29 (2.88)	0.14 (2.44)	-0.30 (-1.41)
ret_{t-8}	0.23 (3.45)	1.93 (4.02)	0.13 (2.41)	-0.31 (-1.43)
ret_{t-9}	0.24 (3.64)	1.62 (3.80)	0.17 (3.19)	-0.38 (-1.88)
ret_{t-10}	0.50 (8.13)	2.15 (6.24)	0.40 (7.28)	-0.07 (-0.43)
ret_{t-11}	0.46 (7.53)	2.28 (6.14)	0.40 (7.13)	-0.64 (-4.70)
ret_{t-12}	0.70 (11.4)	3.11 (10.2)	0.60 (10.4)	-0.55 (-5.55)
ret_{t-13}	1.14 (14.4)	4.66 (21.0)	0.55 (10.3)	4.14 (17.1)

Table 4.3: **Cross-sectional regressions of half-hour returns: European data**

This table presents the estimation results of the intraday return predictability pattern for European data. We divide the 8:00 to 17:30 trading day into 17 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \beta_{1,t} r_{i,t-1} + ... + \beta_{17,t} r_{i,t-17} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t. The cross-sectional regressions are estimated for each half-hour interval t, from January 2002 through December 2012. The data reports time-series averages of $\beta_{k,t}$ in percentages across all half-hour intervals (Column *All hours*), opening half-hour intervals (column *Open*), closing half-hour intervals (column *Close*) and all half-hour intervals except opening and closing ones (column *Middle*). t-statistics in parentheses are computed based on standard errors adjusted for autocorrelation.

Variable	All hours	Open	Middle	Close
ret_{t-1}	-26.51 (-179.4)	-42.37 (-61.6)	-24.85 (-117.0)	-35.63 (-60.5)
ret_{t-2}	-13.00 (-125.6)	-14.49 (-23.8)	-12.47 (-78.9)	-19.48 (-38.8)
ret_{t-3}	-8.10 (-52.2)	-5.86 (-9.53)	-7.96 (-39.7)	-12.37 (-30.8)
ret_{t-4}	-5.17 (-63.8)	-1.62 (-2.38)	-5.12 (-43.0)	-9.51 (-19.6)
ret_{t-5}	-3.53 (-43.4)	0.47 (0.68)	-3.49 (-31.4)	-8.07 (-15.4)
ret_{t-6}	-2.34 (-27.4)	1.89 (3.05)	-2.34 (-22.9)	-6.63 (-13.2)
ret_{t-7}	-1.68 (-21.3)	2.84 (3.64)	-1.72 (-17.5)	-5.52 (-12.2)
ret_{t-8}	-0.89 (-12.3)	5.03 (6.74)	-1.08 (-13.4)	-3.97 (-8.99)
ret_{t-9}	-0.49 (-6.64)	4.93 (6.51)	-0.65 (-8.46)	-3.43 (-6.68)
ret_{t-10}	-0.22 (-2.87)	4.59 (7.02)	-0.36 (-5.05)	-2.96 (-4.67)
ret_{t-11}	-0.02 (-0.30)	5.14 (7.83)	-0.17 (-2.46)	-2.99 (-5.93)
ret_{t-12}	0.21 (3.08)	6.33 (9.40)	-0.01 (-0.10)	-2.74 (-7.28)
ret_{t-13}	0.28 (4.15)	6.38 (9.62)	0.06 (0.89)	-2.65 (-5.43)
ret_{t-14}	0.41 (6.12)	5.69 (9.19)	0.23 (3.41)	-2.09 (-3.90)
ret_{t-15}	0.67 (10.9)	6.91 (15.9)	0.41 (6.72)	-1.65 (-3.33)
ret_{t-16}	0.78 (13.4)	6.58 (14.0)	0.56 (9.26)	-1.62 (-4.44)
ret_{t-17}	1.06 (16.0)	5.31 (20.5)	0.60 (9.14)	3.58 (5.75)

Table 4.4: **Cross-sectional regressions of half-hour returns: controlling for trade imbalance**

This table presents the estimation results of the intraday return predictability pattern. We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \beta_t^1 r_{i,t-1} + ... + \beta_t^{13} r_{i,t-13} + \gamma_t^1 itib_{i,t-1} + ... + \gamma_t^{13} itib_{i,t-13} + \delta_t^1 tib_{i,t-1} + ... + \delta_t^{13} tib_{i,t-13} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t, $tib_{i,t}$ denotes total trade imbalance in stock i and time t and $itib_{i,t}$ corresponds to institutional trade imbalance. The cross-sectional regressions are estimated for each half-hour interval t, from January 2006 through December 2010. The data reports time-series averages of $\beta_{k,t}$ in percentages across all half-hour intervals (Column *All hours*), opening half-hour intervals (column *Open*), closing half-hour intervals (column *Close*) and all half-hour intervals except opening and closing ones (column *Middle*). t-statistics in parentheses are computed based on standard errors adjusted for autocorrelation.

Variable	All hours	Open	Middle	Close
ret_{t-1}	-9.80 (-72.4)	-19.63 (-29.7)	-8.76 (-61.6)	-11.48 (-20.2)
ret_{t-2}	-1.98 (-29.3)	-5.89 (-13.6)	-1.55 (-24.3)	-2.86 (-8.82)
ret_{t-3}	-0.67 (-11.0)	-1.99 (-3.62)	-0.50 (-9.51)	-1.23 (-4.67)
ret_{t-4}	-0.32 (-5.39)	-1.05 (-2.16)	-0.20 (-3.71)	-0.96 (-3.99)
ret_{t-5}	-0.23 (-4.01)	-0.51 (-0.97)	-0.14 (-2.98)	-0.90 (-3.76)
ret_{t-6}	-0.10 (-1.70)	-0.60 (-1.43)	-0.02 (-0.32)	-0.52 (-1.86)
ret_{t-7}	0.14 (2.51)	1.09 (2.34)	0.11 (2.15)	-0.43 (-2.16)
ret_{t-8}	0.27 (5.11)	1.88 (3.75)	0.19 (4.16)	-0.43 (-2.16)
ret_{t-9}	0.25 (4.83)	1.66 (3.62)	0.17 (3.72)	-0.32 (-1.65)
ret_{t-10}	0.41 (7.92)	1.75 (4.45)	0.36 (7.55)	-0.39 (-2.91)
ret_{t-11}	0.43 (8.54)	2.03 (4.90)	0.37 (7.56)	-0.47 (-3.15)
ret_{t-12}	0.69 (14.4)	3.18 (8.67)	0.56 (11.4)	-0.38 (-4.56)
ret_{t-13}	1.01 (23.0)	4.27 (21.3)	0.49 (10.6)	3.46 (14.6)
$itib_{t-1}$	-6.52 (-4.34)	-4.87 (-2.78)	-6.60 (-3.96)	-7.23 (-2.51)
$itib_{t-2}$	-1.69 (-1.39)	-7.8 (-1.61)	-1.19 (-0.74)	-1.04 (-0.67)
$itib_{t-3}$	0.48 (0.25)	-3.52 (-0.89)	1.13 (0.47)	-2.56 (-1.13)
$itib_{t-4}$	-3.21 (-2.36)	-7.12 (-0.49)	-2.73 (-1.56)	-4.54 (-2.25)
$itib_{t-5}$	-0.64 (-0.29)	23.56 (1.24)	-2.29 (-1.15)	-6.70 (-1.53)
$itib_{t-6}$	2.30 (0.90)	6.93 (0.29)	2.35 (1.28)	-2.88 (-0.98)
$itib_{t-7}$	-5.11 (-0.83)	-0.44 (-0.03)	-5.46 (-0.74)	-5.96 (-0.86)
$itib_{t-8}$	-0.38 (-0.11)	-45.59 (-1.43)	4.14 (1.12)	-4.71 (-1.91)
$itib_{t-9}$	-0.84 (-0.25)	-0.33 (-0.06)	-0.73 (-0.19)	-2.61 (-1.15)
$itib_{t-10}$	-25.05 (-0.83)	-391.8 (-1.00)	5.19 (1.44)	10.19 (1.31)
$itib_{t-11}$	-10.94 (-0.78)	-6.05 (-0.76)	-12.98 (-0.78)	6.77 (1.41)
$itib_{t-12}$	8.95 (0.78)	2.12 (0.30)	10.14 (0.75)	2.75 (0.69)
$itib_{t-13}$	-1.06 (-0.40)	-1.64 (-0.13)	-1.29 (-0.47)	2.08 (1.22)
tib_{t-1}	1.60 (16.3)	0.07 (0.20)	1.79 (16.1)	1.06 (4.25)
tib_{t-2}	0.16 (2.33)	0.27 (0.55)	0.19 (3.79)	-0.35 (-1.54)
tib_{t-3}	-0.01 (-0.17)	0.03 (0.04)	0.00 (0.07)	-0.22 (-1.12)
tib_{t-4}	-0.03 (-0.48)	-0.33 (-0.50)	-0.03 (-0.59)	0.28 (0.84)
tib_{t-5}	-0.14 (-1.23)	-0.76 (-0.83)	-0.06 (-1.14)	-0.34 (-1.66)
tib_{t-6}	-0.02 (-0.15)	1.19 (0.89)	-0.06 (-1.07)	-0.69 (-1.53)
tib_{t-7}	-0.03 (-0.44)	0.18 (0.35)	-0.06 (-1.17)	0.15 (0.45)
tib_{t-8}	-0.05 (-0.72)	0.47 (1.03)	-0.07 (-1.33)	-0.30 (-2.02)
tib_{t-9}	-0.18 (-2.77)	-0.49 (-1.00)	-0.15 (-2.29)	-0.20 (-0.70)
tib_{t-10}	0.02 (0.21)	1.37 (2.28)	-0.11 (-1.55)	0.13 (0.44)
tib_{t-11}	-0.02 (-0.30)	0.56 (1.61)	-0.06 (-1.03)	-0.18 (-1.01)
tib_{t-12}	-0.24 (-2.52)	-0.94 (-1.00)	-0.17 (-3.39)	-0.26 (-1.56)
tib_{t-13}	-0.10 (-1.47)	0.07 (0.10)	-0.12 (-2.12)	-0.10 (-0.39)

Table 4.5: **Cross-sectional regressions of half-hour returns: controlling for lagged and contemporaneous trade imbalance**

This table presents the estimation results of the intraday return predictability pattern. We divide the 9:30 to 16:00 trading day into 13 disjoint half-hour return intervals. For every half-hour interval t we run the multivariate cross-sectional regression $r_{i,t} = \alpha_t + \beta_t^1 r_{i,t-1} + ... + \beta_t^{13} r_{i,t-13} + \gamma_t itib_{i,t} + \gamma_t^1 itib_{i,t-1} + ... + \gamma_t^{13} itib_{i,t-13} + \delta_t tib_{i,t} + \delta_t^1 tib_{i,t-1} + ... + \delta_t^{13} tib_{i,t-13} + u_{i,t}$, where $r_{i,t}$ is the return on stock i in the half-hour interval t, $tib_{i,t}$ denotes total trade imbalance in stock i and time t and $itib_{i,t}$ corresponds to institutional trade imbalance. The cross-sectional regressions are estimated for each half-hour interval t, from January 2006 through December 2010. The data reports time-series averages of $\beta_{k,t}$ in percentages across all half-hour intervals (Column *All hours*), opening half-hour intervals (column *Open*), closing half-hour intervals (column *Close*) and all half-hour intervals except opening and closing ones (column *Middle*). t-statistics in parentheses are computed based on standard errors adjusted for autocorrelation.

Variable	All hours	Open	Middle	Close
ret_{t-1}	-10.01 (-72.4)	-19.85 (-30.7)	-8.95 (-61.3)	-11.78 (-19.9)
ret_{t-2}	-2.06 (-30.7)	-6.08 (-14.2)	-1.61 (-25.2)	-3.00 (-8.95)
ret_{t-3}	-0.73 (-12.0)	-2.25 (-4.13)	-0.53 (-10.3)	-1.35 (-5.20)
ret_{t-4}	-0.35 (-5.96)	-1.18 (-2.45)	-0.21 (-4.07)	-1.04 (-4.40)
ret_{t-5}	-0.25 (-4.48)	-0.62 (-1.21)	-0.16 (-3.29)	-0.94 (-4.00)
ret_{t-6}	-0.12 (-2.04)	-0.71 (-1.66)	-0.02 (-0.40)	-0.60 (-2.19)
ret_{t-7}	0.13 (2.37)	1.06 (2.25)	0.11 (2.21)	-0.53 (-2.71)
ret_{t-8}	0.27 (5.19)	1.76 (3.54)	0.21 (4.64)	-0.51 (-2.60)
ret_{t-9}	0.25 (4.85)	1.51 (3.35)	0.19 (4.06)	-0.35 (-1.88)
ret_{t-10}	0.41 (7.87)	1.63 (4.16)	0.38 (7.82)	-0.45 (-3.38)
ret_{t-11}	0.44 (8.77)	1.93 (4.57)	0.39 (8.13)	-0.50 (-3.53)
ret_{t-12}	0.72 (14.9)	3.14 (8.52)	0.59 (12.0)	-0.39 (-4.79)
ret_{t-13}	1.04 (23.6)	4.23 (20.6)	0.53 (11.4)	3.45 (14.5)
$itib_t$	6.24 (2.08)	103.2 (2.87)	-2.79 (-1.64)	8.24 (9.55)
$itib_{t-1}$	-6.37 (-4.16)	-5.03 (-2.91)	-6.40 (-3.78)	-7.36 (-2.54)
$itib_{t-2}$	-1.81 (-1.46)	-6.03 (-1.67)	-1.46 (-0.92)	-1.38 (-0.97)
$itib_{t-3}$	0.77 (0.40)	-3.84 (-1.04)	1.43 (0.62)	-1.85 (-0.81)
$itib_{t-4}$	-4.27 (-2.18)	-12.07 (-0.98)	-3.54 (-1.43)	-4.43 (-2.13)
$itib_{t-5}$	1.42 (0.37)	32.65 (1.23)	-0.71 (-0.27)	-6.54 (-1.85)
$itib_{t-6}$	-0.46 (-0.19)	-1.71 (-0.07)	-0.13 (-0.10)	-2.83 (-1.04)
$itib_{t-7}$	-3.33 (-0.63)	7.98 (0.78)	-3.97 (-0.68)	-7.68 (-0.92)
$itib_{t-8}$	1.78 (0.58)	-26.79 (-1.53)	4.98 (1.28)	-4.82 (-1.55)
$itib_{t-9}$	-3.01 (-0.80)	-5.68 (-1.07)	-2.76 (-0.63)	-3.12 (-1.29)
$itib_{t-10}$	-23.43 (-0.85)	-344.0 (-1.01)	2.60 (0.87)	12.17 (1.48)
$itib_{t-11}$	-9.23 (-0.84)	-6.16 (-0.68)	-10.72 (-0.82)	4.18 (1.05)
$itib_{t-12}$	3.25 (0.41)	-7.20 (-0.96)	4.22 (0.45)	3.10 (0.85)
$itib_{t-13}$	-3.58 (-1.26)	-11.23 (-0.93)	-3.28 (-1.11)	0.79 (0.45)
tib_t	19.65 (35.9)	30.88 (12.4)	19.13 (33.4)	14.16 (10.2)
tib_{t-1}	-0.81 (-12.8)	-1.46 (-3.71)	-0.67 (-9.42)	-1.75 (-9.21)
tib_{t-2}	-1.07 (-16.1)	-1.26 (-2.87)	-0.97 (-20.4)	-1.91 (-6.96)
tib_{t-3}	-0.90 (-12.5)	-1.38 (-2.66)	-0.82 (-13.1)	-1.31 (-5.33)
tib_{t-4}	-0.78 (-12.0)	-1.43 (-2.40)	-0.71 (-12.0)	-0.82 (-2.29)
tib_{t-5}	-0.72 (-8.06)	-1.52 (-2.77)	-0.61 (-10.2)	-1.14 (-5.88)
tib_{t-6}	-0.61 (-8.91)	-0.36 (-0.38)	-0.55 (-10.2)	-1.52 (-3.31)
tib_{t-7}	-0.55 (-9.12)	-1.19 (-2.24)	-0.49 (-9.13)	-0.60 (-1.80)
tib_{t-8}	-0.54 (-7.34)	-0.67 (-1.16)	-0.48 (-9.30)	-1.03 (-5.47)
tib_{t-9}	-0.61 (-8.71)	-1.56 (-3.14)	-0.50 (-7.35)	-0.87 (-2.85)
tib_{t-10}	-0.44 (-5.07)	0.12 (0.20)	-0.49 (-7.53)	-0.52 (-1.88)
tib_{t-11}	-0.49 (-9.38)	-0.88 (-2.53)	-0.42 (-8.61)	-0.85 (-4.45)
tib_{t-12}	-0.68 (-6.78)	-2.27 (-2.54)	-0.52 (-9.48)	-0.79 (-4.23)
tib_{t-13}	-0.66 (-11.2)	-1.99 (-3.69)	-0.52 (-7.97)	-0.78 (-2.88)

Table 4.6: **Economic value of execution costs**

This table presents average returns from trading against existing intraday price reversals. We divide the 9:30 to 16:00 trading day into 13 half-hour intervals. We analyze equal-weighted portfolio trading strategies with holding periods of one half-hour. Every half-hour interval, stocks are grouped into 10 portfolios according to past half-hour performance. The portfolio are formed every half-hour (row *Average*) or only at the specific half-hour interval each trading day. P_1 corresponds to the portfolio of stocks with the worst past half-hour performance while P_{10} denotes portfolio with the highest past half-hour performance. T-statistics for $P_1 - P_{10}$ portfolio are given in parentheses. All returns are in basis points. Sample goes from January 2006 to December 2010.

Half-hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	$P_1 - P_{10}$
9:30	42.15	8.16	2.85	0.48	-1.21	-2.73	-3.24	-5.30	-8.63	-31.17	73.32 (56.1)
10:00	20.30	1.84	0.11	-0.78	-1.49	-2.43	-3.22	-4.62	-7.11	-28.70	49.00 (52.2)
10:30	13.75	-1.77	-2.46	-1.75	-1.77	-1.21	-0.53	0.34	-0.07	-15.40	29.15 (44.9)
11:00	12.42	-1.94	-2.10	-1.89	-1.79	-1.20	-1.01	-0.73	-0.83	-13.70	26.12 (43.5)
11:30	12.73	-0.77	-1.06	-1.14	-0.59	-0.57	0.22	0.65	0.54	-10.81	23.54 (41.8)
12:00	13.44	0.66	-0.18	-0.47	-0.30	-0.39	0.12	-0.44	-0.59	-12.05	25.49 (44.7)
12:30	14.46	1.23	0.40	-0.01	0.01	0.18	0.23	0.17	-0.14	-10.44	24.90 (50.0)
13:00	14.16	2.16	1.10	0.49	0.22	0.34	0.17	0.18	-0.46	-11.84	26.00 (49.4)
13:30	12.45	0.65	-0.13	-0.24	-0.38	-0.38	-0.40	-0.70	-1.14	-11.41	23.86 (47.2)
14:00	13.58	1.26	0.29	-0.45	-0.82	-0.84	-1.07	-1.61	-2.37	-13.79	27.37 (52.9)
14:30	15.01	2.59	1.68	1.35	1.10	0.90	0.87	0.64	0.30	-10.40	25.41 (44.4)
15:00	15.31	2.61	1.21	0.85	0.53	0.38	0.35	-0.14	-1.05	-12.55	27.86 (47.2)
15:30	27.10	5.05	3.04	2.16	1.97	1.37	1.26	0.99	0.75	-5.94	33.04 (50.2)
Average	17.45	1.67	0.37	-0.11	-0.35	-0.51	-0.48	-0.81	-1.60	-14.48	31.93 (94.2)

Chapter 5

Conclusion

In this thesis, we studied the impact of transaction costs on stocks prices and examined the impact of institutional investors and high frequency traders (HFTs) on market quality and transaction costs.

We documented a causal negative impact of a larger tick size on stock prices and calculate the liquidity premium implied by the change in tick size. The sources of stock price variation appear different across various treated stocks in the program. We showed that the decline in stock prices is associated with an increase in spreads and in price impact, and with a reduction in volume for groups 1 and 2 stocks. For these stocks, we showed that there is an increase in investor horizon consistent with the view that transactions costs have a direct effect over stock prices holding expected returns constant, as in Amihud and Mendelson (1986). However, for group 3 stocks, we showed that there is a change in quoted spreads but no change in effective spreads or in trading volume. We also studied the indirect effect on stock prices through expected returns (net of transactions costs) of the change in tick size. We show that there is no statistically significant change in liquidity risk across all test groups. However, we show that all stocks experience a decline in price efficiency suggesting that information risk and thus expected returns increased for the treated stocks. This evidence is consistent with firm's cost of capital being affected by market microstructure features.

In the analysis of the effects of multimarket HFT activity on systematic liquidity co-movements within a network of European markets, we use the staggered introduction of an alternative trading platform, Chi-X, in 11 European equity markets as our instrument for an exogenous increase in multimarket HFT activity. We found that liquidity co-movements within the aggregate European market significantly increase after the introduction of Chi-X in a given country and are even higher than liquidity co-movements within the corresponding home market. We further showed that European-wide liquidity co-movements are stronger in down markets and for stocks with a higher intensity of HFT market making activity in the post-Chi-X period. Overall, our findings are consistent with the notion that multimarket HFT activity induces stronger network-wide liquidity co-movements, thus making propagation of liquidity shocks easier across different markets.

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

In our analysis of the effect of the sub-optimal execution by trading desks on predictable patterns in trading volume and return predictability, we found that the execution of orders by brokers are predictable within a trading day and executions are clustered at the end of the day where trading costs is the highest. We also showed that the execution strategy of high performing institutions outperform their peer brokers, who have a tendency to trade at the end of the day. Executions of trades by poor performing brokers coincides with periodic and predictably intraday price pressure. An important contribution our study makes to the literature is the empirical link between an broker's execution performance and intraday return predictability. The economically significant magnitude of the trading-alpha exploiting this intraday return predictability suggests that the current execution algorithm and strategy of most brokers are sub-optimal.

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