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Identifying Cross-Sided Liquidity Externalities

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Abstract

We study the relevance of the cross-sided externality between liquidity makers and takers from the two-sided market perspective. We use exogenous changes in the make/take fee structure, minimum tick-size and technological shocks for liquidity takers and makers, as experiments to identify cross-sided complementarities between liquidity makers and takers in the U.S. equity market. We find that the externality is on average positive, but it decreases with adverse selection. We quantify the economic significance of the externality by evaluating an exchange's revenue after a make/take fee change.

Keywords: Liquidity cycle; Liquidity externality; Two-sided markets; Make/take fees.
JEL Classification: G10; G20; G14.

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1 Introduction

The interaction among economic agents, either direct or indirect, forms the foundation of economic theory. The structure of a market determines the degree of this interaction. A two-sided market is one with an intermediary or platform that enables interactions between two sets of agents, and the decisions of each set of agents affect the outcome of the other group through some form of network and membership externality (see Rochet and Tirole, 2006; Rysman, 2009). In some cases, while not losing money overall, the intermediary appropriately charges or rewards each set of agents to entice them to the platform. An example of a two-sided market is a "Ladies' night," where a nightclub (a platform for gentlemen and ladies to meet each other) exempts female patrons (one set of agents) from paying cover charges and provides them free drinks, while male patrons (the other set of agents) are charged a fee. The externality that more female patrons will attract more male patrons, in turn attracting more female patrons, makes the platform more attractive and thus profitable. Although the platform subsidizes the female patrons (a money-losing strategy), the overall profitability of the platform can be positive because of the network externality. Thus identifying the network externality has important pricing implications for the platform, because it determines how the platform sets prices for both sides of the market.

This paper empirically investigates the economics of two-sidedness in financial markets by identifying a new network externality and by evaluating the pricing effectiveness of a trading platform.[1] In particular, we empirically identify the cross-sided externality between liquidity consumption and provision. We address the issue of identification by using two exogenous instruments, a fee change and a technological shock in a trading

[1]A two-sided market is different from the two-sided trading in Sarkar and Schwartz (2009), who propose a new liquidity measure called "sidedness", using the linear dependence between seller- and buyer-initiated trades. They define two-sidedness as the negative correlation and one-sidedness as the positive correlation between the buyer- and seller-initiated trades. By two-sided market, we refer to a setting where a platform or an intermediary courts buyers and sellers, accounting for the externality between the buyers and sellers.

platform. Using the estimated cross-sided externality, we evaluate the pricing strategy of a U.S. trading platform and economically quantify the cross-sided liquidity externality. Our paper is the first in the financial economics literature to empirically study the economic implications of a two-sided market.[2] Our work is important for trading venues that are attempting to understand the effectiveness of their pricing strategies. It is also important for regulators, who evaluate how alterations of make/take fees by trading venues might affect market quality from a social optimum perspective, in making decisions on related financial regulations. In addition this paper sheds light on the way the order-posting behavior of liquidity demanders and suppliers is interrelated and contributes to the on-going policy debate on the maker/taker practices in U.S. equity markets.

The first model that applies the two-sided market setup to financial markets is Foucault, Kadan, and Kandel (2013). They introduce a new type of liquidity externality (cross-sided) between liquidity makers and takers, according to which an increase in the monitoring intensity of liquidity makers induces a positive externality on liquidity takers, thereby increasing the speed of liquidity consumption. This induced increase in turn affects the actions of liquidity makers and begets liquidity supply, giving rise to liquidity cycles. A positive cross-sided liquidity externality exists because it is beneficial for liquidity makers and takers to find each other. The model explains the widespread adoption of maker/taker pricing and that presents a rationale for differentiating trading fees between liquidity makers (liquidity suppliers) and takers (liquidity demanders).

However, negative cross-sided liquidity externalities can exist if liquidity makers and takers incur a cost from meeting one another. For example, such a cost can occur if makers face information uncertainty or are afraid of being adversely selected by takers. In today's markets liquidity makers rarely have obligations to provide liquidity, and they

[2]Studies on two-sided markets are more common in the empirical industrial organization and marketing science literature. Empirical work in these literatures focuses on two-sided markets such as: operating systems, dating service, credit card, game console media, and advertising markets among many others, (see Rysman, 2009, for references).

might refrain from providing liquidity after trades, thereby leading to a negative liquidity externality.[3] If a venue alters its take fee to entice more takers, makers concerned about execution certainty and speed of execution might withdraw their liquidity provision to become takers, when the overall cost of posting a market order is lower. Thus the existence and the sign of cross-sided liquidity externalities are unclear and remain an empirical question.

We investigate and identify the cross-sided liquidity externality using a set of high quality and detailed limit order book (LOB) data from the NASDAQ OMX BX, formerly known as Boston Stock Exchange (BX hereafter).[4] The excellent data quality and the existence of a technological shock and a fee change that affect only liquidity consumption in BX provide an ideal setup for identifying cross-sided externalities. To measure the speed of liquidity consumption and provision, we build the LOB for all points in time with microsecond accuracy and construct measures of the time it takes for liquidity to replenish (make cycle) after periods of liquidity consumption (take cycle), consistent with Biais, Hillion, and Spatt (1995) and Foucault et al. (2013). We measure make cycles as the time taken for restoring liquidity after a series of aggressive liquidity depleting market orders and take cycles as the time it takes for a series of market orders to deplete the liquidity. Thus, we can view make cycles as an alternative model-free measure of resiliency for a limit order market to the popular model-specific Vector Autoregressive model (VAR) approach to measuring resiliency in Coppejans, Domowitz, and Madhavan (2004).

The make and take cycles over the sample period exhibit strong positive correlation at the intraday and daily level. We find that the duration of make cycles is significantly longer than the duration of take cycles. The average make cycle is 631 seconds, while the

[3]Senator Kaufman has expressed concerns about the voluntary liquidity provision role of high-frequency trading and statistical arbitrage firms for a large proportion of the U.S. market. He suggests that the Securities and Exchange Commission (SEC) should impose liquidity provision obligations on high-frequency traders (see `www.sec.gov/comments/s7-27-09/s72709-96.pdf`).

[4]NASDAQ OMX completed the acquisition of the Boston Stock Exchange on August 29, 2008. On January 16, 2009, NASDAQ OMX launched NASDAQ OMX BX.

average take cycle is 62 seconds. Liquidity cycles exhibit an intraday pattern where the cycles are shorter at the beginning and at the end of the day, and longer in the middle of the day. This pattern is consistent with the trading volume pattern in Admati and Pfleiderer (1988). In addition, both make and take cycles are shorter for larger stocks and for stocks with higher trading activity.

We use the Foucault et al. (2013) model to guide our identification strategy. To establish causality and to identify the cross-sided liquidity externality, we study two exogenous events that should affect the monitoring intensity of market takers through a reduction in their monitoring costs. First, we use an increase in the takers' rebate as an instrument for the speed of reaction to trading opportunities for liquidity demanders.[5] An increase in the taker's rebate directly incentivizes liquidity demanders (but not liquidity providers) to increase their monitoring intensities, which should decrease take cycles. Second, we use a technology shock that reduces the monitoring cost (and thus increases the monitoring intensity) of the taker side. Because the exogenous shocks directly affect only the take cycle, we can use them to identify the cross-sided liquidity externality and the causal effect of take cycles on make cycles.

We use an instrumental variable (IV) regression for the sample period: October 1, 2010 through March 31, 2011. The IV regression with fixed effects allows us to pin down causality and to account for confounding effects, market wide effects, and potential estimation problems. We identify a positive liquidity externality between liquidity providers and takers. In particular, we find that an increase in the taker rebate increases the takers' response speed to changes in liquidity and decreases take cycles. Consequently, there is an increased intensity of market orders, which consume the liquidity available at the best quotes and which lead to wider bid-ask spreads. This drop in liquidity, which increases the number of profit opportunities for liquidity makers, attracts more liquidity suppliers,

[5]In BX, differently from most trading venues, there is a rebate for taking liquidity, and a fee is paid for filling the limit order book for NASDAQ- and NYSE-listed stocks.

who post new aggressive limit orders that replenish liquidity. The new best prices in turn create new trading opportunities for liquidity takers. Thus the analysis using the first instrument, the increase in the taker rebate, shows that cross-sided liquidity externalities are positive, i.e. liquidity demand begets liquidity supply. This result is further substantiated by our second instrument, a technological change that reduces the monitoring cost and improves the monitoring ability of liquidity takers, which naturally reduces the duration of take cycles. Using the technological change as an instrument, we find that a reduction in the duration of taker liquidity cycles causes a decrease in the duration of maker liquidity cycles. When we use an alternative estimation strategy of a two-sample, or split sample, IV estimator to address any potential concerns about weak instruments, our results remain qualitatively similar.[6] Our results are also robust to various ways of measuring make/take cycles.

Although we find that on average liquidity demand begets liquidity supply, we also find some empirical evidence that negative liquidity externalities exist because of adverse-selection risk. By sorting the sample into groups based on different proxies for pick-off risk (market capitalization, relative spread, and return volatility), we find that the magnitude of the cross-sided externalities for stocks with smallest relative spread and largest volatility and market capitalization is smaller relative to other stocks. This suggests that both effects of liquidity demand begets liquidity supply and pick-off risk are at play but the effect of the former dominates the latter.

Our sample period lies in the period after the introduction of Regulation National Market System (RegNMS), when the U.S. equity market is highly fragmented. To address concerns related to the effect of market fragmentation on our findings, we construct measures that proxy for make/take cycles for the whole market based on Trade and Quote

[6] In the split sample two-stage least square, we randomly divide our sample and use one half to estimate parameters of the first-stage equation. We then use the estimated first-stage parameters to construct fitted values and estimate the second stage from the other half of the sample.

(TAQ) data. We use these proxies as robustness to study two exogenous events in periods when the U.S. market is less fragmented. We exploit staggered introductions of Autoquote by the New York Stock Exchange (NYSE) in 2003, a technology that reduces the monitoring cost of market makers and make cycle, to identify the existence and sign of the cross-sided externality.[7] In addition, we also study the reduction of minimum tick size by NYSE in 2001, which reduces the incentive of market maker to monitor the market. We find evidence that liquidity supply begets liquidity demand, consistent with our earlier results, in environments with less market fragmentation and higher marginal costs of monitoring.

Using the estimated cross-sided externality, we highlight its economic importance and significance by evaluating a make/take fee change in BX, where the take rebate increases from one cent to two cents per hundred shares. The change in pricing increases liquidity consumption, which in turn induces more liquidity provision. However, the increase in revenue from the increased trading rate is exceeded by the loss in revenue from the increased subsidization for liquidity demanders. Overall the estimated drop in revenue is about $770,000 per year for the exchange after the fee change and the estimated economic significance of the cross-sided externality is $200,000 per year. Our result highlights the importance of appropriately accounting for cross-sided liquidity externality in trading venues' pricing strategies.

Our paper contributes to the participation externality literature that studies whether the entry of additional investors in a market exerts an externality on other investors (see Mendelson, 1982, 1985, 1987; Pagano, 1989; Hendershott and Mendelson, 2000). Our work contributes to this literature as the first empirical paper that investigates how participation of liquidity demanders affects the participation of liquidity providers and

[7] Hendershott, Jones, and Menkveld (2011) study the impact of algorithmic trading on market liquidity using this empirical setup. They provide a detailed documentation about the introduction of Autoquote and the validity of instrumental variables based on Autoquote.

that economically quantifies this participation externality.

We join the handful of papers that identify the presence of liquidity externalities in financial markets. Amihud, Mendelson, and Lauterbach (1997) document how a change in trading mechanisms improves liquidity not only for affected stocks but also for correlated non-affected stocks. Barclay and Hendershott (2004) examine how the large differences in the amount of informed trading between regular trading hours and off-exchange trading hours affect adverse selection costs. Hendershott and Jones (2005) study how the reduction of transparency in one market affects the trading cost in other trading venues where transparency does not change. Bessembinder, Maxwell, and Venkataraman (2006) show how the introduction of transaction reporting for corporate bonds through TRACE on a subset of bonds also decreases the trading cost of non-TRACE-eligible bonds. Differently from work in this literature, which focuses on liquidity externalities related to trading costs across assets, this paper is the first to examine the cross-sided externalities related to the provision and consumption of liquidity.

While our paper focuses on two-sided markets and the identification of the liquidity externality between liquidity provision and consumption, it is also related to papers studying the impact of make/take fees on market quality. Colliard and Foucault (2012) analyze a microstructure model with make/take fees, where investors can choose to be makers or takers when deciding how to execute their trades. In a related paper, Malinova and Park (2011) empirically study the impact of a change in both the make and the take fee schedule on market quality of 60 cross-listed stocks in the Toronto Stock Exchange. Battalio, Shkilko, and Ness (2012) show that the cost of liquidity in pay-for-order flow and in maker/taker exchanges is similar when one takes the make fee rebates into account. In contrast, our paper sheds light on the way the order posting behavior of makers and takers is interrelated and contributes to the ongoing policy debate on the maker/taker practices in U.S. equity markets. In addition, we study the economic effectiveness and profitability of the pricing strategy of a U.S. exchange.

Resiliency, the ability of the limit order book (LOB) to revert to its normal shape promptly after large trades, is an under-studied but important measure of liquidity especially in today's electronic LOB markets. In a dealership market, the resiliency of the market is always high because the designated market marker has the obligation to provide liquidity. However, the change in market structure towards LOB in recent years, where there is little obligation for liquidity provision among LOB market makers, points to the need for measuring and understanding the resiliency dimension of liquidity.[8] We join the theoretical work of Foucault, Kadan, and Kandel (2005); Goettler, Parlour, and Rajan (2005); Roşu (2009, 2010), and Foucault et al. (2013) and the empirical work of Biais et al. (1995); Coppejans et al. (2004); Degryse et al. (2005), and Large (2007) in studying how the LOB replenishes after trades. We contribute to the literature with a new and model-free measure of resiliency. In contrast to the empirical papers in this literature, which focus on measuring resiliency in terms of how long it takes for the LOB to replenish after an event, our results suggest that the cycles of depletion and replenishment are endogenous and should be studied together when measuring and discussing resiliency.

2 Cross-sided Liquidity Externality

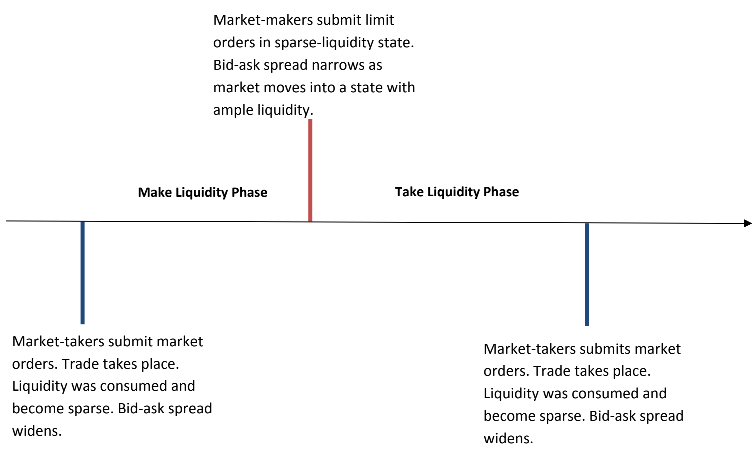
Foucault et al. (2013) develop a model of trading, with specialized market making and taking sides, in which the speed of reaction to trading opportunities for market makers and takers is endogenous. They interpret the market-making side as proprietary trading firms that specialize in high-frequency market making and the market-taking side as brokers using smart order routers to execute market orders when liquidity is ample and the cost of

[8]The recent episode of "flash crash," introduction of maker/taker pricing structure, introduction of innovations of new trading products and services offered by competing trading venues, and a shift towards automation in trading has led regulators, politicians, and market participants to question the new dynamic relation between liquidity providers and demanders in an environment without obligatory liquidity provision responsibility.

trading is low. They show that the maker/taker pricing model allows the trading platform to minimize the duration of liquidity cycles and therefore maximize its expected profit.

Foucault et al. (2013) define liquidity cycles as consisting of two phases: “make liquidity” and “take liquidity.” A “make liquidity” phase (make cycle) is the period when liquidity suppliers (makers) compete to provide liquidity after a trade. A “take liquidity” phase (take cycle) is the period when liquidity demanders (takers) compete to consume liquidity (see Figure 1). Thus a fluid trading process with short liquidity cycles requires makers to aggressively compete for providing liquidity when liquidity is low, and takers to consume liquidity when it is available at favorable prices. The liquidity cycle is a time-dimension measure of liquidity analogous to the liquidity measure of resiliency (Harris, 1990).

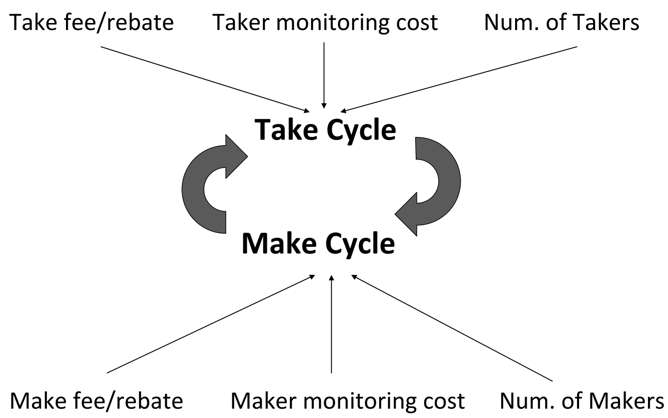
Figure 1
Flows of Events in a Cycle (Foucault et al., 2013)



In Foucault et al.’s (2013) model, where make/take fee, monitoring cost, and the number of takers and makers are exogenous, make/take fees and monitoring costs affect the gains from trade of liquidity makers and takers, while the number of makers (takers) affects the competition for supplying (consuming) liquidity. One implication of the model is that changes in fee structures, monitoring costs, and the number of market makers and takers will affect the monitoring intensities of makers and takers and the make/take cycles. Because the speed of reaction to trading opportunities is endogenous, an increase in monitoring intensity of liquidity makers (takers) will increase the monitoring intensity of takers (makers). This reinforcing effect between makers and takers implies that an improvement in the monitoring technology for either makers or takers or an increase in the number of either market makers or takers will reduce the duration of liquidity cycles, and thus increase the trading rate and the profitability of the trading venue.

The endogeneity of the monitoring intensities introduces a cross-sided liquidity externality between liquidity provision and consumption. Foucault et al. (2013) suggest that exogenous shocks or changes to make/take fees, monitoring costs, and the number of takers/makers can be used as instruments for the identification of cross-sided liquidity externalities. The exogenous and endogenous relations among the variables appear in Figure 2. This paper focuses on identifying the existence of this cross-sided liquidity externality.

Figure 2
Endogenous and Exogenous Relation among Variables in Foucault et al. (2013)



3 Data

This paper uses the complete set of quotes and trades in the NASDAQ OMX BX system for the period October 1, 2010 to March 31, 2011. The data is obtained from NASDAQ ITCH-TotalView system on special order. We retain stocks for which information is available in Trades and Quotes (TAQ), Center for Research in Security Prices (CRSP), and Compustat. Following the literature, we retain only common stocks (Common Stock Indicator Type=1) and focus only on common shares (Share Code 10 and 11) and stocks that do not change primary exchange, ticker symbol, or CUSIP over the sample period (Hasbrouck, 2009; Goyenko, Holden, and Trzcinka, 2009; Chordia, Roll, and Subrahmanyam, 2000). We also exclude stocks that exhibit a price lower than $5 or higher than $1000, and market capitalization less than $1,000,000 at any point in time during the sample period. Finally, we exclude any day/stock observation with less than 10 trades a day. Our final sample comprises 1,867 stocks and 101,176 stock/day observations.

To reconstruct the complete limit order book (LOB) for all the stocks in BX for the whole sample period, we employ the complete dataset of new order messages, updates, cancelations, deletions and executions. We use the LOB information to calculate daily stock characteristic variables in BX. Specifically, we construct realized volatility (*Volatility*) as the sum of squared five minute returns, number of trades (*Trades*) as the sum of trades per stock during the day, number of traded shares (*Traded Shares*) as the sum of the number of shares traded across all trades during the day, and trading volume (*Volume*) as *Traded Shares* times price of trade. All the variables constructed from the LOB are defined in Table A1 in the Appendix.

In BX, there is a rebate for taking liquidity and a fee for filling the LOB for NASDAQ and NYSE listed stocks (Tape A and C). For all non-NASDAQ and non-NYSE listed stocks (Tape B), there is a rebate for providing liquidity and a fee for taking liquidity. Tape B stocks constitute about 2% of our total number of day/stock observations. Table

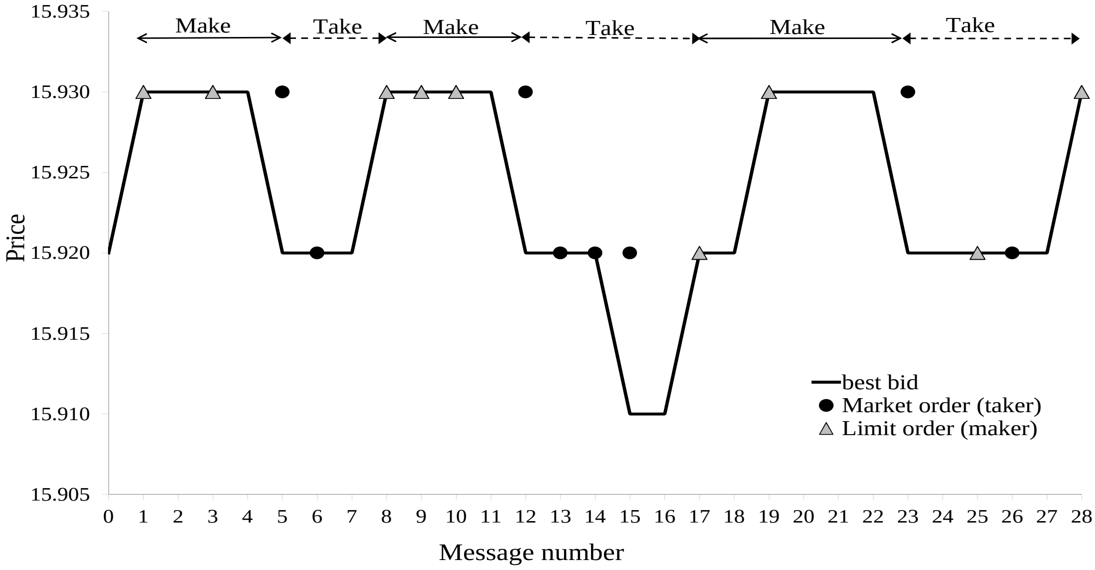
A2 in the Appendix shows that Tape B stocks are quite small and not very heavily traded. Make/take fee changes affect Tape B stocks in the opposite way of Tape A and C stocks. Because Tape B stocks can confound the results, we exclude them from the sample.

3.1 Constructing the make and take cycles

To carry out our analysis, we need to conceptualize and create a measure of cycles that is compatible with Foucault et al. (2013) and that matches Figure 1. We calculate take cycles as the difference in time between the first market order and the first subsequent limit order that improves the best price after the last trade. We calculate make cycles as the difference in time between the first limit order that improves the best prevailing quote after one or a series of market orders and the first market order. Figure 3 provides an example of the cycle calculation taken from the sample.

For illustration, we only focus on the bid side in Figure 3, the calculation is analogous for the ask side. Starting from the left, the first triangle (at message number 1 in the x-axis) represents a limit order that improves the best prevailing bid. This initiates the make cycle, which lasts until a market order to sell arrives at message number 5, at which point the make cycle stops. The make cycle is the time difference between message 5 and message 1, $t_5 - t_1$. The time of the first trade is included in the make cycle, because one needs to capture how quickly market takers are responding to the incentive of lower spreads, provided by market makers. The take cycle starts at message 5 and continues until a quote improving limit order arrives at message number 8. The take cycle is the time difference between message 8 and message 5, $t_8 - t_5$. Then a new make cycle starts. Messages 4, 7, 16 and 21 are related to changes in the limit order book that do not affect the best price, e.g. new quotes/updates/cancellations in other levels of the LOB. For robustness, we construct alternative measures of make/take cycles and present analysis based on these measures in Section 6.3.

Figure 3
Make Take Cycles



For the calculation of make cycles, the use of limit orders that *improve* the best price is important, because the make cycle should capture how the LOB is replenished after one (or more) trade(s) that takes away the best price. This is exemplified in the last take cycle in Figure 3 where a limit order that matches the current best bid arrives at message number 25 without stopping the take cycle. The take cycle stops only when the quote improving limit order arrives at message number 28. Limit orders that add depth to the existing LOB quotes at either the best price or in other layers do not replenish what was taken away from the trade.[9]

3.2 Fee structure in BX

Island ECN introduced the maker/taker pricing model in 1997. Liquidity makers usually receive a rebate (make rebate) for their services while liquidity takers pay a fee (take fee). The reason is that good prices take longer to be posted by liquidity makers due

[9]We also construct cycles that include limit orders at the best price. The results of this analysis remain qualitatively similar and are available from the authors upon request. [IS THIS OK HERE? SHOULD WE MENTION IT AT ALL?]

to the free option problem related to limit orders (Copeland and Galai, 1983). This pricing model incentivizes liquidity provision, because it rewards liquidity providers, by giving them rebates, and charges participants who remove liquidity from the exchange. NYSE, NYSE Euronext's Arca, BATS, Direct Edge X, NASDAQ OMX, and NASDAQ PSX are some of the U.S. trading venues that use a maker/taker pricing system. An inverse maker/taker pricing system ("taker/maker pricing" hereafter) first adopted by Direct Edge in 2008, also exists. The inverse pricing encourages traders to "take," or execute against, prices quoted on the exchange, by offering them rebates. This pricing system aims at profiting from transaction costs by attracting brokerages/investors that execute large volumes of trades. The target clients of such a pricing system are agency automated trading strategies for trading at the volume-weighted average price (VWAP), not at a single price. The inverted pricing model was also directed towards low-price stocks with lots of dark pool activity. While three venues-BX, BATS-Y and Direct Edge A-adopted the taker/maker model, Direct Edge A discontinued it in August 1, 2011.

3.3 Summary statistics

Table 1 provides an overview of the sample characteristics. On average there are 290 trades a day per stock. In BX the trade size of 107 shares is much smaller than the order size of 196 shares. Following Goldstein and Kavajecz (2000), the cumulative depth is calculated as the sum of all shares available at a particular price or better on the LOB, at successively distant prices. The table presents depth at 5 and 10 levels away from the best quotes. On average there are 3,700 and 6,149 shares in the first five and 10 levels of the book, respectively. Depth, on the bid and ask side, increases on average by 188 shares per tick for the first five levels of the book (Slope5) and by 394 shares for the first 10 levels of the book (Slope10). The average daily dollar trading volume is about $2 million and the average number of traded shares is 38,725.

We calculate the cycles first by taking the mean and the median daily cycle within stocks and then generating statistics across stocks. Table 2 shows characteristics of the cycle durations across stocks measured in seconds. The mean represents the cross-sectional characteristics of the within-stock mean (WS Mean), while the median represents the cross-sectional characteristics of the within-stock median (WS Median). The take cycles are much shorter than the make cycles. It takes on average about 631 seconds for liquidity to be filled in the market before liquidity is consumed in about 62 seconds. Median cycle times, i.e., the cross-sectional mean and median of the within-stock median, are much lower than mean cycle times, implying the existence of periods and stocks with very long cycle durations. The differences between the mean and the median cycles and between the make and take cycles are statistically different from zero.

Next, we sort stocks in terciles based on market capitalization and the daily number of trades. Table 3 presents the statistics for the make and take cycles for stocks grouped by trade (Panel A) and market capitalization (Panel B) terciles. Tercile 1 refers to small-cap stocks and Tercile 3 corresponds to large-cap stocks. We present the statistics for both the mean and the median within stocks. The make cycle continues to be longer than the take cycle across different size and trade terciles. Within the terciles, the difference between the mean and the median is smaller than for the entire sample, and the standard deviations are lower than those in Table 2. We also find a cross-sectional difference in the make/take cycle between stocks that have different sizes and numbers of trades per day. Larger and more traded stocks have shorter make and take cycles.

We also provide a graph of the variation in liquidity cycles during the day. Figure 4 shows the average cycle length across the day. The intraday length of the make and take cycles is highly positively correlated (94%), suggesting the existence of cross-sided liquidity externality. The make/take cycles are shorter in the morning as information and news are updated into the market. The cycles become longer as the day progresses but decrease towards the end of the day, when investors trade more aggressively to complete their portfolio rebalancing and market makers balance their positions or close their inventories. This pattern is the mirror image of the trading volume pattern in Admati and Pfleiderer (1988), where more participants enter the market in the morning and at the end of the trading day.[10]

Table 4 presents univariate daily correlations between the make and take cycles (means and medians) and number of trades, trade size, spreads, volume, and market capitalization. The correlation between daily make and take cycles is large and positive, matching the intraday-correlation evidence in Figure 4. There is a positive correlation among make and take cycles, and spreads: quoted and relative spreads. The make and take cycles are negatively correlated to the number of trades and traded shares. In Foucault et al.'s (2013) theoretical model, the relation is a mechanical one, showing why a trading platform would like to shorten make/take cycles. Shorter cycles imply a larger number of trades and traded shares, which will increase the trading venue's profit.

3.4 Panel regression

We specify regressions for the daily panel as follows:

$$D_{it}^{(maker)} = \alpha_i^{maker} + \gamma_t^{maker} + \beta^{maker} D_{it}^{(taker)} + \delta^{maker\prime} X_{it} + \epsilon_{it}^{maker} \tag{1}$$

and,

$$D_{it}^{(taker)} = \alpha_i^{taker} + \gamma_t^{taker} + \beta^{taker} D_{it}^{(maker)} + \delta^{taker\prime} X_{it} + \epsilon_{it}^{taker}, \tag{2}$$

[10]The positive correlation between make and take cycles is not due to the make/take fee structure in BX. We observe a similar pattern when constructing the cycles for NASDAQ for the same time period. Due to capacity limitations we construct the make/take cycles for only 188 stocks in NASDAQ, see Skjeltorp, Sojli, and Tham (2012) for more details on the stock selection procedure. Figure A1 in the Appendix shows a similar pattern to the BX intraday cycles and the correlation between make and take cycles is 0.94. The NASDAQ cycles are shorter because there is much more quoting and trading activity at the NASDAQ.

where $D_{it}^{(maker)}$ and $D_{it}^{(taker)}$ are the within-stock mean make and take cycle durations (in seconds) respectively for stock i in day t and X_{it} is a vector of control variables. The control variables are chosen using the correlations in Table 4. We include trade size, number of trades, traded shares, volatility, and quoted spread. α_i are firm fixed effects and γ_t are day of the week dummies. The firm fixed effects capture the impact of the level of make/take fees and number of market makers and takers on the level of the cycles.

One could alternatively use a non-linear specification such as survival analysis for panel data. However, we choose to use OLS over a non-linear specification throughout all of our analysis for two reasons. Although a correctly specified non-linear model may fit the conditional expectation function more closely than a linear model, a mispecified non-linear model often performs worse. OLS provides a robust approach as the best linear estimator for the non-linear relation. Moreover, Angrist (2005) argues for the use of linear model and OLS over nonlinear models for causal inference, because treatment effects generated by correctly specified nonlinear models are likely to be indistinguishable from OLS regression coefficients. Secondly, the literature on instrumental variables for nonlinear models and the statistical properties of nonlinear estimators are poorly developed and are not well understood.

Table 5 provides the result for the fixed effects panel regression with clustered standard errors at the stock level. We use the trade size, number of trades, traded shares, volatility, and quoted spread as control variables. The estimated coefficients of the take and the make cycle are positive and statistically significant, indicating that an increase in the take cycle is associated with an increase in the make cycle and vice versa. The impact of take cycles on make cycles appears to be stronger than the opposite effect. An increase by one standard deviation in the make cycle increases the take cycle by 55 seconds, while an increase in the take cycle by one standard deviation increases the make cycle by 114 seconds. From the control variables, number of trades, shares traded, and quoted spread have a strong and significant impact on both make and take cycles.

The panel regression allows us to establish a positive time-series association between make and take cycles. As both are endogenous variables, the results are insufficient to make any statement about the existence of cross-sided liquidity externality. To establish causality and to identify the liquidity externality, we need to rely on instrumental variables.

4 Identification

4.1 Identification using changes in make/take fees

The Foucault et al. (2013) model implies that changes in either the make or take fees in only one trading venue will allow us to identify the cross-side liquidity externality. For example, in the case of the reverse fee structure in BX, an increase in take rebate should increase the takers' monitoring intensity (take cycle) because it serves as a monetary incentive for liquidity consumption but not for liquidity provision. However, the increase in the speed of liquidity consumption will increase the speed of liquidity provision, because it exerts a positive externality on market makers. Higher liquidity consumption increases the rate at which liquidity makers find trading opportunities that will make liquidity providers better off. Our first identification channel for the cross-side externality is to use changes in *either* make *or* take fees/rebates in BX.

We exploit one change of the maker/taker pricing in BX on November 1, 2010, to identify the impact of make/take fees on the liquidity cycle. On November 1, 2010, BX increased the take rebate by 100%, from one cent to two cents per 100 shares. As this event significantly decreases the trading cost of takers, it should increase their monitoring and result in shorter take cycles in BX.

4.2 Identification using technological shock to liquidity takers

As monitoring the market can be costly, Foucault et al. (2013) argue that liquidity cycles depend on the monitoring decisions of liquidity makers and takers. Liquidity makers and takers decide on their optimal monitoring activity by considering the trade-off between being the first to identify a profitable opportunity and the cost of monitoring. Thus a shock to the monitoring cost of takers (makers) affects the monitoring intensity of makers (takers) because of the cross-side externality. Our second identification strategy of the cross-side liquidity externality uses a technological change in BX, which decreases the monitoring cost of takers. As the technological shock affects only the monitoring cost of takers, it provides an ideal instrument for identifying how the change in taker's monitoring intensity (take cycle) will affect the monitoring of liquidity makers (make cycle).

More specifically, we use the introduction of the CART order routing strategy offered from March 7, 2011. CART aims to minimize trading costs for liquidity demanders and automatically routes marketable orders to different venues in a specific sequence to obtain execution. Orders entered using CART are first routed to BX (receiving a rebate if executed) and, if unexecuted, routed to PSX (paying a fee if executed). Then, if the order remains unexecuted, the algorithm checks the NASDAQ book, where the orders pay a fee if executed. Finally, if the order remains unexecuted in all three OMX venues and is not an immediate-or-cancel order, it will be posted on the NASDAQ limit order book as a regular limit order (receiving a regular rebate offered to make orders if executed).

The CART facility clearly reduces the monitoring cost for market takers, because the CART routing system does the monitoring for the taker, while the CART strategy offers no benefit to a market maker.[11] To identify the make side liquidity externality, the analysis treats the introduction of this routing technology as an exogenous event that

[11] At the same time as the CART facility was introduced, NASDAQ also introduced the QSAV strategy which behaves similarly to CART, but routes to other destinations after checking the NASDAQ book. Pricing for QSAV is the same as CART.

affects the take side monitoring cost in BX. We expect the durations of the make/take cycles in BX to decrease substantially after the introduction of CART.

4.3 Validity of instruments

As liquidity take and make cycles are endogenous variables, the slope coefficients from estimating Equations (1) and (2) via OLS are biased estimates of the causal effect of a change in the take cycle on the make cycle (and vice versa). To address this problem, the instrumental variable should affect take cycles but be uncorrelated with the error term ϵ_{it}^{maker}, the exogeneity assumption. In addition, it is important that the instrument does not suffer from the weak instrument problem highlighted by Bound, Jaeger, and Baker (1995).

We believe that the validity of both our instruments is well supported and motivated by the theoretical and structural model of Foucault et al. (2013), as described in Section 2. The theoretical grounding of our instruments addresses the common criticism of many instrumental variable studies, in which there is no underlying theoretical relation among the variables (see Rosenzweig and Wolpin, 2000).

The exogeneity assumption of our instruments is strengthened by BX stating in its SEC filing that the reason for the BX fee change is a direct and immediate response to fee changes in October 2010 by competitors (e.g., DirectEdge and BATS Y-Exchange) and not due to observed changes in cycles within the exchange.[12] This decision-making process is consistent with Foucault et al. (2013), where the trading platform chooses its make/take fee in the first stage of the game, and liquidity makers and takers choose their monitoring intensities according to those make/take fees. Moreover, the validity of the instrument is further supported by the U.S. equity market's being a competitive market

[12] See `www.sec.gov/rules/sro/bx/2010/34-63285.pdf`, `www.sec.gov/rules/sro/edga/2010/34-63053.pdf`, `www.sec.gov/rules/sro/byx/2010/34-63154.pdf`, and `www.sec.gov/rules/sro/byx/2010/34-63149.pdf`.

with a large number of market makers and takers, where makers and takers are likely to be price takers to the make/take fees provided by various trading venues.

For the second instrument, BX states that the purpose of introducing CART, which reduces the taker's monitoring cost, is to give market participants an additional voluntary routing option that will enable them to easily access liquidity available on all of the national securities exchanges operated by the NASDAQ OMX Group. The routing strategy benefits participants who neither use high-frequency trading strategies nor have rapid access to liquidity that is provided in many venues.[13] Moreover, as announcements of these changes occur many weeks before they are implemented, it is highly unlikely that the introduction of changes is correlated with idiosyncratic make cycles weeks into the future. Given the reasons stated by BX in the SEC filings, we argue that both our instruments are exogenous to the make and take cycles.

Lastly, the exclusion restriction assumption requires the instruments to affect the make cycle only via the take cycle. We have argued that our instruments are relevant only for the take cycle and that they are unlikely to affect the make cycle via non-taker cycle related reasons. One potential alternative avenue through which our instruments can affect the make cycle is other liquidity variables, such as the bid-ask spread. This channel is possible if liquidity makers widen the bid-ask spread by not posting limit orders at the best bid-ask prices, in anticipation of the reduction in taker's fee and monitoring cost. We argue that this is strategy suboptimal for market makers, because the expected payoff of being the first to post a limit order at the best bid-ask price is higher than waiting at other bid-ask prices with wider spread. When one considers the possibility of off-the-equilibrium play or the trembling hand equilibrium, an equilibrium where the bid-ask spread is widened as a response to increased benefits to takers, the wider spread is likely to be unstable. Even if one ignores the previous argument and considers the

[13]See `www.sec.gov/rules/sro/nasdaq/2011/34-63900.pdf`.

bid-ask spread channel, the impact of the bid-ask spread on the make cycle will only bias against finding any or finding a negative cross-sided liquidity externality.

An alternative channel could be the response of competing trading venues to the fee change in BX, a response implying that competing venues will adopt strategies to drive orderflow *away from and not into* BX. Another avenue could be makers choosing to switch to being takers because of the increase in rebates and improvement in technology. In such a case, we expect the number of makers relative to takers to decrease, for a fixed total number of makers and takers. Thus the make cycle would increase while the take cycle decreases. The competing trading venues and endogenous choice of becoming maker and taker channels imply a negative, not a positive, cross-sided externality. Taking into consideration these channels suggests that we underestimate the magnitude of the positive cross-sided externality. However, we admit that we cannot test these conjectures and that our conclusions on causality rely on the intuitively attractive and logical argument just presented - but that the exclusion restriction assumption is ultimately untestable. We discuss the potential issue of weak instruments in the next section.

5 Results

5.1 Regressions

Given that we want to identify the cross-sided liquidity externality in an endogenous system of liquidity makers' and takers' monitoring intensities, we use changes in the take fee and the exogenous technological shock as instruments in a two-stage least squares procedure. To address the endogenity problem, we use the instrumental variables (IV) methodology in which the endogenous variables are the make and the take cycles.[14]

[14] We also conduct an event study around the introduction of the two instruments. We find that the introduction of both instruments significantly reduces both make and take cycles across trade and market capitalization terciles. This type of analysis is only indicative of the validity of the instruments, because of omitted variable bias, and therefore we focus on the regression analysis. We provide these results in a

To control for other important conditioning variables such as number of trades, volatility, and spread, we run a two-stage least squares regression of the within-stock mean make cycle, using the two shocks as instruments. *Fee Shock* is a dummy variable equal to 1 for the period November 01, 2010 - December 31, 2010, and zero otherwise, and *Technology Shock* is a dummy variable equal to 1 for the period March 07, 2011 - March 31, 2011, and zero otherwise. We include trade size, number of trades, number of traded shares, volatility, and quoted spread as control variables. In addition, we include firm and time fixed effects and cluster standard errors by firm. Columns (1)-(4) in Table 6 show the results for the just identified IV regression analysis, one instrument per IV regression. The first-stage results show that the two shocks lead to a significant decrease in take cycles. The Angrist-Pischke F-test statistic (Angrist and Pischke, 2009) for the hypothesis that instruments do not enter the first stage regression is greater than 10 with a p-value (0.00) for all regressions. The null hypothesis of under-identification is also rejected with a p-value of 0.00, using the Kleibergen-Paap LM test. Thus we are unlikely to be affected by an under-identification or a weak instrument problem. The second-stage regression results show strong and statistically significant positive externalities between liquidity cycles. Spread appears to be statistically significant for both the make and take cycles, and larger spreads lead to longer cycles.[15]

In addition to using each instrument separately, we use both shocks as instruments in the IV regression. The use of two instruments leads to overidentification. Columns (5) and (6) in Table 6 show the results for the overidentified IV regression analysis. The first-stage results show that the two shocks lead to a significant decrease in take cycles. Moreover, the second-stage regression results confirm the previously found results of strong and statistically significant externalities between make and take liquidity cycles. As expected,

previous version of the paper available at: `http://www.norges-bank.no/pages/92226/Norges_Bank_Working_Paper_2012_20.pdf`.

[15]The results are robust to using other measures of liquidity, e.g., relative spread. To conserve space, the results are not presented but are available from the authors upon request.

the test statistics for under- and weak-identification are even stronger than for the single instrument regressions.

5.2 Internal vs. external validity

The market share of BX is about 5% during the sample period. One potential concern is whether the average treatment effect that we estimate is representative of the population, i.e. across the entire U.S. market. In other words, one might have concerns over the estimated average treatment effect, which is a local average treatment effect (LATEs) estimated across a subsample of the population. Ideally, while we would like to have natural experiments and valid instruments to estimate the average treatment effect of the population, such a set-up is both difficult and rare in all social science studies. Motivated by and consistent with the econometric and labor economics literature, we argue that having good and credible estimates of the average treatment of a subpopulation is more important than having poor and biased estimates without valid instruments, with little credibility for the entire population. According to the causal inference literature, there is a trade-off between internal validity and external validity. In the spirit of Imbens and Wooldridge (2009) and Imbens (2010), we focus on the importance of having internal validity and claim that it is "better to have LATEs than nothing."

5.3 Specialization in market making

In practice, liquidity providers use both limit and market orders, which deviates from the assumption that firms specialize either in market making or taking by Foucault et al. (2013). However, the assumption is not unreasonable because many large market participants like Global Electronic Trading Company (GETCO), Optiver, and Knights Capital Group specialize in market making. Examples of specialized market makers can been seen from Optiver's and Getco's claims that they continuously quote both bid and ask prices for financial instruments and try to maintain a neutral position at all times. Their business model is facilitated by the entry of buyers and sellers into the markets at different times and allows buyers and sellers to immediately transfer their risk, ensuring liquidity in the market and execution certainty for investors.[16] These high frequency and algorithm-based market making firms constitute a very large volume of trades in the U.S, with Getco and Knights together accounting for about 37% of daily trading volume.

In addition, these high-frequency market-makers execute most of their trades with limit orders. Menkveld (2011) finds that about 78% of high-frequency market makers' trades are executed with limit orders. Using a detailed dataset where one can identify HFT trades, their trading strategies, and the category of HFT firms, Hagströmer and Nordén (2012) show that HFT market makers constitute about 70% of the trading volume and 81-86% of limit order traffic.

Even if makers choose to switch and become takers because of changes in rebates and in technology, the number of makers relative to takers will decrease (for a fixed total number of makers and takers) and the make cycle will increase while the take cycle decreases. This is opposite to what we find in the empirical analysis. Given these arguments, the explanation that liquidity provision begets liquidity consumption on average is a more convincing explanation for our results.

5.4 Negative liquidity externality

Although we find that on average there is a positive liquidity externality, we also know that liquidity providers face the risk of being adversely picked off. Thus, it is interesting and important to understand the local negative externality effect. If negative liquidity externalities exist because of pick-off risk, then the liquidity externality effect should be smaller or even negative among stocks with higher adverse selection.

[16] See `http://www.optiver.com/amsterdam/the-company/core-business` and `http://www.getcollc.com/what-we-do/market-making`.

Hasbrouck (1991) finds that trades are more informative for smaller firms relative to larger firms. He concludes that market capitalization and adverse selection are negatively related. Copeland and Galai (1983) argue that bid-ask spreads are informative about adverse selection and bid-ask spread increases with increasing pick-off risk by informed traders. Glosten and Harris (1988) suggest that asset return volatility is positively correlated to adverse selection costs. To determine if negative externality is also at work, we first sort stocks into three groups based on market capitalization, relative spread, and return volatility as proxies for pick-off risk. We re-estimate the two-stage least square regression for these sub-groups, using both shocks as instruments.

Results in Table 7 provide support for the existence of a negative externality. Across all pick-off risk proxies, the cross-sided liquidity externality is the smallest among stocks with the highest pick-off risk. The magnitude of the cross-sided externality for stocks with largest relative spread and volatility, and smallest market capitalization is smaller compared to stocks with less pick-off risk. Although we find that the average treatment effect of cross-sided externality is positive, Table 7 suggests that the negative effect of cross-sided externality is higher among stocks with more adverse selection and pick-off risk.

6 Robustness

6.1 Median effect

Table 2 shows that the average daily distribution of cycles is skewed. To ensure that the results we obtain are not driven by outliers, we re-estimate the instrumental variable regression on the within-stock median cycles. The results in Table 8 show the existence of positive and statistically significant cross-sided liquidity externalities for the median cycles. The impact of take cycles on make cycles is even larger when we use the within-stock median cycles instead of the within-stock mean cycles.

6.2 Split sample IV

Two-stage least squares (2SLS) estimates are biased toward the probability limit of OLS in finite samples with normal disturbances. This problem is exacerbated in samples with non-normal disturbances. All things being equal, the bias of 2SLS is greater if the excluded instruments explain a smaller share of the variation in the endogenous variable. Angrist and Krueger (1995) propose a split-sample instrumental variables (SSIV) estimator that is not biased towards OLS. In SSIV, the sample is randomly split in two halves. The first half of the sample is used for estimating the first-stage regression parameters and for obtaining the fitted values of the instrumented variable. The instrumented variable is then used in the second stage of the regression estimated in the second part of the sample. SSIV is a special case of the two-sample instrumental variables estimator in Angrist and Krueger (1992). In addition, to account for the SSIV bias towards 0, Angrist and Krueger (1995) introduce the unbiased SSIV.

Table 9 presents the results for the split sample IV regression. The first stage regression results, estimated on half the sample, are very close to the first stage results presented in the full sample estimates in Table 6. The second stage coefficients of the instrumented variable, take cycle, are positive and larger than those in the 2SLS estimation in Table 6 and are highly statistically significant.

6.3 Alternative measures of cycles

We construct two alternative measures of the make/take cycles. The first measure calculates the make cycle as the time between the first quote that improves the limit order book after a trade and the last quote that improves the limit order book before a trade, Make1. The take cycle is calculated as the time difference between the first trade and the last trade in a cluster, Take1. Panel A of Figure A2 in the Appendix presents an example of the cycle calculation. The make cycle starts with message 1 (in the x-axis), the first quote improving limit order, and ends with message 3, the last limit order before a trade in message 5 (message 4 is not related to the best bid, but to quotes in other levels of the book). Thus, the make cycle duration is $t_3 - t_1$. The take cycle starts with message 5, the first trade, and ends with message 6, the last trade before a quote improvement. Thus, the take cycle duration is $t_6 - t_5$. This alternative measure addresses the concern that the make cycle depends on the actions of the taker and the take cycle depends on the action of the makers in our main make/take cycle measure.[17]

Another way to measure cycles is to treat them as the reaction time of makers and takers to each-other's actions. Therefore, we construct a second measure that calculates the reaction time of makers and takers. *MakeR* is the difference in time between the last trade and the first quote, *TakeR* is the difference between the last quote and the first trade. Panel B of Figure A2 in the Appendix presents an example of the cycle calculation. The TakeR cycle starts with message 3, the last limit order before a trade, and ends with the trade in message 5. Thus, the TakeR cycle duration is $t_5 - t_4$. The MakeR cycle starts with message 6, the last trade, and ends with message 8, the first quote improving limit order. Thus, the take cycle duration is $t_8 - t_6$.

Panel A of Table A3 in the Appendix shows the summary statistics for these alternative cycles. The cycles are shorter using these measures. Panel B of Table A3 provides the results for fixed effects panel regressions with clustered standard errors at the stock level. We use the trade size, number of trades, traded shares, volatility, and quoted spread as control variables. The estimated coefficients of the take and the make cycle are positive and statistically significant, indicating that an increase in the take cycle is associated with

[17]In cases where there might be only one trade in between quote improving limit orders, the take cycle will be zero. Thus we create the take cycle considering only cases where there are more than one trade in a take cycle. The results remain quantitatively similar as for Take1 and are available upon request.

an increase in the make cycle and vice versa, as in Section 3.4.

Table A4 in the Appendix presents the results of the IV regression using the new cycles. The effects of the take cycle shocks on the make cycle remain large and significant. The events also affect the reaction time of the market participants substantially.

6.4 Market fragmentation and RegNMS

The dominance of traditional trading venues such as NYSE has decreased since Regulation NMS in 2005.[18] Today, trading volume is shared roughly equally among NYSE, NASDAQ, BATS, DirectEdge and "dark pools". Figure A3, taken from Angel, Harris, and Spatt (2011), presents the evolution of the market share of different trading venues from 2003 to 2011 for NYSE-listed stocks. The competitive landscape and the role of RegNMS in the sample period are potentially important for the analysis, because orderflows and trading activities in other markets might have an impact on BX. Thus, competition and fragmentation may affect the make/take cycles in BX. However, it is challenging to study the demand and supply of liquidity and make/take cycles across markets because of lack of detailed data from all the U.S. trading venues. To address concerns about the role of market fragmentation on our results, we create a cycle measure for the aggregate market, using TAQ data, and investigate two events that affect the whole market in periods when the market is less fragmented (pre-RegNMS).

We create cycles in TAQ by using the number of quote updates, the number of trades and the number of seconds the market is trading (9:30-16:00 EST, 23,400 seconds). The average take cycle is equal to the total trading time divided by the number of trades, 23,400 seconds divided by the number of trades. The average make cycle is equal to the total trading time divided by the number of quote updates, 23,400 seconds divided by

[18]Regulation NMS approved by the SEC is a series of initiatives to promote fair and efficient price formation across U.S. financial markets, through competition among market participants.

the number of quote updates.[19] The correlation between the TAQ and BX cycles for the period October 1, 2010 and March 31, 2011 is 0.20.

We study two events when the market is dominated by NYSE and is less fragmented, the first one is the introduction of Autoquote by NYSE in the first half of 2003, and the second is the reduction in tick size in January 2001. Autoquote was introduced as a means to reduce the work load of clerks and automatically update the inside quote at the NYSE. Autoquote allowed algorithmic liquidity suppliers to, say quickly notice an abnormally wide inside quote and provide liquidity accordingly via a limit order. This measure affects the monitoring cost of market makers because it reduces their burden of having to manually update quotes. Autoquote was introduced in phases, the first batch of six large-cap stocks started using Autoquote on January 29, 2003. Then 200 more stocks were added until May 27, 2003. The last batch was introduced on May 27, 2003. Hendershott, Jones, and Menkveld (2011) provide detailed documentation about the introduction of Autoquote and the validity of instrumental variables based on Autoquote. The natural experiment setup based on Hendershott et al. (2011) provides a clean platform to study the cross-sided liquidity externality in a less fragmented market environment.

In addition, we study an event where the marginal cost of monitoring is more significant. On January 29, 2001, NYSE reduced the minimum tick size from $1/16 to $0.01. This shock affects market makers, by reducing their profit margin, i.e. it's a reduction in compensation for market making. This naturally decreases the incentive, the fraction of gains from trade, for market makers to monitor and thus increases the make cycle. On the other hand, the reduction in minimum tick size increases the takers' fraction of gains from trade, thus there is more incentive for takers to monitor markets with a small tick

[19] This measure is a good approximation to the make/take cycles for the period pre RegNMS, because liquidity supply and demand were mainly taking place in NYSE. This measure is not very appropriate for the post-2005 period for three reasons. First, it is not clear if a trade in Exchange A should be in the same take cycle as a trade in Exchange B. Second, quotes of odd-lot shares are not reported in TAQ. Third, data from TAQ is not ordered sequentially according to the time in which actions happened in the whole market, but is ordered by exchange.

size. This suggests a decrease in the take cycle due to the shock. The opposite effect of the minimum tick-size change on takers and makers' incentive to monitor allows us to conduct a robustness test on the existence of cross-sided externality. If the negative shock to makers causes a negative shock to takers or the positive shock to takers causes a positive shock to makers, the externality will be positive. Otherwise, the externality will be negative.

Panel A of Table A5 in the Appendix shows the IV regression using Autoquote as an instrument. The estimation period is November 1, 2002 - July 31, 2003. *Autoquote* is a dummy variable equal to 1 for the period after Autoquote was introduced by NYSE, and zero otherwise. This period varies by stock from January 29, 2003 - May 27, 2003.[20] We use control variables similar to Hendershott et al. (2011). We include spread, volume, volatility, reverse of price, and market capitalization, constructed from CRSP. The introduction of Autoquote has a very strong effect in reducing make cycles by 60 seconds. The effect of the make cycles on the take cycles is large and positive.

Panel B of Table A5 in the Appendix shows the IV regression using the Tick size as instrument. The estimation period for Panel B is December 1, 2000 - March 31, 2001. *Tick Shock* is a dummy variable equal to 1 for the period after January 29, 2001, and zero otherwise. We use the same control variables as in Panel A. The reduction in tick size increases the average make cycle by 156 seconds, and as a result the take cycles also increases significantly. Thus, there is support for the existence of positive cross-sided externalities, since we observe an increase in the make cycle after the reduction in minimum tick size (positive coefficient in the first stage regression) and a positive and statistically significant coefficient in our second stage IV regression. Both these events on the make cycle, using market wide measure and a period where the market was not fragmented, corroborate the previous evidence obtained from events in BX.

[20] The dates on the introduction of Autoquote to various stocks are available from Terry Hendershott's web page `http://faculty.haas.berkeley.edu/hender/`.

7 Economic Significance

With the estimated cross-sided liquidity externality, we can evaluate the effectiveness of BX's pricing strategy of changing their take rebate from one cent to two cent per 100 shares on November 1, 2010. The make fee remains unchanged at three cents per 100 shares. After the price change, the make/take spread is one cent per 100 shares traded. To compute the profitability of the trading platform's change in pricing strategy, we consider the expected profit of BX per unit time Π_e, see equation 12 in Foucault et al. (2013):

$$\Pi_e \equiv \bar{c}.R(\bar{\mu}, \bar{\tau}) = (c_m + c_t).\frac{1}{D_{maker} + D_{taker}}, \tag{3}$$

where $R(\bar{\mu}, \bar{\tau})$ is the trading rate or average number of transaction per unit time, D_{maker} is the average duration of the make cycle, D_{taker} is the average duration of the take cycle, c_m is the make fee, c_t is the take fee, and $\bar{c}$ is the make/take spread charged by the platform. Equation 3 states that the profit of the trading platform depends on the make/take spread, $\bar{c}$, and the trading rate, $R(\bar{\mu}, \bar{\tau})$.

By taking the total derivative of Π_e with respect to c_t, we can approximate the change in revenue of the exchange for a fee change with the following first order approximation:

$$\Delta\Pi_e = \frac{\delta\Pi}{\delta c_t} \times \Delta c_t, \tag{4}$$

where,

$$\begin{aligned}
\frac{\delta\Pi}{\delta c_t} &= \frac{\delta\Pi}{\delta\bar{c}}\frac{d\bar{c}}{dc_t} + \frac{\delta\Pi}{\delta D_{maker}}\frac{dD_{maker}}{dc_t} + \frac{\delta\Pi}{\delta D_{taker}}\frac{dD_{taker}}{dc_t} \\
&= \frac{1}{D_{maker}+D_{taker}} - (\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{maker}}{dc_t} \times \bar{c} - (\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{taker}}{dc_t} \times \bar{c} \\
&= \frac{1}{D_{maker}+D_{taker}} - ((\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{maker}}{dD_{taker}}\frac{dD_{taker}}{dc_t} - (\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{taker}}{dc_t}) \times \bar{c}
\end{aligned}$$

Using the information on the length of cycles, c_t= 0.02 cnt/share, c_m=0.03 cnt/share, D_{maker}=208 seconds, D_{taker}=31 seconds, the IV estimates of $\frac{dD_{taker}}{dc_t}$=772 sec/(cnt/share) from the first stage regression, and cross-sided externality $\frac{dD_{maker}}{dD_{taker}}$=1.63 from Table 6:

$$\frac{\delta\Pi}{\delta c_t} = 0.0061.$$

If there are on average 1,867 stocks trading 7.5 hours per day over 250 days, we find that BX suffers a loss of approximately $768,737 after implementing the fee change. However, this finding does not suggest that BX is losing money in their business but reflects the drop in revenue after the fee change. The reason for the drop in revenue is the over-subsidization of takers with a two cent rebate. Even though the trading rate increased due to the positive cross-sided liquidity externality, the loss in revenue from the subsidization exceeds the increase in revenue from the increase of trading rate. We calculate the economic cost of ignoring the cross-sided externality. By setting $\frac{dD_{maker}}{dD_{taker}}$=0, BX incurs a loss of $969,252. Thus we estimate the economic cost of ignoring the cross-sided externality to be -$969,252+$768,737 =-$200,515 for 1,867 stocks across a year, a significant loss for a small exchange such as BX. This example highlights the importance of estimating the liquidity externality and choosing the appropriate subsidization for one side of the market.

8 Conclusion

In this paper, we empirically investigate the economics of two-sided markets and test the theoretical prediction of the existence of a positive liquidity externality in Foucault et al. (2013). Using detailed data from Nasdaq OMX BX, we estimate the magnitude of cross-sided externality between liquidity providers and demanders. We also evaluate the economic significance of this externality and assess the effectiveness of a make/take fee change by BX using the estimated externality.

Extrapolating from Foucault et al. (2013), for identification we use exogenous changes in the make/take fee structure and technological shocks for liquidity takers as instruments to cleanly identify a new type of liquidity externality and cross-side complementarities of liquidity makers and takers in U.S. equity markets. We find a positive and strong cross-sided liquidity externalities between liquidity providers and takers. Shocks to fees of either makers or takers cause changes in the length of the liquidity cycles of both makers and takers. A change in technology that improves market takers ability to monitor the market reduces both the maker and taker liquidity cycles.

Through the economic evaluation on the effectiveness of a make/take fee change by BX, we find the magnitude of the externality and its economic significance to be substantially large. By studying the estimated revenue of the fee change, we estimate that BX suffers a loss in revenue of $770,000. Even though the trading rate in BX has increased after the fee change, due to the positive cross-sided liquidity externality, the loss in revenue comes from the over-subsidization of one side of the market. Our study shows that consideration of two-sided markets and identification of network externality have important pricing implications for the trading platform, as they determine how the platform should set prices for both sides of the market.

Our paper lays the basic framework and strategies for examining network and participation externality of two-sided markets in the finance literature. An important extension of our work is the identification not only of cross-sided externality but also of cross-platform externality in a two-sided market framework with competitive intermediaries. While our focus is on two-sided market and network externalities, our work also has implications on the study of liquidity resiliency, the debate over make/take pricing in the U.S. equity market, and the new dynamic relation between liquidity demanders and suppliers with the changing structure of financial markets.

Figure 4
Intraday Variation in Make/Take Cycles

The figure presents the average time of a make cycle and of a take cycle at 15 minute intervals for aggressive limit orders. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean daily cycle within stocks.

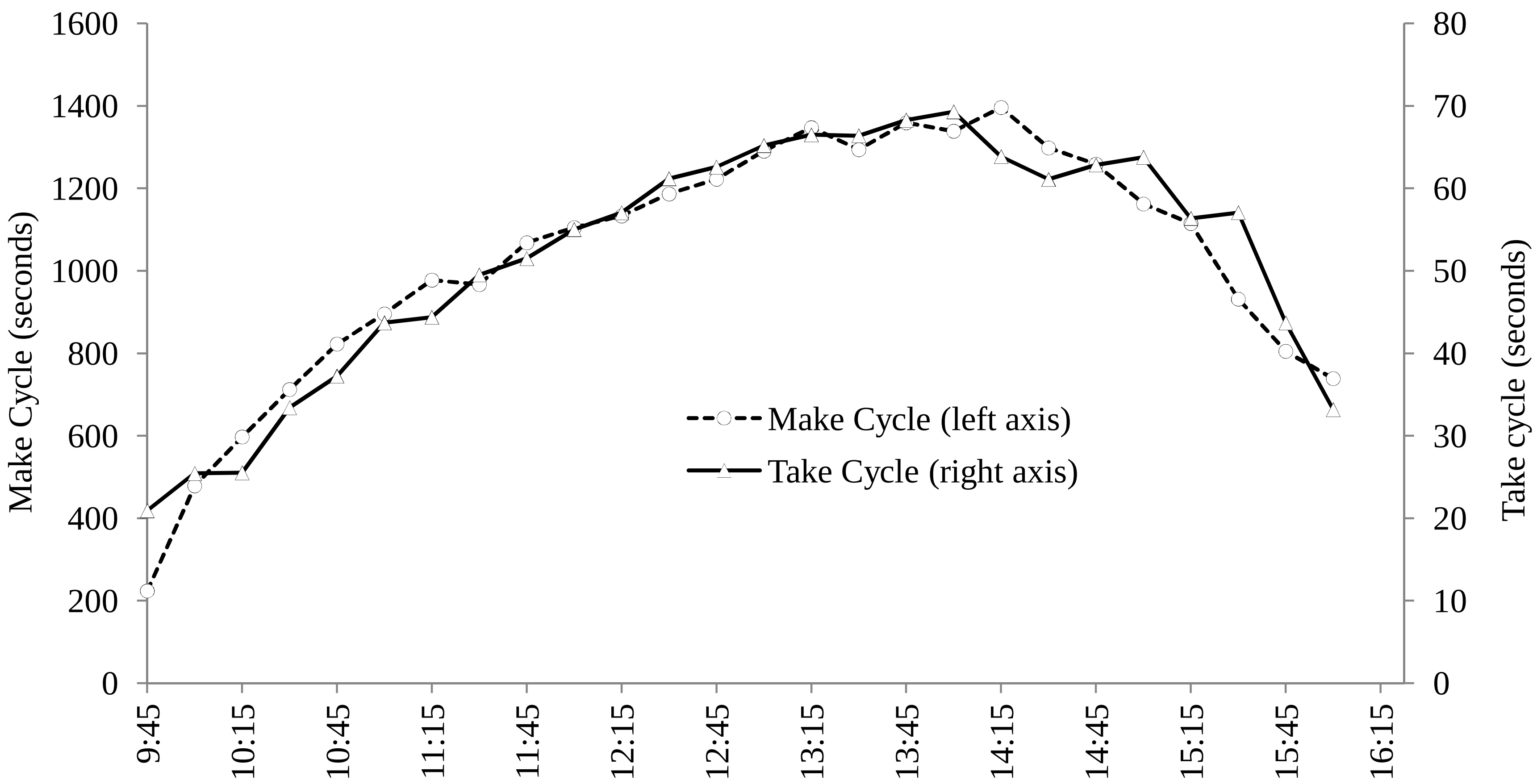


Table 1
Sample Characteristics

Table shows the daily sample characteristics for the period October 1, 2010 to March 31, 2011. *Trades* is the daily number of trades, *Trade Size* is the average size of trades, *Order Size* is the average size of limit orders, *Spread* is the bid-ask spread, ask price - bid price in $, *Rel. Spread* is Spread/((ask+bid)/2) in %, *ILR* is the illiquidity ratio |return|/dollar volume for a million shares, *Slope 5* and *10* are the slopes for the first five and ten levels of the limit order book, respectively, and *Depth 5* and *10* is the cumulative number of shares standing in the first five and ten levels of the book, respectively, *Volatility* is the realized volatility calculated as the sum of squared five minute returns, *Volume* is the trading dollar volume in 000s, *Traded Shares* is the number of traded shares, and *Mkt Cap* is the market capitalization in $ million. All variables are defined in Table A1.

	Trades	Trade Size	Order Size	Spread	Relative Spread	ILR	Slope 5	Slope 10	Depth 5	Depth 10	Volatility	Volume	Traded Shares	Mkt Cap
Mean	290	107	196	0.322	0.800	2.40	188	394	3,700	6,149	0.06	2,269	38,725	12,308
Median	59	101	171	0.232	0.621	1.14	58	179	3,877	4,796	0.03	242	6,181	3,822
25th	23	95	132	0.081	0.283	0.56	42	79	2,856	3,860	0.02	81	2,300	1,764
75th	213	112	233	0.457	1.062	2.33	118	395	4,100	5,623	0.06	829	22,733	9,975
St. Dev.	791	27	98	0.332	0.709	5.56	731	907	4,078	10,120	0.98	319,442	154,148	28,817

Table 2
Make Take Cycles

Table shows the daily cycle durations in seconds. *Make* and *Take* cycles are calculated using only limit orders that improve the best price, as described in Figure 3. The cycles are calculated by taking the mean and the median daily cycle within stocks. *WS Mean* represents the cross-sectional characteristics of the within-stock mean, *WS Median* represents the cross-sectional characteristics of the within-stock median. *Obs* refers to the total number of firm/date observations.

	WS Mean		WS Median	
	Make	Take	Make	Take
Mean	631	62	265	27
Median	391	24	100	7
25th	121	12	30	3
75th	957	49	327	16
St. Dev.	687	306	458	271
Obs	101,176	101,176	101,176	101,176

Table 3
Make Take Cycles - Terciles

Table shows the daily cycle durations in seconds across three trade and market capitalization terciles for liquidity cycles. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean and the median daily cycle within stocks. Panel 1 shows the average cycle durations across three trade terciles. Terciles are calculated using the average number of trades per stock over the sample period. Panel 2 shows the average cycle durations across three market capitalization terciles. Terciles are calculated using the average size (market capitalization) per stock over the sample period. *WS Mean* represents the cross-sectional characteristics of the within-stock mean, *WS Median* represents the cross-sectional characteristics of the within-stock median. Tercile 1 contains the least traded/lowest size stocks, and tercile 3 contains the most traded/largest market capitalization stocks.

	Tercile 1		Tercile 2		Tercile 3	
	Make	Take	Make	Take	Make	Take
Panel 1. Number of Trades						
A. WS Mean						
Mean	1335	100	440	56	94	29
Median	1226	43	378	24	70	12
25th	885	25	254	14	36	6
75th	1661	81	549	42	120	23
St. Dev.	695	423	294	291	95	108
B. WS Median						
Mean	598	48	157	23	31	9
Median	452	14	111	7	22	3
25th	236	7	60	3	12	2
75th	786	28	201	13	40	7
St. Dev.	636	393	187	245	33	51
Panel 2. Market Cap						
A. WS Mean						
Mean	1016	124	604	42	260	18
Median	889	46	415	25	123	13
25th	408	25	162	14	41	7
75th	1468	92	885	44	337	22
St. Dev.	820	512	570	80	348	22
B. WS Median						
Mean	448	60	244	14	99	5
Median	261	14	109	7	31	3
25th	87	6	39	3	13	2
75th	605	31	307	15	101	6
St. Dev.	637	462	344	33	186	8

Table 4
Correlations

Table shows the daily correlations for the period October 1, 2010 to March 31, 2011. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean and the median daily cycle within stocks. *Make Mean* is the within-stock mean make cycle, *Take Mean* is the within-stock mean take cycle, *Make Med* is the within-stock median make cycle, *Take Med* is the within-stock median take cycle, *Trades* is the daily number of trades, *Trade Size* is the average size of trades, *Order Size* is the average size of limit orders, *Fill Rate* is the average fill rate, *Spread* is the bid-ask spread, ask price - bid price in $, *Rel. Spread* is Spread/((ask+bid)/2) in %, *Slope 5* and *10* are the slopes for the first five and ten levels of the limit order book, respectively, and *Depth 5* and *10* is the cumulative number of shares standing in the first five and ten levels of the book, respectively, *Volatility* is the realized volatility calculated as the sum of squared five minute returns, *Volume* is the trading dollar volume in 000s, *Traded Shares* is the number of traded shares. All variables are defined in Table A1. Coefficients in bold are significant at the 10% level.

	Make Mean	Take Mean	Make Med	Take Med	Trades	Trade Size	Spread	Relative Spread	Volatility	Volume	Traded Shares
Take Mean	**0.23**	**1.00**									
Make Med	**0.82**	**0.27**	**1.00**								
Take Med	**0.19**	**0.93**	**0.25**	**1.00**							
Trades	**-0.29**	**-0.05**	**-0.19**	**-0.03**	**1.00**						
Trade Size	**-0.13**	**0.07**	**-0.10**	**0.04**	**0.33**	**1.00**					
Spread	**0.38**	**0.02**	**0.27**	0.00	**-0.25**	**-0.15**	**1.00**				
Relative Spread	**0.53**	**0.10**	**0.37**	**0.06**	**-0.29**	**-0.13**	**0.67**	**1.00**			
Volatility	**0.04**	0.00	**0.03**	0.00	**-0.02**	-0.01	**0.09**	**0.09**	**1.00**		
Volume	**-0.01**	0.00	0.00	0.00	**0.03**	**0.02**	0.00	**-0.01**	0.00	**1.00**	
Traded Shares	**-0.20**	**-0.03**	**-0.13**	**-0.02**	**0.92**	**0.42**	**-0.19**	**-0.21**	**-0.02**	**0.03**	**1.00**
Mkt. Cap	**-0.26**	**-0.07**	**-0.17**	**-0.03**	**0.52**	**0.17**	**-0.10**	**-0.27**	**-0.02**	**0.01**	**0.43**

Table 5
Preliminary Panel Regressions

Table shows panel regressions of within-stock mean make and take cycles on each other and control variables. $D_{it}^{(maker)} = \alpha_i^{maker} + \gamma_t^{maker} + \beta^{maker} D_{it}^{(taker)} + \delta^{maker} X_{it} + \epsilon_{it}^{maker}$ and $D_{it}^{(taker)} = \alpha_i^{taker} + \gamma_t^{taker} + \beta^{taker} D_{it}^{(maker)} + \delta^{taker} X_{it} + \epsilon_{it}^{taker}$. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean daily cycle within stocks. *Trade Size* is the average number of shares per trade, *Trades* is the number of trades per day, *Traded Shares* is the number of shares traded a day, per 1000 shares, *Volatility* is the daily realized volatility, and *Spread* is the quoted spread. All regressions include firm fixed effects and day of the week dummies. Standard errors are clustered at firm level.

	Take			Make		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Make	0.08	7.78	0.00			
Take				0.37	3.91	0.00
Trade Size	0.09	0.48	0.63	0.21	0.91	0.37
Trades	0.01	2.71	0.01	-0.19	-5.72	0.00
Traded Shares	-0.04	-1.88	0.06	0.51	4.53	0.00
Volatility	-28.77	-1.64	0.10	-125.41	-1.01	0.31
Spread	12.23	1.70	0.09	304.69	7.47	0.00

Table 6
Instrumental Variable Regression

Table shows the instrumental variable regression for within-stock mean take cycle shocks on the make cycle. *1st Stage* presents the result for the first-stage regression of Take Cycle on the instrument (the shock dummy variable) and control variables and *2nd Stage* presents the results for the second-stage regression, where the Make Cycle is regressed on the Fitted Take Cycle and control variables. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean daily cycle within stocks. *Fee Shock* is a dummy variable equal to 1 for the period November 1, 2010 - December 31, 2010, and zero otherwise, and *Technology Shock* is a dummy variable equal to 1 for the period March 7, 2011 - March 31, 2011, and zero otherwise. *Trade Size* is the average number of shares per trade, *Trades* is the number of trades per day, *Traded Shares* is the number of shares traded a day, per 1,000 shares, *Volatility* is the daily realized volatility, and *Spread* is the quoted spread. *AP Test* presents the Angrist-Pischke F-statist for weak identification and the associated p-value, *Under-Identification* presents the LM statistic for the Kleibergen-Paap under-identification test and the associated p-value, *Weak-Identification* and *Kleibergen-Paap Wald* present the Cragg-Donald and Kleibergen-Paap F statistic for weak-identification, respectively. All regressions include firm fixed effects and day of the week dummies. p-values in brackets are calculated using firm clustered standard errors.

	Event 1 - Fee Shock				Event 2 - Technology Shock				Combined Events			
	1st Stage (1)		2nd Stage (2)		1st Stage (3)		2nd Stage (4)		1st Stage (5)		2nd Stage (6)	
Take			1.63	(0.08)			11.10	(0.00)			4.22	(0.00)
Fee Shock	-7.72	(0.00)							-9.58	(0.00)		
Technology Shock					-5.55	(0.00)			-9.82	(0.00)		
Trade Size	0.11	(0.59)	0.06	(0.82)	0.11	(0.60)	-1.02	(0.67)	0.10	(0.64)	-0.23	(0.76)
Trades	-0.01	(0.01)	-0.19	(0.00)	-0.01	(0.04)	-0.13	(0.00)	-0.01	(0.02)	-0.17	(0.00)
Traded Shares	0.00	(0.89)	0.51	(0.00)	0.00	(1.00)	0.50	(0.04)	0.00	(0.92)	0.50	(0.00)
Volatility	-40.68	(0.00)	-74.92	(0.50)	-40.26	(0.00)	304.31	(0.15)	-41.25	(0.00)	28.61	(0.79)
Spread	37.59	(0.00)	256.97	(0.00)	36.62	(0.00)	-101.48	(0.50)	35.40	(0.00)	159.11	(0.01)
AP Test	9.38	(0.00)			8.42	(0.00)			11.75	(0.00)		
Under-Identification	9.30	(0.00)			8.43	(0.00)			23.23	(0.00)		
Weak-Identification	27.65				7.66				24.20			
Kleibergen-Paap Wald	9.38				8.42				11.75			

Table 7
Instrumental Variable Regression by Pick-off Risk

Table shows the instrumental variable regression for within-stock mean take cycle shocks on the make cycle for stocks sorted on pick-off risk proxies. Results are presented based on terciles sorted by market capitalization, relative spread, and return volatility. *1st Stage* presents the result for the first-stage regression of Take Cycle on the instrument (the shock dummy variable) and control variables and *2nd Stage* presents the results for the second-stage regression, where the Make Cycle is regressed on the Fitted Take Cycle and control variables. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean daily cycle within stocks. *Fee Shock* is a dummy variable equal to 1 for the period November 1, 2010 - December 31, 2010, and zero otherwise, and *Technology Shock* is a dummy variable equal to 1 for the period March 7, 2011 - March 31, 2011, and zero otherwise. All regressions are estimated with control variables and estimates of control variables are suppressed to conserve space. The control variables are: *Trade Size*, *Trades*, *Traded Shares*, *Volatility*, and *Spread* as described in Table A1 in the Appendix. All regressions include firm fixed effects and day of the week dummies. p-values in brackets are calculated using firm clustered standard errors.

	Market Capitalization				*Rel. Spread*				*Volatility*			
	1st Stage		2nd Stage		1st Stage		2nd Stage		1st Stage		2nd Stage	
	Group 1 - Largest				Smallest spread				Smallest volatility			
Take			12.40	(0.00)			17.63	(0.00)			8.31	(0.00)
Fee Shock	-4.76	(0.00)			-3.72	(0.00)			-8.26	(0.00)		
Technology Shock	-2.26	(0.00)			-2.19	(0.01)			-2.77	(0.06)		
	Group 2											
Take			9.55	(0.00)			10.07	(0.00)			9.52	(0.00)
Fee Shock	-8.73	(0.00)			-8.53	(0.00)			-8.77	(0.00)		
Technology Shock	-4.80	(0.00)			-6.62	(0.00)			-4.87	(0.00)		
	Group 3 - Smallest				Largest spread				Largest volatility			
Take			4.14	(0.00)			4.16	(0.00)			8.21	(0.00)
Fee Shock	-14.07	(0.00)			-17.48	(0.00)			-11.67	(0.00)		
Technology Shock	-1.52	(0.79)			-7.42	(0.09)			-9.12	(0.01)		

Table 8
Instrumental Variable Regression - Median

Table shows the 2^{nd} stage of the instrumental variable regression for the within-stock median take cycle shocks on the make cycle. The 2^{nd} stage presents the results for the second-stage regression, where the Make Cycle is regressed on the Fitted Take Cycle and control variables. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the median daily cycle within stocks. *Fee Shock* is a dummy variable equal to 1 for the period November 1, 2010 - December 31, 2010, and zero otherwise, and *Technology Shock* is a dummy variable equal to 1 for the period March 7, 2011 - March 31, 2011, and zero otherwise. *Trade Size* is the average number of shares per trade, *Trades* is the number of trades per day, *Traded Shares* is the number of shares traded a day, per 1000 shares, *Volatility* is the daily realized volatility, and *Spread* is the quoted spread. *AP Test* presents the Angrist-Pischke F-statist for weak identification and the associated p-value, *Under-Identification* presents the LM statistic for the Kleibergen-Paap under-identification test and the associated p-value. All regressions include firm fixed effects and day of the week dummies. p-values are calculated using firm clustered standard errors.

	Fee Shock		Technology Shock		Combined Events	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Take	7.48	0.00	3.77	0.02	6.67	0.00
Trade Size	-0.02	0.99	-0.02	0.96	-0.02	0.98
Trades	-0.06	0.00	-0.07	0.00	-0.06	0.00
Traded Shares	0.20	0.06	0.20	0.00	0.20	0.04
Volatility	89.28	0.14	32.90	0.59	77.22	0.17
Spread	38.22	0.32	79.47	0.00	47.04	0.15
AP Test	13.20	0.00	9.33	0.00	12.00	0.00
Under-identification	13.09	0.00	9.35	0.00	23.79	0.00

Table 9
Split Sample Instrumental Variable

Table shows the split sample instrumental variable regression, Angrist and Krueger (1995), for within-stock mean take cycle shocks on the make cycle. *1st Stage* presents the result for the first-stage regression of Take Cycle on the instrument (the shock dummy variable) and control variables for half the sample, randomly selected. *2nd Stage* presents the results for the second-stage regression, where the Make Cycle is regressed on the Fitted Take Cycle in the *1st Stage* and control variables for the other half of the sample, randomly selected, see Section 5.1 for more details on the methodology. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean daily cycle within stocks. *Fee Shock* is a dummy variable equal to 1 for the period November 1, 2010 - December 31, 2010, and zero otherwise, and *Technology Shock* is a dummy variable equal to 1 for the period March 7, 2011 - March 31, 2011, and zero otherwise. *Trade Size* is the average number of shares per trade, *Trades* is the number of trades per day, *Traded Shares* is the number of shares traded a day, per 1000 shares, *Volatility* is the daily realized volatility, and *Spread* is the quoted spread. All regressions include firm fixed effects and day of the week dummies. Panel A presents the first stage regression results. Panels B and C present the second stage regression results using the split sample IV (2nd Stage SSIV) and the unbiased split sample IV (2nd Stage USSIV) estimator.

	Fee Shock		Technology Shock		Combined Events	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Panel A. 1st Stage						
Fee Shock	-5.83	0.03			-7.66	0.01
Technology Shock			-5.12	0.01	-8.28	0.00
Trade Size	0.27	0.23	0.27	0.24	0.26	0.25
Trades	-0.01	0.10	0.00	0.16	0.00	0.12
Shares Traded	0.00	0.94	0.00	0.85	0.00	0.91
Volatility	-29.87	0.00	-29.24	0.00	-29.83	0.00
Spread	37.43	0.00	36.43	0.00	35.50	0.00
Panel B. 2nd Stage SSIV						
Take	2.57	0.04	13.04	0.00	6.10	0.00
Trade Size	-0.30	0.48	-3.20	0.00	-1.27	0.00
Trades	-0.19	0.00	-0.13	0.00	-0.17	0.00
Shares Traded	0.59	0.00	0.63	0.00	0.60	0.00
Volatility	-91.90	0.47	215.48	0.12	11.54	0.93
Spread	197.24	0.00	-196.37	0.02	64.79	0.15
Panel C. 2nd Stage USSIV						
Take	2.57	0.09	13.04	0.01	6.10	0.00
Trade Size	-0.30	0.63	-3.20	0.39	-1.27	0.38
Trades	-0.19	0.00	-0.13	0.00	-0.17	0.00
Shares Traded	0.59	0.00	0.63	0.04	0.60	0.00
Volatility	-91.90	0.42	215.48	0.20	11.54	0.91
Spread	197.24	0.00	-196.37	0.29	64.79	0.44

Table A1
Variable Definitions

Table presents the definitions of all the variables used in the study. All variables are calculated from intraday data.

Variable	Acronym	Definition	Units
Number of daily trades	Trades		
Trade size		Average daily number of shares per trade	
Order size		Average daily number of shares per limit order	
Spread		Average $\mathsf{ask} - \mathsf{bid}$	$
Relative Spread	Rel. Spread	Average $(\mathsf{ask} - \mathsf{bid}) * 100/((\mathsf{ask} + \mathsf{bid})/2)$	%
Amihud Illiquidity Ratio	ILR	Average $\lvert\mathsf{return}\rvert$*100/dollar volume	price change per 10$
Slope 5 Ask	slope_{A5}	$(\mathsf{askdepth}_5 - \mathsf{askdepth}_1)/(\mathsf{ask}_5 - \mathsf{ask}_1)$	number of shares per level in the book
Slope 5 Bid	slope_{B5}	$(\mathsf{biddepth}_5 - \mathsf{biddepth}_1)/(\mathsf{bid}_5 - \mathsf{bid}_1)$	number of shares per level in the book
Slope 5		Average $(\mathsf{slope}_{A5} + \mathsf{slope}_{B5})/2$	number of shares per level in the book
Slope 10		Average $(\mathsf{slope}_{A10} + \mathsf{slope}_{B10})/2$	number of shares per level in the book
Depth 5		Average (ask depth_5+bid depth_5)/2	cumulative number of shares
Depth 10		Average (ask depth_{10}+bid depth_{10})/2	cumulative number of shares
Realized Volatility	Volatility	$\sum_{t=1}^{78} \mathsf{return}_{t,5min}^2$	
Dollar volume	Volume	Sum of (Traded shares*Midpoint price)/1000	$ 000s
Traded shares		Sum of Trades*Trade size	
Firm size	Mkt Cap	(m_t*Outstanding Shares)/1000000	$ million

Table A2
Listing Descriptions

Table shows the average daily characteristics for stocks listed in different exchanges and classified as Tape A, B, and C. Tape A are NYSE listed stocks, Tape C are NASDAQ listed stock, and all other stocks are classified as Tape C. Panel A presents the characteristics of all the Tape A and C stocks (45,254 day-stock observations). Panel B shows the characteristics for the Tape B stocks (1,067 day-stock observations). All variables are defined in Table A1.

	Price	Volume	Returns	Mkt Cap
Panel A. AC Stocks				
Mean	35	55	0.07	6,427
Median	27	8	0.02	1,221
25th	16	1	0.01	388
75th	43	38	0.04	3,949
St. Dev.	37	207	0.22	20,995
Panel B. B Stocks				
Mean	33	0.82	0.31	267
Median	18	0.09	0.14	90
25th	11	0.01	0.05	43
75th	66	0.45	0.40	271
St. Dev.	56	3.47	0.43	469

Table A3
Alternative Make Take Cycles

Table shows the daily characteristics of cycle durations in seconds for alternative measures of cycles. *Make1* cycles are calculated the time between the first quote that improves the limit order book after a trade and the last quote that improves the limit order book before a trade, and *Take1* is calculated as the time difference between the first trade and the last trade in a cluster. *Take2* is calculated excluding take cycles that consist of only one trade. *MakeR* is the difference in time between the last trade and the first quote, *MakeR* is the difference between the last quote and the first trade. The cycles are calculated by taking the mean and the median daily cycle within stocks. Panel A presents the descriptive statistics. *WS Mean* represents the cross-sectional characteristics of the within-stock mean, *WS Median* represents the cross-sectional characteristics of the within-stock median. Panel B presents panel regressions of within-stock mean make and take cycles on each other and control variables. $D_{it}^{(maker)} = \alpha_i^{maker} + \gamma_t^{maker} + \beta^{maker} D_{it}^{(taker)} + \delta^{maker} X_{it} + \epsilon_{it}^{maker}$ and $D_{it}^{(taker)} = \alpha_i^{taker} + \gamma_t^{taker} + \beta^{taker} D_{it}^{(maker)} + \delta^{taker} X_{it} + \epsilon_{it}^{taker}$.

Panel A - Cycle Description

	Make1	Take1	MakeR	TakeR
WS Mean				
Mean	602	23	49	40
Median	341	2	22	20
25th	107	1	9	10
75th	872	7	49	40
St. Dev.	771	245	140	110
Obs	84,879	84,970	84,874	84873
WS Median				
Mean	262	7	19	14
Median	75	0	4	5
25th	20	0	1	2
75th	277	0	17	12
St. Dev.	649	220	111	86
Obs	84,879	84,870	84,874	84873

Panel B - Panel Regression

	Take1		Make1		TakeR		MakeR	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Make	0.08	5.49			0.19	3.75		
Take			0.72	4.83			0.36	5.80
Trade Size	0.08	0.56	0.52	2.12	0.01	0.32	0.00	-0.01
Trades	0.02	3.65	-0.16	-5.81	-0.01	-5.13	-0.01	-4.02
Traded Shares	0.00	-0.26	0.00	4.46	0.00	2.74	0.00	2.65
Volatility	-0.25	-0.02	-154.64	-1.46	-14.51	-2.51	-44	-3.14
Spread	-21.32	-2.86	296.53	8.67	22.27	4.17	58.79	6.72

Table A4
Alternative Cycle Instrumental Variable Regression

Table shows the instrumental variable regression for within-stock mean take cycle shocks on the make cycle using the alternative cycle calculations. *Make1* cycles are calculated the time between the first quote that improves the limit order book after a trade and the last quote that improves the limit order book before a trade, and *Take1* is calculated as the time difference between the first trade and the last trade in a cluster. *MakeR* is the difference in time between the last trade and the first quote, *TakeR* is the difference between the last quote and the first trade. *1st Stage* presents the result for the first-stage regression of Take Cycle on the instrument (the shock dummy variable) and control variables and *2nd Stage* presents the results for the second-stage regression, where the Make Cycle is regressed on the Fitted Take Cycle and control variables. The cycles are calculated by taking the mean daily cycle within stocks. *Fee Shock* is a dummy variable equal to 1 for the period November 1, 2010 - December 31, 2010, and zero otherwise, and *Technology Shock* is a dummy variable equal to 1 for the period March 7, 2011 - March 31, 2011, and zero otherwise. *Trade Size* is the average number of shares per trade, *Trades* is the number of trades per day, *Traded Shares* is the number of shares traded a day, per 1,000 shares, *Volatility* is the daily realized volatility, and *Spread* is the quoted spread. *AP Test* presents the Angrist-Pischke F-statist for weak identification and the associated p-value, *Under-Identification* presents the LM statistic for the Kleibergen-Paap under-identification test and the associated p-value, *Weak-Identification* and *Kleibergen-Paap Wald* present the Cragg-Donald and Kleibergen-Paap F statistic for weak-identification, respectively. All regressions include firm fixed effects and day of the week dummies. p-values in brackets are calculated using firm clustered standard errors.

	Make 1				MakeR			
	1st Stage		2nd Stage		1st Stage		2nd Stage	
Take			4.80	(0.00)			1.35	(0.00)
Fee Shock	-9.36	(0.00)			-7.41	(0.00)		
Technology Shock	-1.02	(0.49)			-6.80	(0.00)		
Trade Size	0.12	(0.43)	0.00	(1.00)	0.00	(0.92)	-0.01	(0.75)
Trades	0.00	(0.34)	-0.17	(0.00)	-0.01	(0.00)	0.00	(0.11)
Traded Shares	0.00	(0.25)	0.000	(0.00)	0.00	(0.00)	0.00	(0.67)
Volatility	-14.29	(0.03)	-98.22	(0.36)	-25.54	(0.00)	-19.50	(0.03)
Spread	2.02	(0.57)	282.85	(0.00)	34.86	(0.00)	22.69	(0.59)
AP	8.66	(0.00)			60.14	(0.00)		
Under-Identification	17.18	(0.00)			111.80	(0.00)		
Weak-Identification	12.99				65.58			
Kleibergen-Paap Wald	8.66				60.14			

Table A5
TAQ Events Instrumental Variable Regression

Table shows the instrumental variable regression for make cycle shocks on the take cycle using TAQ data. *Make* cycles are calculated as 23,400 trading seconds divided by the number of limit order book improving quotes. *Take* is calculated as 23,400 trading seconds divided by the number of trades. *1st Stage* presents the result for the first-stage regression of Make Cycle on the instrument (the shock dummy variable) and control variables and *2nd Stage* presents the results for the second-stage regression, where the Take Cycle is regressed on the Fitted Make Cycle and control variables. Panel A presents the shock to the make cycle using Autoquote. The estimation period for Panel A is November 1, 2002 - July 31, 2003. *Autoquote* is a dummy variable equal to 1 for the period after Autoquote was introduced by NYSE, and zero otherwise. This period varies by stock from January 29, 2003 - May 27, 2003. Panel B presents the shock due to the decrease in the minimum tick size on January 29, 2001. The estimation period for Panel B is December 1, 2000 - March 31, 2001. *Tick Shock* is a dummy variable equal to 1 for the period after January 29, 2001, and zero otherwise. The control variables are calculated from CRSP using end-of-day quotes and prices: *Volume* is the total number of shares traded per day, *Spread* is the quoted spread, *Volatility* is the daily returns squared, *P Inv.* is the inverse of price, and *Mkt Cap* is the market capitalization of the stock. *AP Test* presents the Angrist-Pischke F-statist for weak identification and the associated p-value, *Under-Identification* presents the LM statistic for the Kleibergen-Paap under-identification test and the associated p-value, *Weak-Identification* and *Kleibergen-Paap Wald* present the Cragg-Donald and Kleibergen-Paap F statistic for weak-identification, respectively. All regressions include firm fixed effects and day of the week dummies. p-values in brackets are calculated using firm clustered standard errors.

	1st Stage		2nd Stage	
Panel A. Autoquote				
Make			6.95	(0.00)
Autoquote	-60.37	(0.00)		
Volume	-0.02	(0.00)	0.01	(0.00)
Spread	-47.32	(0.00)	449.38	(0.00)
Volatility	17.03	(0.00)	-104.49	(0.00)
1/P	75.40	(0.00)	-267.10	(0.00)
Mkt Cap	0.00	(0.00)	0.00	(0.02)
AP	211.79	(0.00)		
Under-Identification	201.21	(0.00)		
Panel B. Tick Change				
Make			4.57	(0.00)
Tick	155.66	(0.00)		
Volume	0.01	(0.00)	0.04	(0.00)
Spread	-53.62	(0.02)	407.82	(0.00)
Volatility	-1.73	(0.74)	10.87	(0.62)
1/P	14.10	(0.30)	-93.86	(0.11)
Mkt Cap	0.00	(0.52)	0.00	(0.00)
AP	138.18	(0.00)		
Under-Identification	134.44	(0.00)		

Figure A1
Intraday Variation in NASDAQ Make/Take Cycles

The figure presents the average time of a make cycle and of a take cycle at 15 minute intervals for aggressive limit orders for 188 stocks in NASDAQ. *Make* and *Take* cycles are calculated using limit orders improving the best price, as described in Figure 3. The cycles are calculated by taking the mean daily cycle within stocks.

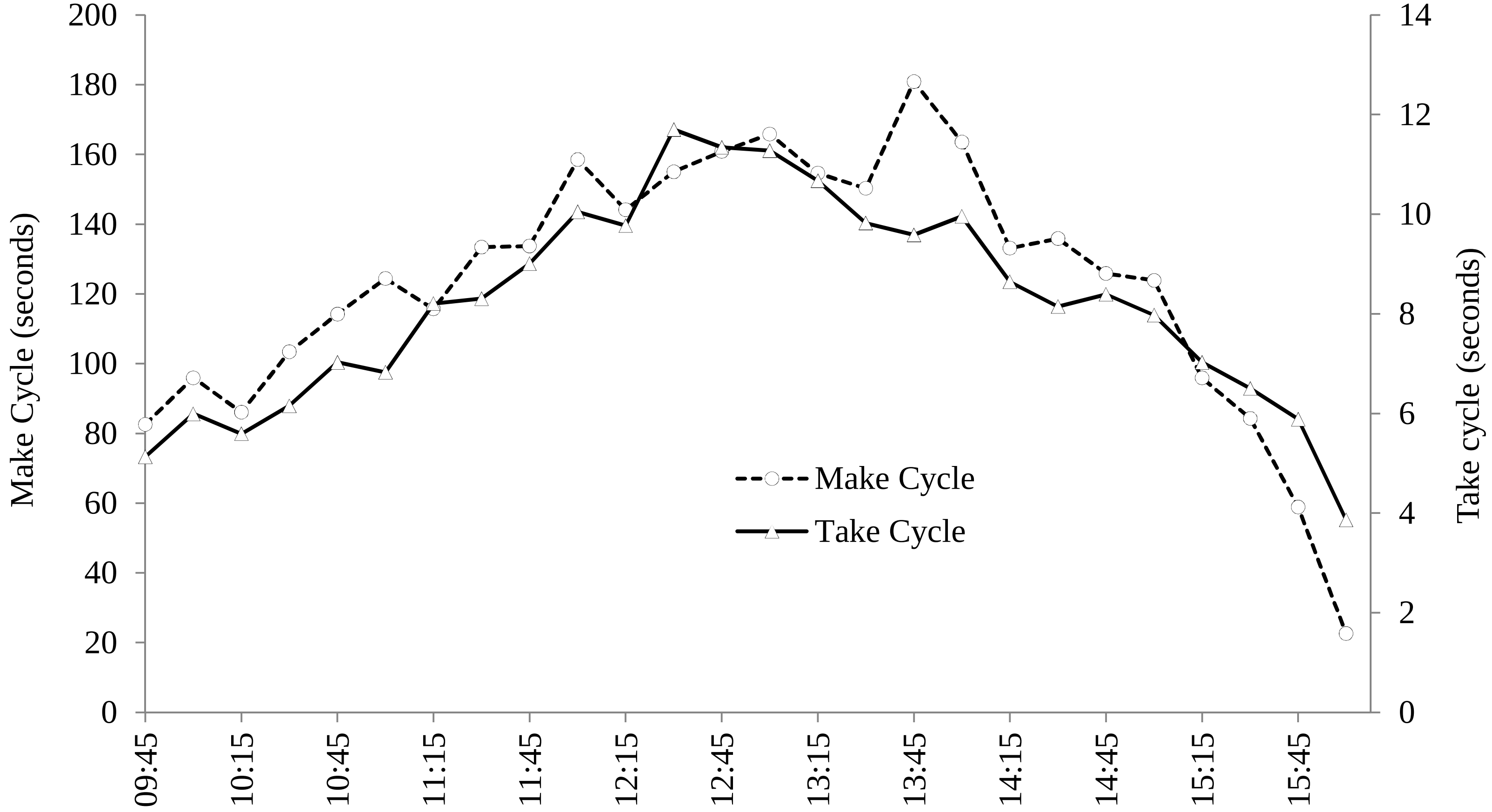
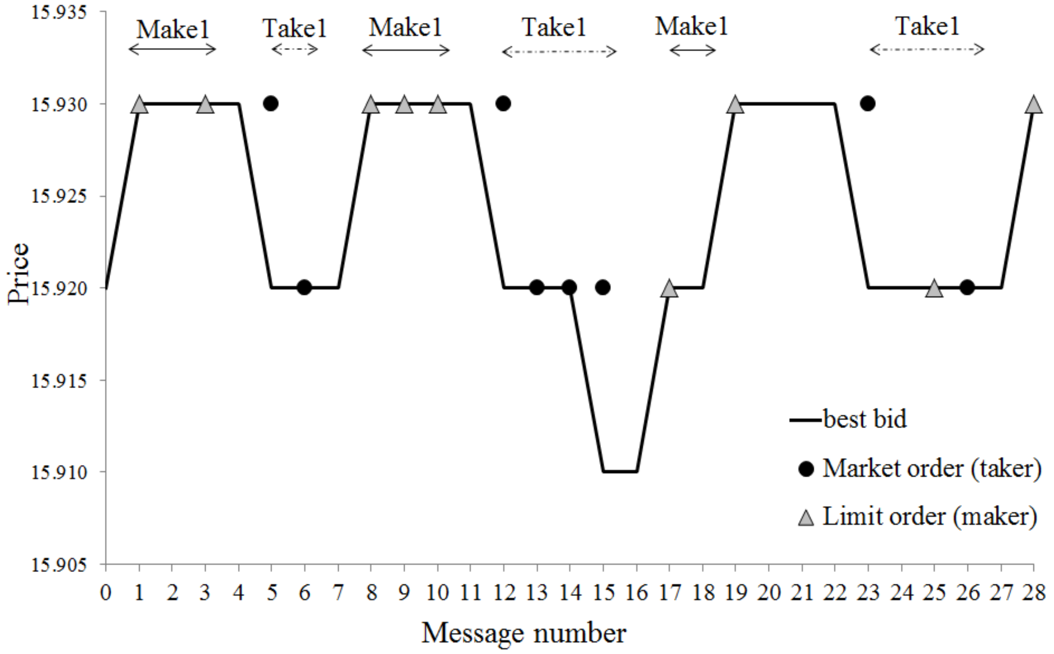


Figure A2
Construction of Alternative Cycles

The figure presents the construction of alternative make and take cycles. In Panel A, make cycles are calculated the time between the first quote that improves the limit order book after a trade and the last quote that improves the limit order book before a trade, and take cycles are calculated as the time difference between the first trade and the last trade in a cluster. In Panel B, make cycle, *MakeR* is the difference in time between the last trade and the first quote, the take cycle, *TakeR* is the difference between the last quote and the first trade.

(a) ***Panel A. Cycle 2***



(b) ***Panel B. Reaction Cycles***

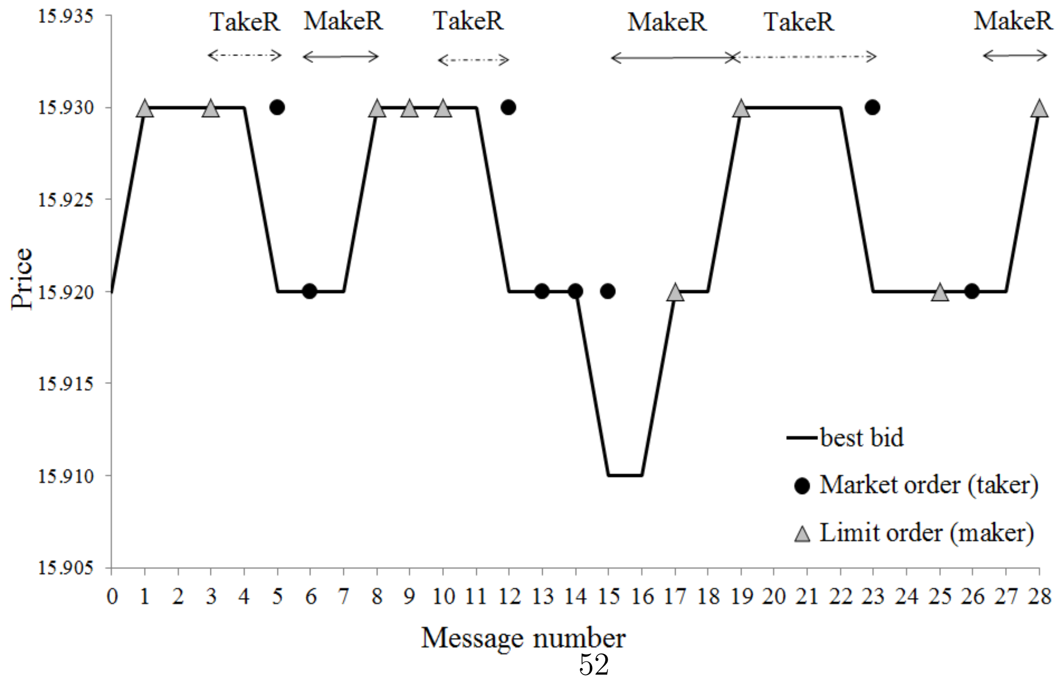
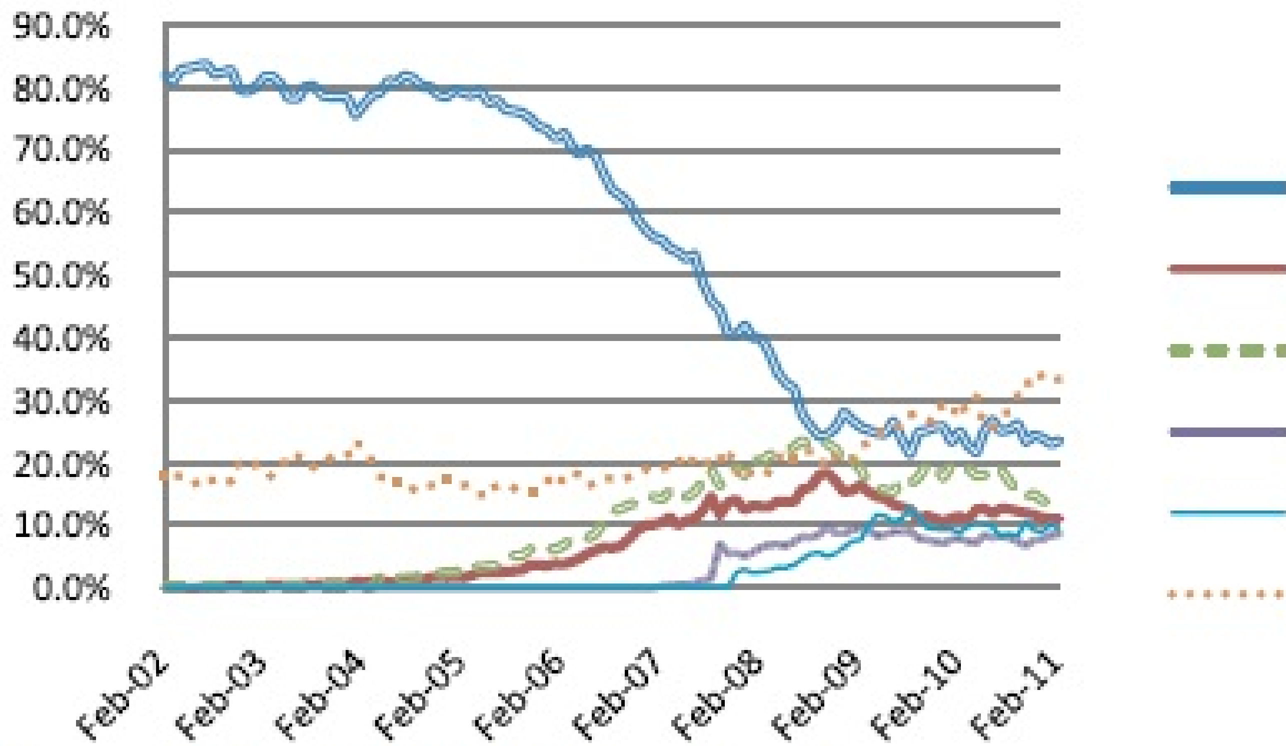


Figure A3
NYSE-listed Market Share (Angel et al. (2011))

The figure highlights the drop in NYSE market share of volume from 80% in 2003 to 25% in 2009 after the introduction of Regulation NMS in 2005.



Source: Barclays Capital Equity Research.

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