Identifying Cross-Sided Liquidity Externalities: A Tale of the Two-sided Markets*

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Abstract

We investigate the cross-sided liquidity externality between market makers and takers, by testing the empirical implications of the Foucault, Kadan, and Kandel (2012) model and study its relevance from the two-sided market perspective. We use exogenous changes in the make/take fee structure and a technological shock for liquidity takers, as experiments to identify a new type of liquidity externality and cross-side complementarities of liquidity makers and takers in the U.S. equity market. We find support for positive liquidity externalities between liquidity providers and takers. Using the estimate of the externality from the instrumental variable regression, we find that the loss in revenue due to the increased subsidization of liquidity demanders from a fee change in a trading venue exceeds the increase in trading rate and revenue from the positive cross-sided liquidity externality. Our findings highlight the importance of accounting for liquidity externalities in the pricing strategy of trading venues. Our findings also shed light on the way the order-posting behavior of market makers and takers is interrelated and contribute to the on-going policy debate on the maker/taker practices in U.S. equity markets.

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 directly or indirectly, 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) and Rysman (2009). In some cases, the intermediary charges/rewards, while not losing money overall, each set of agents appropriately to entice them to the platform. An example of a two-sided market is a "Ladies' night" where a bar/nightclub (a platform for gentlemen and ladies to meet each other) exempts female patrons (one set of agents) from paying cover charges and provides free drinks, while the male patrons (the other set of agents) are charged a fee. The externality that more female patrons will attract more male patrons, which in turn attract more female patrons, makes the platform more attractive and thus profitable. Although the platform is subsidizing the female patrons, which is 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.

In this paper, we empirically investigate the economics of two-sidedness in financial markets by identifying a new network externality and evaluating the pricing effectiveness of a trading platform. In particular, we attempt to empirically identify the liquidity externality between liquidity consumption and provision, cross-sided liquidity externality, motivated by the theoretical work of Foucault, Kadan, and Kandel (2012). We address the issue of identification using two exogenous instruments, a fee change and a technological shock. Using the identified cross-sided externality, we evaluate the pricing strategy of a U.S. trading platform and economically quantify the cross-sided liquidity externality. In doing so, our paper has general implications for the economic literature of two-sided markets. To the best of our knowledge, our paper is the first to empirically study the economic implications of a two-sided market in the financial economic literature.[1] Our work is important for trading venues trying to understand the effectiveness of their pricing strategies. It is also important for regulators to evaluate how alterations of make/take fees by trading venues might affect market quality from a social optimum perspective. Thus our work might be useful to regulators in making decisions on related financial regulation.

Foucault et al. (2012) develop a model which provides an explanation for the widespread adoption of maker/taker pricing and presents a rationale for differentiating trading fees between liquidity makers and takers. They propose that the speed of reaction of liquidity suppliers (makers) and liquidity demanders (takers) is endogenous to trading opportunities. A trader's choice of reaction speed is determined by the trade-off between the benefits associated with being the first to identify (and seize) trading opportunities, and the monitoring cost associated with such identification. Foucault et al. (2012) introduce a new type of liquidity externality (cross-sided) between liquidity makers and takers, where an increase in the monitoring intensity of liquidity makers induces a positive externality on liquidity takers, which increases the speed of liquidity consumption. This induced increase in liquidity consumption in return affects the actions of market makers and begets liquidity supply. A positive cross-sided liquidity externality exists because it is beneficial for liquidity makers and takers to find each other.

However, there can be negative cross-sided liquidity externalities if liquidity makers and takers incur a cost from meeting each-other. For example, such a cost can occur if makers are afraid of being adversely selected by takers or face information uncertainty. Since there is no liquidity provision obligations on today's liquidity makers, they might abstain from providing liquidity resulting in a negative liquidity externality.[2] A negative

[1]Works on two-sided markets are more common in the empirical industrial organization and marketing science literature. Existing empirical work in these literatures focus on two-sided markets like: operating systems, dating service, credit card, game console media, and advertising markets among many others, see Rysman (2009) and references therein.

[2]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.

externality might also occur if one relaxes the assumption of market-making and taking specialization in Foucault et al. (2012).[3] Although there is undoubtedly market making and taking specialization in the market, there are also high-frequency market makers and smart routers who use both market and limit orders. If a venue alters its take fee to entice more takers, a maker, who is concerned about execution certainty and speed of execution, might withdraw its liquidity provision to become a taker if the overall cost of posting a market order is lower. Thus, the existence and the sign of cross-sided liquidity externality are unclear and remain an empirical question.

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. An increase in the taker's rebate directly incentivizes liquidity demanders (but not liquidity providers) to increase their monitoring intensities which ought to decrease take cycles. Our second identification strategy uses a technology shock that reduces the monitoring cost (and hence increases the monitoring intensity) of the taker side. Because the exogenous shocks affect only the take cycle directly, we can use them to identify the cross-sided liquidity externality and the causal effect of take cycles on make cycles.

We apply two methods to identify the cross-sided externality: (i) an event study around the two exogenous shocks (the change in taker rebate and the introduction of the new technology) and (ii) an instrumental variable (IV) regression for the sample period: October 1, 2010 - March 31, 2011. The event study approach minimizes the impact of any confounding effects in our analysis. The IV regression allows us to pin down causality and to account for confounding effects and for potential estimation problems.

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] To measure the speed of liquidity

[3] See p.10 in Foucault, Kadan, and Kandel (2012).

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

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 Foucault et al. (2012). The excellent data quality and the existence of a technological shock and a fee change that only affect liquidity consumption in BX provide an ideal setup for the identification of liquidity externalities.

We identify a positive and strong 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. As a consequence, there is an increased intensity of market orders that consume the liquidity available at the best quotes and that leads to a wider bid-ask spread. This drop in liquidity, which increases the number of profit opportunities for market makers, attracts more liquidity suppliers who post new aggressive limit orders that replenish liquidity. The new best prices in turn create new trading opportunities for liquidity takers. Thus, our first instrument, the increase in the taker rebate, supports the hypothesis of the existence of positive cross-sided liquidity externalities where liquidity demand begets liquidity supply. This result is further substantiated by our second instrument, a technological change that reduces the monitoring cost and improves monitoring ability of liquidity takers, which naturally reduces the duration of take cycles. Using this 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. Using an alternative estimation strategy of a two-sample, or split sample, IV estimator to address any potential concerns about weak instruments and as a robustness check, our results remain qualitatively similar.[5]

We highlight the economic importance and significance of cross-sided liquidity externalities by evaluating a make/take fee change in BX, where the take rebate increases from one cent to two cent per hundred shares, using the estimated cross-sided externality. The change in pricing increases liquidity consumption which induces more liquidity provision.

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

However, the increase in revenue from the increased trading rate is exceeded by the loss in revenue from the increased subsidization for liquidity demanders. This results in an estimated drop in revenue of about $768,737 per year for the exchange after the fee change and an estimated economic significance of the cross-sided externality of $200,514 per year. This highlights the importance of appropriately accounting for cross-sided liquidity externality in trading venues' pricing strategies.

Understanding liquidity externalities and time variation of liquidity is very important because it has implications for changes in trading activities (Biais, Glosten, and Spatt, 2005), commonality in liquidity (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001), leverage buyout activity (Gaspar and Lescourret, 2009), privatization (Borttolotti, de Jong, Nicodano, and Schindele, 2007), market design and transparency (Madhavan, 2000; Barclay and Hendershott, 2004; Bessembinder, Maxwell, and Venkataraman, 2006), and market regulation (Macey and O'Hara, 1999; Hendershott and Jones, 2005). Despite its importance, there is little empirical work on liquidity externalities, because identifying and empirically measuring liquidity externalities is extremely challenging (see, Barclay and Hendershott, 2004; Hendershott and Jones, 2005).

Our paper contributes to the literature on participation externality where one is concerned about whether the entry of one additional investor in a market exerts an externality on other investors, see Mendelson (1982, 1985, 1987), Pagano (1989), and 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 that quantifies this participation externality.[6]

We join the handful of papers that identify the presence of one sided liquidity externalities in financial markets. Amihud, Mendelson, and Lauterbach (1997) document how a change in trading mechanisms not only improves liquidity for affected stocks but

[6]We would like to emphasize that two-sided market is different from the two-sided trading in Sarkar and Schwartz (2009). Sarkar and Schwartz (2009) 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 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 consumers and sellers accounting for the externality between the consumers and sellers.

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 of other trading venues where transparency does not change. Bessembinder et al. (2006) shows 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 the existing work which focuses on liquidity externalities related to trading costs across assets, this is the first paper to examine the temporal liquidity externalities of liquidity cycles 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 works studying the impact of make/take fees on market quality. Colliard and Foucault (2011) analyze a microstructure model with make/take fees where investors can chose 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. Finally, Battalio, Shkilko, and Ness (2012) show that the cost of liquidity in pay-for-order flow and in maker/taker exchanges is similar when taking into account the make fee rebates. Differently from existing work in this literature, our paper sheds light on the way the order posting behavior of makers and takers is interrelated and contributes to the on-going policy debate on the maker/taker practices in U.S. equity markets.

Resiliency, a less studied dimension of liquidity, is an important measure of liquidity especially in today's electronic LOB markets. Resiliency measures how fast the LOB is replenished after a large trade has occurred. Given the apparent relation between resiliency and make cycles, we join the theoretical work of Foucault, Kadan, and Kandel (2005), Goettler, Parlour, and Rajan (2005), Rośu (2009), Rośu (2010), and Foucault et al. (2012) and the empirical work of Biais et al. (1999), Degryse, De Jong, Ravenswaaij, and Wuyts (2005), and Large (2007) in studying how the LOB replenishes after trades. Differently from the empirical papers in this literature, which focus on measuring resiliency i.e. only make cycles, our results suggest that take and make cycles are endogenous and ought to be studied together when measuring and discussing resiliency. In addition, our empirical measure for maker cycle durations constitutes a new empirical proxy of resiliency.

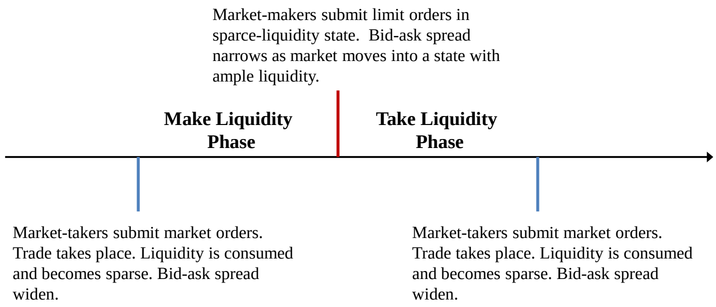
The recent episodes of "flash crash", introduction of maker/taker pricing structure and innovations of new trading products and services offered by competing trading venues, and a shift towards automation in trading has led regulators, politicians, and market participants to question the new dynamic relation between liquidity providers and demanders in an environment without obligatory liquidity provision responsibility. Our analysis provides a first step in understanding the new dynamics of liquidity provision and consumption in the U.S. equity market.

The next section discusses the theoretical foundation for the existence of cross-sided liquidity externalities. Data and preliminary analysis are presented in Section 3. Section 4 describes the identification strategy. Section 5 presents and discusses the results and Section 6 addresses robustness issues. Section 7 presents the economic importance of the cross-sided liquidity externality and Section 8 concludes.

2 Cross-sided Liquidity Externality

Foucault et al. (2012) develop a model of trading, with specialized market making and taking sides, in which the speed of reaction to trading opportunities for liquidity suppliers and demanders 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 cost of trading is low. They show that the maker/taker pricing model is a way for the trading platform to minimize the duration of liquidity cycles and therefore maximize its expected profit. Foucault et al. (2012) define liquidity cycles to consist of two phases: a "make liquidity" and a "take liquidity" phase. 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, depicted in Figure 1.

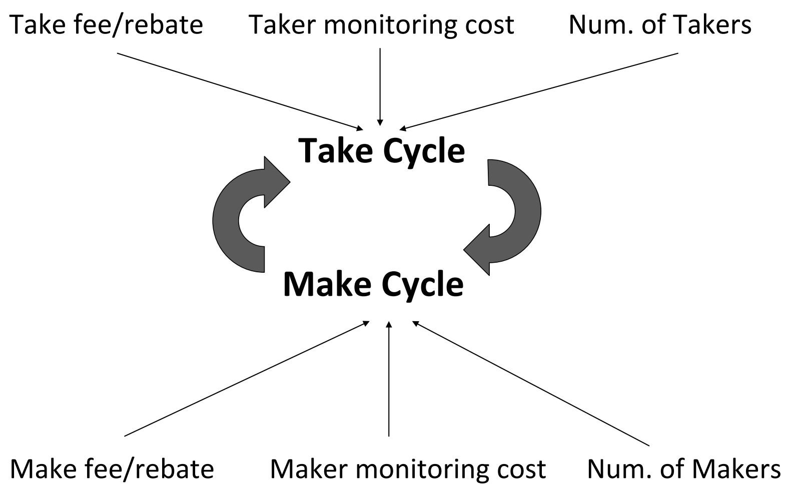
Figure 1
Flows of Events in a Cycle (Foucault et al., 2012)



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 and is analogous to the liquidity measure of resiliency (Harris, 1990).

In the Foucault et al. (2012) 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. This endogenity of the monitoring intensities introduces a cross-sided liquidity externality between liquidity provision and consumption. Given that make/take fees, monitoring costs, and the number of takers and makers are exogenous and they affect the make and take cycle, Foucault et al. (2012) suggest that exogenous shocks or changes to these variables can be used as instruments for the identification of cross-sided liquidity externalities. The exogenous and endogenous relation among the variables can be seen in Figure 2.

Figure 2
Endogenous and Exogenous Relation among Variables in Foucault et al. (2012)



In this paper, we are interested in identifying this cross-sided liquidity externality, and we test the following hypotheses based on corollary 6 of Foucault et al. (2012):

Hypothesis 1a: *An increase (decrease) in the liquidity makers' monitoring intensity (make cycle) increases (decreases) the liquidity takers' monitoring intensities (take cycle).*

Hypothesis 1b: *An increase (decrease) in the liquidity takers' monitoring intensity (take cycle) increases (decreases) the liquidity makers' monitoring intensities (make cycle).*

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

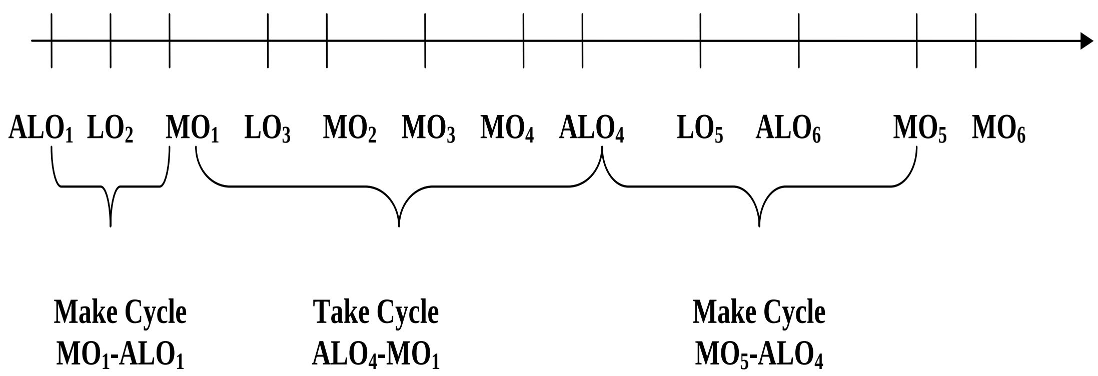
Indicator Type=1) and focus only on common shares (Share Code 10 and 11) and stocks that do not change primary exchange, ticker symbol or CUSIP over the sample period (Hasbrouck, 2009; Goyenko, Holden, and Trzcinka, 2009; Chordia, Roll, and Subrahmanyam, 2000). We also exclude stocks that exhibit a price 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.

We employ the complete dataset of new order messages, updates, cancelations, deletions, executions, and executions against hidden orders and cross-network orders, to reconstruct the complete limit order book (LOB) for all the stocks in BX for the whole sample period following Kavajecz (1999). We use the LOB information to also 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, trading volume (*Volume*) as *Traded Shares* times price of trade, and the proportion of aggressive limit orders to the total of aggressive orders and trades (*LO Ratio*). 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 is paid for filling the limit order book for NASDAQ and NYSE listed stocks (Tape A and C). For all non-NASDAQ and non-NYSE listed stocks (Tape B) and stocks with a price less than \$1, there is a rebate for providing liquidity and a fee is paid 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. We exclude Tape B stocks from the sample because they can confound our results. The exclusion of the small number of Tape B stocks in our sample is not likely to result in any loss of generality for the findings.

In order to carry out our analysis, we need to conceptualize and create a measure of cycles that is compatible with Foucault et al. (2012) and matches Figure 1. We calculate take cycles as the difference in time between the first market order (MO, take) and the first limit order that improves the best price (ALO) after the last trade. We calculate make cycles as the difference in time between the first limit order that improves the best prevailing quote (ALO) after one or a series of market orders and the first market order (MO). Figure 3 below depicts how we calculate the cycles.

Figure 3
Make Take Cycles



For the calculation of make cycles, it is important to use limit orders that improve the best price, because the make cycle should capture how the LOB is replenished after one (or more) trade(s) that takes away the best price. 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.

3.1 Fee structure in BX

Island ECN introduced the maker/taker pricing model in 1997. This pricing model was designed to incentivize 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 trading venues in U.S. that use a maker/taker pricing system. An inverse maker/taker pricing system also exists, taker/maker pricing hereafter, which was first adopted by Direct Edge in 2008. The inverse pricing aims to encourage traders to "take", or execute against prices quoted on the exchange, by offering them rebates. This pricing system aims to profit 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 that aim to trade at the volume-weighted average price (VWAP) and not at a single price. The inverted pricing model was also directed towards low-price stocks with lots of dark pool activity. There are three venues that have adopted the taker/maker model, namely, BX, BATS-Y and Direct Edge A, but Direct Edge A discontinued taker-maker in August 1, 2011.

3.2 Summary statistics

Table 1 provides an overview of the sample characteristics. On average there are 290 trades a day per stock. The trade size of 107 shares is much smaller than the order size of 196 shares in BX. 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, following Goldstein and Kavajecz (2000). 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. On average, depth increases by 188 shares per tick for the first five levels of the book (Slope5) and 394 shares for the first 10 levels of the book (Slope10), on the bid and ask side. The average daily dollar trading volume is about $2 million and the average number of traded shares is 38,725.

The cycles are calculated 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, while the median represents the cross-sectional characteristics of the within stock median. First, the take cycles are much shorter than the make cycles, given the larger number of market takers compared to market makers willing to supply at the best price. It takes on average about 631 seconds for liquidity to be filled in the market before liquidity is consumed in about 62 seconds. The standard deviations are quite large. In addition, median cycle times, i.e. the cross-sectional mean and median of the within stock median, are much lower than mean cycle times implying that there are periods and stocks that have 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 whole sample and the standard deviations are lower than in Table 2. We also find that there is a cross sectional difference in the make/take cycle between stocks that have different sizes and numbers of trades a day. Larger and more traded stocks have shorter make and take cycles. Panel A of Table 3 shows that cycles are much longer for stocks that are less traded. Panel B of Table 3 shows that cycles are much longer for smaller stocks compared to larger stocks. The difference between size terciles is not as pronounced as the difference between trade terciles.

We also provide a graph of the variation in liquidity cycles during the day. Figure 4 shows the average cycle length across the day for BX stocks. The intraday length of the make and take cycles is highly positively correlated, 94%, which is suggestive about the existence of cross-sided liquidity externality. The make/take cycles are relatively faster/shorter in the morning, as information and news are updated into the market. The cycles become longer as the day progresses and 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 is the mirror image of the trading volume pattern in Admati and Pfleiderer (1988), where more participant enter the market in the morning and at the end of the trading day.

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. It is interesting to note that the correlation between daily make and take cycles is large and positive. This matches 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. The relation is a mechanical one in the theoretical model of Foucault et al. (2012) and shows the reason 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. All cycle variable are significantly autocorrelated.

3.3 Panel regression

We specify regressions for our daily panel as follows:

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

and,

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

where $D_{it}^{(maker)}$ and $D_{it}^{(taker)}$ are the make and take cycle durations (in seconds) respectively for stock i in day t and X_{it} is a vector of control variables, including trade size, volatility, and quoted spread. α_i are firm fixed effects and γ_t are calendar fixed effects. The 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.

Table 5 provides the result for the two-way fixed effects panel regression with clustered standard errors at the stock level. It is not clear what the determinants of make/take cycles should be, so we use the correlation table as a guidance for our control variables.

We use the trade size, number of trades, traded shares, volatility, and quoted spread as control variables. The sign of the take and the make cycle coefficients in Equation 1 and 2 is 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 the 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. We need to rely on instrumental variables to establish causality and to identify the liquidity externality.

4 Identification

4.1 Identification using changes in make/take fees

Liquidity makers usually receive a rebate (make rebate) for their services while liquidity takers pay a fee (take fee), because good prices take a longer time to be posted by liquidity makers due to the free option problem related to limit orders (Copeland and Galai, 1983). When liquidity provision is slow and suboptimal, a trading platform can increase its rebate for market makers to provide a stronger incentive to quickly reinject liquidity and increase the trade rate. Thus, changes in either the make or take fees only in one trading venue will allow us to identify this 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 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 a cent to two cents per 100 shares.[7] This event significantly decreases the trading cost of takers and it should increase their monitoring and result in shorter take cycles in BX.

4.2 Identification using technological shock to liquidity takers

Since monitoring the market can be costly, Foucault et al. (2012) argue that the liquidity cycle depends 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) will have an impact on the monitoring intensity of makers (takers) because of the cross-side externality. Our second identification strategy of the cross-side liquidity externality uses a specific technological change at the BX, which decreased the monitoring cost of the takers. As the technological shock only affects the monitoring cost of the takers, it provides an ideal instrument to identify 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 is aimed at minimizing the trading costs for liquidity demanders and automatically routes the order to different venues in a specific sequence to obtain execution. Orders entered using CART are first routed to BX (receiving a rebate

[7]For more details about the fee change, see www.sec.gov/rules/sro/bx/2010/34-63285.pdf.

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 they 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.[8] In the analysis, the introduction of this routing technology is treated as an exogenous event that affects the take side monitoring cost in BX, to identify the make side liquidity externality. 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 both the 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, we have to find an instrumental variable that affects take cycles but is 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. (2012), described in Section 2. The theoretical grounding of our instruments addresses the common criticism of many instrumental variable studies where 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 their

[8] At the same time as the CART facility was introduced, NASDAQ also introduced the QSAV strategy which behaves similarly to CART, but checks the NASDAQ book before routing to other destinations. Pricing for QSAV is the same as CART.

SEC filing that the reason for the BX fee change is a direct and immediate response to fee changes by competitors like EDGA Exchange, EDGX Exchange and BATS Y-Exchange in October 2010 and not observed changes in cycles within the exchange.[9] This is consistent with Foucault et al. (2012), 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 given the make/take fees. Moreover, the validity of the instrument is further supported by the fact that the U.S. equity market is a competitive market 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.

BX states that the purpose for the introduction of CART, which reduces the taker's monitoring cost, is to provide market participants with 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 aims to benefit participants that do not employ high-frequency trading strategies, with rapid access to liquidity provided on the multiple venues.[10] Moreover, announcements of these changes occur many weeks before they are implemented, and it seems highly unlikely that the introduction is correlated with idiosyncratic make cycles weeks into the future. Based on the reasons given by BX SEC filings, we argue that both our instruments are exogenous to the take and make cycles.

Lastly, the exclusion restriction requires the instruments to affect the make cycle only via the take cycle. We have argued that our instruments are only relevant for the take cycle and our instruments are unlikely to affect the make cycle via non-taker cycle related reasons. One potential alternative avenue that our instruments can affect the make cycle is through other liquidity variables like 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

[9] 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.

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

this is a suboptimal strategy 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. An equilibrium where the bid-ask spread is widened, as a response to increased benefits to takers, is likely to be unstable when one considers the possibility of off-the-equilibrium play or the trembling hand equilibrium. Even if one considers the bid-ask spread channel despite our argument, the impact of bid-ask spread on make cycle will only bias against us not finding or finding a negative cross-sided liquidity externality. However, we admit that we cannot test these conjectures and our conclusions on causality rely on the intuitively attractive and logical argument above, but the exclusion assumption is ultimately untestable. We will address the potential issue of weak instrument in the next section.

5 Results

5.1 Event study

We first conduct event studies around the days of each external shock to the cycles. We use an eight days event window, four days before and four days after the introduction of the change. The four days window minimizes the impact of other confounding effects. Note that there are no leakage effects in our study, as the behavior of market participants only changes when the pricing/technology changes, not when announced. Market participants can take advantage of the changes only after they occur. In the event study, we compare the make and take cycles and numbers of trades for the pre- and post-event window in BX. This gives us a preliminary illustration of the impact of our instruments on the endogenous variable, similar to what one would see from the result in the first stage of a two stage least square procedure. Tables 6 and 7 show the results of the event study in terciles according to number of trades and size. The tables present the changes in both mean and median cycles.[11]

[11]The results are robust to using other event windows of 6 and 10 days. The results are available from the authors upon demand.

Fee changes

Panel A of Tables 6 and 7 show that when the take rebate in BX increases, both the make and take cycle durations decrease. The effect is observed across all terciles. The largest improvements seem to be coming from stocks that have the least trades, Table 6 and from the smallest stocks, Table 7. In addition, the number of trades increases significantly during this event, 43%, 22%, and 15% for the smallest, medium and largest stocks respectively in Table 7.

Technology shock

The technology shock to market takers leads to a substantial reduction in make and take cycle durations in BX, Panel B of Tables 6 and 7. Mean take cycles decrease by 54%, 57%, and 6% for the smallest, medium, and largest stocks respectively. The technology shock leads to decreases in mean make cycles by 24%, 31%, and 30% for the smallest, medium, and largest stocks respectively, as presented in Panel B of Table 7. The results imply that liquidity externalities exist and they are very strong. These changes are statistically and economically significant. In addition, the number of trades increases substantially around the introduction of the technological shock. The effects are quite similar both in magnitude and significance when sorting by trade terciles, Panel B of Table 6.

5.2 Regressions

While the event studies show that the take cycle is reduced after the fee change and the technological shock, the results are only indicative that the shocks are valid instruments. We investigate this relation more closely with a two-stage least squares procedure. 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. We use the instrumental variables (IV) methodology in which the endogenous variables are the make and the take cycles, to address the endogenity problem.

In order to control for other important conditioning variables like number of trades, volatility, and spread, we run a two-stage least squares regression of the 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 the trade size, the number of trades, the 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 8 show the results for the just identified IV regression analysis, one instrument per IV regression. The first stage results shows 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 (0.000) for all regressions. The null hypothesis of under-identification is also rejected with a p-value of 0.000 using the Kleibergen-Paap LM test. Thus we are unlikely to be affected by an under-identification or a weak instrument problem.

In addition the second stage of the regression results confirms the previously finding that there are 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.[12]

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 8 show the results for the overidentified IV regression analysis. The first stage results shows that the two shocks lead to a significant decrease in take cycles. In addition the second stage regression results confirm the previously found results that there are strong and statistically significant externalities between make and take liquidity cycles. The test statistics for under- and weak-identification are even stronger than for the single instrument regressions, as expected.

[12]The results are robust to using other measures of liquidity like relative spread. The results are not presented to conserve space but are available from the authors upon demand.

5.3 Internal vs. external validity

The market share of BX across the period of our sample is about 5% and one potential concern is whether the average treatment effect that we have estimated representative of those of the population or across the whole U.S. market. In other words, one might have concerns over the estimated average treatment effect in our paper, which is a local average treatment effect (LATEs) estimated across a subsample of the population. Ideally, we would like to have natural experiments and valid instruments to estimate the average treatment effect of the population but unfortunately such a setup is always difficult and rare in all social science studies. Motivated by and consistent with the econometric and labor economics literature, we argue that it is more important to have good and credible estimates of the average treatment of a subpopulation over poor and biased estimates without a valid instruments with little credibility of the whole population. In the words of 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".

6 Robustness

6.1 Median effect

It is obvious from Table 2 that the average daily distribution of cycles is very skewed. In order to ensure that the results we obtain are not driven by outliers, we re-estimate the instrumental variable regression on the median cycles. The results in Table 9 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 using the within-stock median cycles compared to 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 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 to estimate the first stage regression parameters and to obtain 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, Angrist and Krueger (1995) introduce the unbiased SSIV in order to account for the SSIV bias towards 0.

Table 10 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 8. The second stage coefficients of the instrumented variable, take cycle, are positive and larger than those in the 2SLS estimation in Table 8 and highly statistically significant.

7 Economic Significance

With the estimated cross-sided liquidity externality, we are able to evaluate the effectiveness of BX's pricing strategy of changing their take rebate from one cent per two cent per 100 shares on November 1, 2010. The make fee remains unchanged at two and a half cent per 100 shares. This implies that BX makes a profit of half a cent per 100 shares traded after the price change. 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 10 in Foucault et al. (2012):

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

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 fir a fee change with the following first order approximation: $\Delta\Pi_e = \frac{\delta\Pi}{\delta c_t} \times \Delta c_t$, where,

$\frac{\delta\Pi}{\delta c_t} = \frac{\delta\Pi}{\delta\bar{c}}\frac{d\bar{c}}{dc_t} + \frac{\delta\Pi}{\delta D_{maker}}\frac{dD_{maker}}{dc_t} + \frac{\delta\Pi}{\delta D_{taker}}\frac{dD_{taker}}{dc_t}$

$= \frac{1}{D_{maker}+D_{taker}} - (\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{maker}}{dc_t} \times \bar{c} - (\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{taker}}{dc_t} \times \bar{c}$

$= \frac{1}{D_{maker}+D_{taker}} - ((\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{maker}}{dD_{taker}}\frac{dD_{taker}}{dc_t} - (\frac{1}{D_{maker}+D_{taker}})^2 \times \frac{dD_{taker}}{dc_t}) \times \bar{c}$

Using the information in Table 6 c_t= 0.02 cnt/share, c_m=0.03 cnt/share, D_{maker}=208 seconds, D_{taker}=31 seconds, and 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 8:

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

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 this fee change. However, this 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, which is quite significant for a small exchange like BX. The 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. (2012). 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.

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 as suggested by the theoretical work of Foucault et al. (2012). In addition, we also study the impact of make/take fee structures on market liquidity. 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 it determines how the platform should set prices for both side 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 identification of not only cross-sided externality but also cross-platform externality in a two-sided market framework with competitive intermediaries. While our focus i 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.

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 %, *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, *ILR* is the illiquidity ratio |return|/dollar volume for a million shares, *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, *LO Ratio* is the proportion of aggressive limit orders to the total of aggressive orders and trades. All variables are defined in Table A1.

	Trades	Trade Size	Order Size	Spread	Relative Spread	Slope 5	Slope 10	Depth 5	Depth 10	ILR	Volatility	Volume	Traded Shares	LO Ratio
Mean	290	107	196	0.322	0.800	188	394	3,700	6,149	2.40	0.06	2,269	38,725	0.81
Median	59	101	171	0.232	0.621	58	179	3,877	4,796	1.14	0.03	242	6,181	0.86
25th	23	95	132	0.081	0.283	42	79	2,856	3,860	0.56	0.02	81	2,300	0.75
75th	213	112	233	0.457	1.062	118	395	4,100	5,623	2.33	0.06	829	22,733	0.91
St. Dev.	791	27	98	0.332	0.709	731	907	4,078	10,120	5.56	0.98	319,442	154,148	0.16

Table 2
Make Take Cycles

Table shows the average cycle durations in seconds. *Make* and *Take* 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. *Mean* represents the cross-sectional characteristics of the within stock mean, *Median* represents the cross-sectional characteristics of the within stock median. *Obs* refers to the total number of firm/date observations.

	Mean		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 average cycle durations in seconds across three trade and market capitalization terciles for liquidity cycles. Make and Take are calculated using limit orders improving the best price, as described in Figure 3. Panel A 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 B 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. Tercile 1 contains the least traded/lowest size stocks, and tercile 3 contains the most traded/larges market capitalization stocks.

Panel 1. Number of Trades

Panel A. Mean

	Tercile 1		Tercile 2		Tercile 3	
	Make	Take	Make	Take	Make	Take
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

Panel B. Median

	Tercile 1		Tercile 2		Tercile 3	
	Make	Take	Make	Take	Make	Take
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

Panel A. Mean

	Tercile 1		Tercile 2		Tercile 3	
	Make	Take	Make	Take	Make	Take
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

Panel B. Median

	Tercile 1		Tercile 2		Tercile 3	
	Make	Take	Make	Take	Make	Take
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 sample characteristics for the period October 1, 2010 to March 31, 2011. *Make Mean* is the cross-sectional characteristics of the within stock mean make cycle, *Take Mean* is the cross-sectional characteristics of the within stock mean take cycle, *Make Med* is the cross-sectional median make cycle of the within stock mean make cycle, *Take Med* is the cross-sectional median take cycle of the within stock mean 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, *ILR* is the illiquidity ratio |return|/dollar volume for a million shares, *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, *LO Ratio* is the proportion of aggressive limit orders to the total of aggressive orders and trades. *AR(1)* is the autocorrelation coefficient. 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	LO Ratio
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**	
LO ratio	**0.20**	**-0.30**	**0.20**	**-0.36**	**-0.40**	**-0.33**	**0.14**	**0.02**	**0.01**	**-0.01**	**-0.30**	**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**	**0.45**
AR(1)	**0.64**	**0.48**	**0.41**	**0.32**								

Table 5
Preliminary Panel Regressions

Table shows panel regressions of 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* are calculated using limit orders improving the best price, as described in Figure 3. *Trade Size* is the average number of shares per trade, *Trades* is the average number of trades per day, *Traded Shares* is the average number of shares traded a day, per 1000 shares, *Volatility* is average daily realized volatility, and *Spread* is the quoted spread. All regressions include firm and time fixed effects. Standard errors are clustered at firm level.

	Take			Make		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Take				0.37	3.91	0.00
Make	0.08	7.78	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
Event Study by Trade Terciles

Table shows the eight day event study of changes in make cycle and take cycle durations and number of trades according to terciles based on number of trades per day. *Diff* is the difference between the post and pre-period. t-test is the p-value for the t-test for difference in variables, and Wilcoxon is the p-value of the Wilcoxon test for the difference in variables. Tercile 1 contains the stocks with the least number of trades, and tercile 3 contains the most traded stocks. Panel A shows the event study for the fee change event on November 1, 2011. Panel B shows the event study for the technology shock, introduction of CART, on March 7, 2011.

Panel A. Fee Change

		Mean		Median		
	Tercile	Make	Take	Make	Take	Trades
0	1	1544	236	692	122	18
1		1326	124	410	64	23
Diff		-218	-112	-282	-58	5
t-test		0.00	0.06	0.00	0.29	0.00
Wilcox		0.00	0.00	0.00	0.06	0.00
0	2	842	58	344	21	45
1		578	69	168	22	63
Diff		-264	11	-176	1	18
t-test		0.00	0.49	0.00	0.91	0.00
Wilcox		0.00	0.00	0.00	0.00	0.00
0	3	226	32	71	9	493
1		167	32	46	8	616
Diff		-59	0	-25	-1	124
t-test		0.00	0.97	0.00	0.78	0.00
Wilcox		0.00	0.00	0.00	0.00	0.00

Panel B. Technology Shock

0	1	1579	195	788	131	18
1		1314	73	652	35	21
Diff		-265	-122	-135	-96	3
t-test		0.00	0.00	0.06	0.02	0.00
Wilcox		0.00	0.00	0.00	0.00	0.00
0	2	992	80	434	33	45
1		527	47	225	15	86
Diff		-465	-33	-209	-18	40
t-test		0.00	0.01	0.00	0.00	0.00
Wilcox		0.00	0.00	0.00	0.00	0.00
0	3	232	38	95	13	572
1		101	25	37	7	793
Diff		-131	-13	-58	-5	221
t-test		0.00	0.02	0.00	0.00	0.00
Wilcox		0.00	0.00	0.00	0.05	0.00

Table 7
Event Study by Size Terciles

Table shows the eight day event study of changes in make cycle and take cycle durations and number of trades according to terciles based on market capitalization. *Diff* is the difference between the post and pre-period. t-test is the p-value for the t-test for difference in variables, and Wilcoxon is the p-value of the Wilcoxon test for the difference in variables. Tercile 1 contains the smallest market capitalization stocks, and tercile 3 contains the largest market capitalization stocks. Panel A shows the event study for the fee change event on November 1, 2011. Panel B shows the event study for the technology shock, introduction of CART, on March 7, 2011.

Panel A. Fee Change

		Mean		Median		Number
	Tercile	Make	Take	Make	Take	Trades
0	1	1155	234	495	123	53
1		996	157	387	75	76
Diff		-159	-77	-108	-48	23
t-test		0.02	0.19	0.01	0.34	0.00
Wilcox		0.01	0.06	0.02	0.12	0.00
0	2	774	61	312	18	109
1		633	52	194	14	133
Diff		-141	-9	-118	-4	24
t-test		0.00	0.14	0.00	0.02	0.00
Wilcox		0.00	0.07	0.00	0.40	0.00
0	3	328	22	121	6	442
1		309	21	94	6	510
Diff		-19	-1	-27	0	68
t-test		0.32	0.43	0.80	0.80	0.07
Wilcox		0.21	0.01	0.00	0.00	0.00

Panel B. Technology Shock

0	1	1225	222	563	106	63
1		934	102	436	43	90
Diff		-291	-120	-127	-63	27
t-test		0.00	0.00	0.03	0.00	0.00
Wilcox		0.00	0.00	0.01	0.00	0.00
0	2	904	82	395	41	102
1		616	35	297	11	168
Diff		-288	-47	-98	-30	66
t-test		0.00	0.00	0.00	0.05	0.00
Wilcox		0.00	0.00	0.00	0.00	0.00
0	3	313	21	140	6	529
1		218	15	87	4	690
Diff		-95	-6	-53	-2	161
t-test		0.00	0.00	0.00	0.00	0.00
Wilcox		0.00	0.00	0.00	0.00	0.00

Table 8
Instrumental Variable Regression

Table shows the instrumental variable regression for 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* are calculated using limit orders improving the best price, as described in Figure 3. *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 average number of trades per day, *Traded Shares* is the average number of shares traded a day, per 1,000 shares, *Volatility* is average 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 and time fixed effects. 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 9
Instrumental Variable Regression - Median

Table shows the 2^nd stage of the instrumental variable regression for the 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* are calculated using limit orders improving the best price, as described in Figure 3. *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 average number of trades per day, *Traded Shares* is the average number of shares traded a day, per 1,000 shares, *Volatility* is average 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 and time fixed effects. 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 10
Split Sample Instrumental Variable

Table shows the split sample instrumental variable regression, Angrist and Krueger (1995), for 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. *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. *Make* and *Take* are calculated using limit orders improving the best price, as described in Figure 3. *Trade Size* is the average number of shares per trade, *Trades* is the average number of trades per day, *Shares Traded* is the average number of shares traded a day, per 1,000 shares, *Volatility* is average daily realized volatility, and *Spread* is the quoted spread. All regressions include firm and time fixed effects. p-values are calculated using firm clustered standard errors. Panel A presents the first stage regression results. Panels B and C present the second stage regression results using the split sample IV (SSIV) and the unbiased split sample IV (USSIV) estimator.

	Fee Shock		Technology Shock		Combined Events	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Panel A. First 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. 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. 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

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.

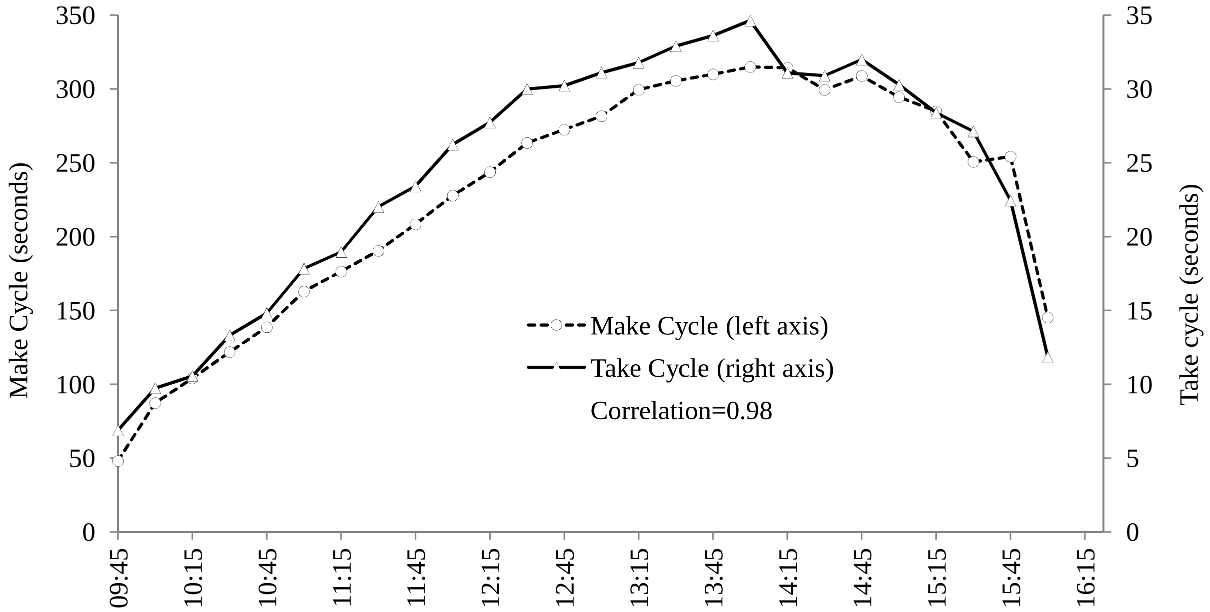


Table A1
Variable Definitions

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 $\|\mathsf{return}\|$*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
Limit Order Ratio	LO Ratio	Aggressive limit orders/(aggressive limit orders + trades)	
% Midpoint price	m_t	End of day $(\mathsf{ask}_1 + \mathsf{bid}_1)/2$	$
Traded shares		Sum of Trades*Trade size	
Dollar volume	Volume	Sum of (Traded shares*Midpoint price)/1000	$ 000s
Firm size	Mkt Cap	(m_t*Outstanding Shares)/1000000	$ million
Realized Volatility	Volatility	$\sum_{t=1}^{78} \mathsf{return}_{t,5min}^2$	

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

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