Multiple Markets, Algorithmic Trading, and Market Liquidity

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Key Words: Algorithmic Traders, High Frequency Traders, HFT, Market Liquidity, Intraday Liquidity, Latency, Thor

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Abstract:

Using a sample of NYSE firms from the first quarter of 2012, we show that the U-shaped pattern of spreads is now an S-shape, with higher spreads at the open and lower spreads at the close. NBBO depth has an inverse pattern to that of spreads. Composite liquidity, which is the ratio of NBBO depth to NBBO spread is negatively affected by quote competition between exchanges and by excess Algorithmic Trading (AT) activity, but positively impacted by volume fragmentation. Trade execution quality also decreases with higher quote competition and AT activity but is better with higher volume fragmentation.

1. Introduction

Variations and patterns of market liquidity are of interest to practitioners and market regulators. Variations in market liquidity impact practitioners via execution costs, price impacts, and implementation shortfalls of desired stock positions. Regulators must monitor and assess the impact of market structure and the regulatory environment on market liquidity. Early studies, in a1/8th tick environment, find that intraday patterns of bid-ask spreads are different between NYSE and NASDAQ listed securities. On the NYSE, researchers (McInish and Wood, 1992; Brock and Kleidon, 1992; Chan, Chung, and Johnson, 1995; Lee, Mucklow, and Ready, 1993; Chung, Van Ness, and Van Ness, 1999) find a U-shaped pattern, with high spreads at the market open and the market close, and lower spreads in the middle of the trading day.

Chan, Christie, and Schultz (1995) find a different intraday pattern of spreads for NASDAQ listed stocks in a 1/8th tick environment. Chan, Christie, and Schultz do not find that NASDAQ stocks follow a U-shaped pattern, but rather spreads are high at the open, increase during the first 30 minutes, then gradually fall during the trading day, and fall sharply at the end of the trading day. Chan, Christie, and Schultz attribute this decrease in spreads to the lack of an affirmative obligation (AO) of NASDAQ dealers. Since NASDAQ dealers need not take both sides of transactions at the market close, unlike NYSE specialists, NASDAQ dealers decrease spreads in an effort to manage accumulated inventory positions over the trading day according to Chan, Christie, and Schultz (1995). Barclay, Christie, Harris, Kandel and Schultz (1999) revisit the intraday pattern of NASDAQ stocks after the January 20, 1997 order handling rule change and find that spreads are greatest at the open, decline through the trading day, as well as at the close.[1]

Over the past few years the role of liquidity supply in the stock market has been filled by Algorithmic Traders (AT). AT's do not have an affirmative obligation under SEC or exchange rules. With the growth in AT trading, the replacement of NYSE specialists with Designated Market Makers (DMM), the implementation of Regulation National Market System (Reg NMS), the adoption of high speed intermarket communications systems, as well as other changes, we feel it is important to reexamine liquidity behaviors for NYSE listed firms.

This study finds that intraday spreads for NYSE stocks follow an S-shaped pattern with high spreads at the market open, lower and relatively constant spreads during the middle of the trading day, followed by a decrease in spreads at the market close. In addition, aggregate display depth at the National Best Bid and Offer (NBBO) price is low at the market open and increases throughout the trading day. During the last 30 minutes of trading NBBO depth increases substantially. Under the current market

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[1] Chung and Van Ness 2001 show that this pattern is similar even after NASDAQ stocks tick sizes were reduced from 1/8th to 1/16th.

structure the most liquid period of the trading day, by far, is at the market close. These findings are robust across firm trading intensity (high, medium, and low). In addition, the findings are not driven by changes in the intraday pattern of volume or message traffic, both of which are U-shaped.

Prior research finds that inter-market competition improves market liquidity (Bessembinder, 2003). In addition, several studies focus on AT's and High Frequency Traders (HFT), a subset of AT, find that competition between AT's improve market liquidity (Menkveld, 2013, Hasbrock and Saar, 2013, Brogaard, Hendershott, and Riordan, 2013, Hendershott, Jones, and Menkveld, 2011). However, the adoption of AT and the speed associated with computerized trading introduces a new risk into stock markets; latency risk. Latency risk reflects the increase in potential adverse selection costs when AT liquidity suppliers attempt to manage resting orders in a multi-market center trading environment. Under the latency risk hypothesis, when quoted depth becomes more fragmented or when message traffic consumes more bandwidth, slowing intermarket communications, latency risk will increase and market liquidity will decrease. Although bandwidth is established based on peak use, in today's markets normal message traffic consumes the majority of the available bandwidth.[2] In effect, higher competition between market centers and AT's may decreases liquidity.

Quote fragmentation is measured as the average time weighted Herfindahl Index of ask NBBO depth and bid NBBO depth. Regression results indicate that as quote fragmentation increases, spreads increase and NBBO display depth decreases. Also, as the standardized measure of quote message traffic on an individual stock increases, one proxy for bandwidth consumption, percent quoted spreads increase and NBBO display depth for the stock decreases. Furthermore, the same results are found for the standardized measure of market wide quote traffic, our second proxy for bandwidth consumption, quoted spreads increase and NBBO display depth decrease.[3] Both of these findings support the latency risk hypothesis.

Execution volume may also fragment. We measure volume fragmentation as the Herfindahl Index of volume which executes over all exchanges in the Daily Trade and Quote (DTAQ) database.[4] We find that the correlation of volume fragmentation and quote fragmentation is relatively low with a maximum value of 0.264. Foucault and Menkveld (2008) propose a model which indicates that greater volume

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[2] With the emphasis on speed in the stock market one might expect excess communications bandwidth in the market. However Nanex, a market data company, shows that each time bandwidth is increased for intermarket communications, message traffic immediately increases to consume the new bandwidth. See http://www.nanex.net/aqck/2804.html.

[3] The Daily Trade and Quote (DTAQ) database only shows quote updates for the top of the book. This creates a negative bias to our results, likely underestimating the impact of message traffic on liquidity because we cannot see the message traffic away from the top of the book.

[4] The Finra Trade Reporting Facility, exchange D in the DTAQ database, is in the assessment of volume fragmentation. All so called TRF trades are reported under this exchange code.

fragmentation will improve market liquidity. Regression results in this study support their model. As volume fragments at the stock level, percent quoted spreads decrease and NBBO display depth increase.

Using the Preferencing Measure (PM), developed by He, Odders-White, and Ready (2006) we show that trade execution quality is lower when message traffic is high and when quote volume is fragmented across exchanges. However, when volume fragmentation is high, trade execution quality improves.

The balance of the paper is organized as follows. In section 2 a brief literature review is presented, while section 3 develops the testable hypothesis of the research. Section 4 details the data and methods, section 5 discusses the results, and the conclusion is in section 6.

2. Literature Review

Our research intersects several lines of financial literature. First is the investigation of the intraday pattern of liquidity supply in financial markets. Studying intraday spreads on the NYSE, McInish and Wood (1992) find that spreads have a U-shaped pattern with high spreads at the open and the close and lower spreads through the center of the day. Brock and Kleidon (1992) model the intraday bid-ask spread and show that high spreads at the open and close are driven by the specialist's ability to price discriminate during periods of increased transaction demand. Chung, Van Ness, and Van Ness (1999) show that the intraday pattern of spreads on the NYSE is driven by variation in the spread established by limit order traders. Lee, Mucklow, and Ready (1993) study the pattern of intraday liquidity around earnings announcements and find a U-shaped pattern of spreads and an inverse U-shaped pattern of quoted depth.

The U-shaped pattern of spreads is not unique to U.S. markets or even stock markets. Chan, Chung, and Johnson (1995) find a U-shaped pattern of spreads in CBOE options as well as on the NYSE. Ranaldo (2004) finds a U-shaped pattern of spreads in the limit order market of the Swiss Stock Exchange. Vo (2007), examining the Toronto Stock Exchange, again finds a U-shaped pattern of spreads and that depth is negatively correlated with the spread.

While researchers show that quoted spreads follow a U-shaped pattern and depth is negatively correlated with spreads, Chan, Christie, and Schultz (1995) finds that spreads are high at the market open but are narrowest at market close for a sample of NASDAQ stocks prior to the implementation of the Security and Exchange Commission's Order Handling Rules. Barclay, Christie, Harris, Kandel, and Schultz (1999), show that after the implementation of the order handling rules, the intraday pattern of spreads for NASDAQ stocks is similar to those of NYSE stocks near the open, but the patterns diverge at the close. Chan, Christie, and Schultz hypothesize that NASDAQ dealers reduce spreads to manage inventory at the market close. Also, NASDAQ dealers do not have the affirmative obligation to maintain orderly markets like NYSE specialists and thus reduce spreads from one side of the market to balance an excess inventory position. Panayides (2007) and Bessembinder, Hao, and Lemmon (2011) study the impact of the affirmative obligation and argue for the return of an affirmative obligation in order to enhance market quality.

The second area of research that intersects this effort is in the area of quote competition and volume fragmentation. Blume and Goldstein (1997) and Bessembinder (2003) show that when market centers post competitive quotes spreads decrease and volume fragments. Foucault and Menkveld (2008) model the entry of a new market center into an existing market and empirically test their predictions. They show that quoted depth increases and market liquidity improves with the entry of competitive market centers in the presence of smart routers.

This study also examines the impact of volume fragmentation on the liquidity environment of the market. Several studies examine the issue of 'Cream Skimming', the act of executing uninformed order flow away from the open market. The 'Cream Skimming' literature includes Bessembinder and Kaufman (1997), Easley, Kiefer, and O'Hara (1996), and Battalio (1997). These papers generally find that the effects of cream skimming only marginally impact the liquidity environment of the market. However, Battalio, Green, and Jennings (1998), Chung, Chuwonganant, and McCormick (2004), and Larrymore and Murphy (2009) find that cream skimming leads to a reduction in market quality.

The impact of volume fragmentation is still of interest to researchers and a topic that is unresolved. A recent study by O'Hara and Ye (2011) finds that stocks with greater volume fragmentation have lower transaction costs and faster execution speeds, while, Weaver (2011) finds that higher market fragmentation increases both quoted and effective spreads.

In this study we measure volume fragmentation with a Herfindahl Index for volume which executes at all market centers in the DTAQ database. This includes incorporating volume which reports through the Trade Reporting Faculties (TRF) of exchanges and listed under the Finra Exchange, exchange code D, in the DTAQ database. We examine the impact of volume fragmentation on quote based market liquidity and trade execution quality.

This research is also related to the area of AT and potential latency issues associated with computer trading. Hendershott, Jones, and Menkveld (2011) study the use of AT and find that it improves market liquidity. Hasbrouck and Saar (2013) study the impact of low-latency trading, trading that responds to market events in millisecond time frames, and find that low-latency trading improves short term volatility and enhances market liquidity. Menkveld (2013) examines the impact of High Frequency Traders (HFT), and finds that HFT activity improves market liquidity. In addition, Menkveld (2013) shows that HFT's engage in cross market trading strategies and end the trading day with a flat (zero) inventory position. Other studies focus on the impact of HFT trading include Brogaard (2010) and

Brogaard, Hendershott, and Riordan (2013). All of these studies, with the exception of Menkveld (2013) only examine trades which occur on NASDAQ.

There is also current research showing the impact of market latency and AT. Gai, Yao, and Ye (2012) look at quote stuffing, the action of generating thousands of quotes per second in order to increase system latencies, on NASDAQ. They find that market liquidity decreases during quote stuffing events. Egginton, Van Ness, and Van Ness (2013) examine quote stuffing and aggregate market quality in an event study framework. They also find that market quality degrades during quote stuffing events that increase market latencies. McInish and Upson (2013) show high latency (slow) traders can be 'picked off' by low latency (fast) traders at adverse prices. High latency traders see the market from a time delayed standpoint and can route trades to markets that are no longer at the best prices. These trades then execute under the Benchmark Quote Exception of Reg NMS. While markets have seen a dramatic increase in speed over the last ten years, these studies indicate that even small differences in latency between market participants can have significant economic impacts.

3. Hypothesis Development

A more competitive market is often considered to be a better, more efficient, lower cost market. However, market specific externalities can lead to higher costs even when economic measures indicate that there is more competition in the market. Research on the cost of liquidity in stock markets indicates that more competition leads to lower spreads and higher market liquidity. For example, Bessembinder (2003) finds that intermarket competition increases liquidity and reduces transaction costs when regional stock exchanges compete with the NYSE. Thus, higher cross market competition leads to a more liquid market.

Recently, the liquidity supply role in stock markets is aided by AT's, and a subset of AT's, HFT's. Several studies find that competition between and from HFT's reduce quoted spreads. Menkveld (2013) finds that spreads decline by 50% with the entry of HFT traders. Hasbrouck and Saar (2013), studying HFT trading on NASDAQ find that as HFT participation increases, quoted spreads decline and there is an increase in depth. Hendershott, Jones, and Menkveld (2011) find that as Algorithmic trading (AT) increases, which they proxy by the number of quote updates and trades, spreads narrow and liquidity increases. Brogaard, Hendershott, and Riordan (2013) show that HFT's collectively trade in the same direction as permanent price changes and against transitory pricing errors. This collective action implies a competitive process to obtain order flow. This leads to the following hypotheses:

H1A: An increase in AT competition increases market liquidity.

H1B: An increase in cross market quote competition increases market liquidity.

Hypotheses H1A and H1B are statements of competition and do not take potential market externalities into consideration. There has been a dramatic increase in the speed of trading over recent years, with messaging transmission times occurring in milliseconds and exchange matching engines processing trades and quotes in sub-millisecond time frames. At the same time, quote message traffic has dramatically increased with every increase in communications bandwidth, as shown by Nanex.[5] The speed of trades and quotes creates a latency risk for liquidity suppliers, where suppliers will be unable to cancel or update resting orders in reaction to a market liquidity shock, increasing the probability of adverse selection. Latency risk will increase if 1) cross market quote strategies are adopted by the liquidity suppler or 2) if high message traffic on the communications network between or within markets increases transmission times.

The market recognizes latency risk. RBC Capital Markets has a smart routing product known as Thor®, which times order submissions so that orders arrive at multiple trading venues at the same time, thus minimizing latency based information leakage. A traditional spray router will send orders at the same point in time, but latency differences in the communication systems will result in orders arriving at market centers at different times, facilitating latency based information leakage.[6] Routing systems such as Thor® can increase the latency risk of liquidity suppliers and reduce the latency risk of liquidity demanders.[7]

Menkveld (2013) shows that HFT's engage in cross market quoting strategies. In addition, under Regulation NMS, Rule 611 (the order protection rule) trades cannot execute outside of the best ask and bid price of the market. This requires exchanges, ATs, and other liquidity suppliers that use the exchange platform to track pricing on competing exchanges. In effect, Rule 611 forces intermarket competition even if an AT is only operating on a single exchange because the AT's quoted price must match the best market price for execution.[8]As more market centers match the best price, ask or bid, latency risk will increase because smart routing systems such as Thor® can simultaneously execute against all posted liquidity at best prices. In effect, even though a liquidity supplier is posting on a single exchange, they must consider their contribution to the NBBO depth and the ability of Thor® to use their partial contribution for execution of a much larger total liquidity demand execution. However, if depth concentrates on a single market, intermarket transmission latencies are reduced and only issues of the speed of the exchange matching engine and co-location transmission times would be of high

[5]Additional information on computing bandwidth can be found at http://en.wikipedia.org/wiki/Bandwidth_%28computing%29.
[6] For additional information regarding Thor®, see https://www.rbccm.com/thor/file-730060.pdf.
[7] Anecdotally, several market participants have referred to Thor® as generating toxic sweeps, where HFT's are unable to cancel posted liquidity prior to execution by observing order executions on other exchanges.
[8] There are a number of exemptions to the order protection rule, with one of the more frequent being the Intermarket Sweep Order. See Chakravarty, Jain, Upson, and Wood (2012) for more information on Intermarket Sweep Orders.

consideration. Liquidity suppliers may demand higher spreads and reduce posted liquidity as compensation for the higher latency risk when cross market competition is high and spreads may drop and depth increase when only a single exchange is quoting best prices.

Even if a single exchange is quoting the best price latency risk still exists. Gai, Yao, and Ye (2012) examine 'quote stuffing' on the NASDAQ market. Quote stuffing is the action of AT's and other automated liquidity suppliers submitting and cancelling large numbers of orders with the objective of slowing down an exchanges ability to handle quote updates. In addition, Egginton, Van Ness, and Van Ness (2013) find that in periods of intense episodic spikes in quoting activity (20 standard deviations from the mean), higher trading costs and a decrease in market liquidity occurs. This study examines intraday changes in quoting behavior in a continuous time frame work rather than the event study methodology method applied in Egginton, Van Ness, and Van Ness (2013). Even if AT's are not attempting to 'quote stuff', an increase in messaging traffic can still slow systems and lead to an increase in latency risk. Since quote updates on one exchange must be transmitted to all other exchanges, a quote stuffing event on a single exchange can still slow intermarket message traffic between exchanges. This leads to the following hypotheses referred to as the latency risk hypotheses:

H2A: An increase in AT competition decreases market liquidity.

H2B: An increase in cross market quote competition decreases market liquidity.

The impact of volume fragmentation of order flow across markets is also likely to influence the quote based liquidity environment. Parlor and Seppi (2003) investigate the interaction of a pure limit order market and a hybrid specialist/limit order market. They show that competition between exchanges can increase or decrease liquidity. Foucault and Menkveld (2008) modify the Parlour and Seppi (2003) model with the restriction that there is no execution time priority for resting limit orders between markets and that both markets are pure limit order markets. The U.S. equity markets have no intermarket time priority under Reg NMS and are, to a large degree, a pure electronic limit order market, meeting the requirements of the Foucault and Menkveld (2008) model. Foucault and Menkveld show that an increase in order volume fragmentation, via the use of smart routers such as Thor®, will increase aggregate quoted depth.

H3: An increase in volume fragmentation increases market liquidity.

Specifically under proposition 2 (pg 127), Foucault and Menkveld show that display depth will increase when two markets coexist; a condition that clearly exists in the U.S. stock market. In addition, under proposition 3 (pg 130), Foucault and Menkveld state "… traders post more aggressive quotes in this market …", where 'this market' refers to the second market, implying a decrease in NBBO spreads. In short, the Foucault and Menkveld model indicates that depth will increase and spreads will decrease as additional markets post competitive liquidity when smart routers are available to market participants.

4. Data, Sample, and Methods

4.1 Data

The data in this analysis is the Daily Trade and Quote (DTAQ) data. DTAQ is similar to the Monthly Trade and Quote (MTAQ) database but has time stamps to the millisecond on trades and quotes and additional condition codes. The DTAQ database also contains the exchange calculated NBBO, time stamped to the millisecond. The sample period is the first quarter of 2012, from January 3rd through March 30th.

4.2 Sample

Figure 1 shows the distribution of the average number of trades per day of all common NYSE listed stocks in the DTAQ database with an average price between \$5 and \$200 over the sample period. We form the sample in the following manner. First, we remove the top 5% of stocks from the sample selection process; stocks with an average number of daily trades exceeding 34,498. These hyper-liquid stocks skew the distribution of quoted depth with several stocks offering millions of shares at the best ask and bid prices, their quoted spreads are often bound at the minimum tick size of one cent, and frequently have multiple trades, quotes, and NBBO quotes with the same millisecond time stamp.

We then take the next 600 stocks as the sample. The stocks are grouped as low, medium, and high trade intensity with the first 200 stocks in the high intensity group. Descriptive statistics of the sample are discussed in section 4.5.

4.3 Methods

We estimate all regressions on a firm-by-firm basis. We average the dependent and independent variables over 39 ten minute segments for each sample day. The regression results are then aggregated either across firms, where the parameters are weighted based on the precision of the estimate, following Harris and Piwowar (2006). Statistical significance of a parameter is evaluated using the Bayesian framework of DuMouchel (1994). Panayides (2007) and Bessembinder, Panayides, and Venkataraman (2009) also use this framework. Specifically the procedure assumes that for a parameter estimate β_i:

$$\hat{\beta}_i \mid \beta_i \sim i.i.d.\ N(\beta_i, s_i^2) \tag{1.1}$$

and

$$\beta_i \sim i.i.d.\ N(\beta, \sigma^2) \tag{1.2}$$

where N is the Gaussian distribution. s_i^2 is estimated by use of the Newy-West method to correct for autocorrelation and heteroscedasticity, while σ^2 is estimated by maximum likelihood.[9] The aggregated parameter estimate, $\hat{\beta}$, is obtained from N individual regressions as

$$\hat{\beta} = \frac{\sum_{i=1}^{N} \frac{\hat{\beta}_i}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{1.3}$$

The variance of the aggregate parameter estimate is then

$$Var(\hat{\beta}) = \frac{1}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{1.4}$$

However, this assumes independent estimation of errors across firms. Chordia, Roll, and Subrahmanyam (2000, 2005) propose an adjustment to the standard errors that allows for cross-correlation in the regression residuals. They assume the cross-correlation of errors is constant across pairs of stocks. They show that standard errors are inflated by $[1+(N-1)\rho]^{1/2}$, where N is the number of regressions and ρ is the common cross-correlation of the residuals. ρ is estimated as the average cross-correlation of the residual over the 600x599=359,400 unique pairs of stocks. The final t-statistics is estimated as

$$t = \frac{\sum_{i=1}^{N} \frac{\hat{\beta}_i}{(s_i^2 + \sigma_{m.l.e}^2)}}{\left[(1+(N-1)\rho) \sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)} \right]^{1/2}} \tag{1.5}$$

A key attribute of this method is that it weights the aggregated parameter and statistical inference based on the precision of the estimated parameter. This method is directly applied to the firm-by-firm regressions in this analysis.

4.4 Regression specification and variable definitions

The regression analysis uses the following general specification:

$$\begin{aligned} X_{it} = Int + \beta_1 QiDev_{it} + \beta_2 Qfrag_{it} + \beta_3 Vfrag_{it} + \beta_4 MktDev_t \\ + \beta_5 RskDev_{it} + \beta_6 SzDev_{it} + \beta_7 SqNtrd_{it} + \sum D \end{aligned} \tag{1.6}$$

X_{it} is a quote based liquidity measure, either Percentage Quoted Spread or Composite Liquidity. In addition to these variables time of day dummies are included in the regressions, $\sum D$.We define

[9] We estimate Newey-West errors using the GMM method with a Bartlett kernel and a maximum lag length of 5 for the firm-by-firm regression.

Percentage Quote Spread as the time weighted average of $(NBBO_{ask}-NBBO_{bid})/NBBO_{midpoint}$. The Composite Liquidity (CL) measure is derived from Chordia, Roll, and Subrahmanyam (2001) and is defined as the time weighted average of $NBBO_{Depth}$/Percentage $Spread_{NBBO}$ where $NBBO_{Depth}$ is the total Ask and Bid depth at the NBBO price expressed in round lots and Percentage $Spread_{NBBO}$ is expressed in basis points. The use of the CL measure controls for the simultaneity of the choice of quoted depth and quoted spread.

$QiDev_{it}$ is a standardized measure of the total number of quote messages in the DTAQ database for stock *i* in period *t*. Let *QI* (Quote Intensity) be the number of quotes from all exchanges for stock *i* in period *t*. $QiDev_{it}$ is defined as $(QI_{it}-\mu)/\sigma$ where μ and σ are the average and standard deviation for stock *i* in period *t* for the entire sample period of *QI*. *QiDev* proxies for the relative intensity of quote updates from AT's for an individual stock. We recognize that *QiDev* will create a downward bias in our results because *QiDev* only tracks quote updates at the top of the book, while message traffic includes order updates over the full depth of the book and administrative messages. Unlike Hasbrouck and Saar (2013), who used NASDAQ ITCH data, the DTAQ database does not allow for the calculation of the 'Runs' variable they use in their analysis. However, Hendershott, Jones, and Menkveld (2011) use the count of messages (quotes and trades) as a proxy for algorithmic trading.[10] In addition, Bias and Weill (2009) develop a theoretical model on how algorithmic trading has a positive relation with message traffic. While *QI* and *QiDev* contain quotes from market participants other than ATs, Brogaard (2010) estimates that HFT's participate in 77% of market dollar volume, and HFT's are a subset of AT's. Although not perfect, empirical and anecdotal evidence from the market indicates that *QiDev* will largely be driven by AT messaging.[11,12] Higher levels of *QiDev* indicate greater quote traffic and potentially more competition between liquidity suppliers, consistent with Hypothesis 1 (A and B). However, higher levels of *QiDev* could also indicate an over consumption of intermarket transmission systems, slowing the systems and increasing latency risk of resting orders. We also include a measure for the market wide level of message traffic, *MktDev*. *MktDev* is the standardized measure of message traffic for all NYSE listed securities including stocks, ETF's, REIT's, and all other equities.

McInish and Wood (1992) evaluate the determinants of intraday spreads and find that deviations from the average risk level, as proxied by the quote midpoint volatility, and deviations from the average trade size are determinants of percentage spreads. We include these measures in the regression as *RskDev*

[10] Quote message traffic has a 99.99% correlation with quote and trade message traffic in our sample.

[11] If a trade executes at an exchange's quoted ask or bid price, a new quote will generate showing the change in quoted depth. These quote updates are removed from the measure of *QI* in the analysis. However, if they are included the findings do not change.

[12] Anecdotal evidence of the increase in AT quote traffic is available from Nanex. For example http://www.nanex.net/aqck/2804.html shows the 'Rise of the HFT Machines'. Empirical evidence can be found in Brogaard (2010), Menkveld (2013), and Madhavan (2012) .

and *SzDev* are calculated using the same method as *QiDev*. In addition, McInish and Wood find that trade intensity impacts intraday spreads. The regression includes *SqrNtrd* which is the square root of the number of trades for stock *i* in period *t*.[13]

The regression specification also includes two measures of market competition. *Vfrag* is the volume weighted inverse Herfindahl Index of transaction volume. The inverse of a Herfindahl index is simply 1-Herfindahl Index. In this way, increases in the *Vfrag* measure represent increases in volume fragmentation. The *Vfrag* measure is bound between 0 and 1 with 1 being fully fragmented and 0 being fully concentrated. Specifically for each 1 minute interval, of a 10 minute intraday segment, the Herfindahl index of buy and sell volume is calculated, including off exchange (TRF) volume. The buy and sell Herfindahl index values are then averaged for each minute in the segment. Finally, the *Vfrag* measure for the segment is the volume weighted average over each of the 1 minute intervals for the full 10 minute segment. Trade direction inference follows Lee and Ready (1991) and is determined by the NBBO quote in force at the time of the trade.

While market fragmentation is usually a measure of the fragmentation of volume, Blume and Goldstein (1997) and Bessembinder (2003) investigate the impact of quote competition between exchanges and find that competitive quotes attract liquidity. Madhavan (2012) investigates the impact of quote fragmentation during the period of the Flash Crash on May 6, 2010. Madhavan argues that quote fragmentation captures the competition between liquidity suppliers and may be a better proxy for high frequency activity rather than volume fragmentation. We define H^a as the time weighted Herfindahl Index of NBBO ask depth as

$$H_{it}^{a} = \frac{\left(\Delta t \sum_{k=1}^{K} \left(\frac{AskDpth_k \bullet I_k}{NBBO_{AskDepth}} \right)^2 \right)}{T} \tag{1.7}$$

Where Δt is the change in time between two quotes, I_k is an indicator variable that is 1 if the exchanges ask quote equals the NBBO ask quote, $NBBO_{AskDepth}$ is the total depth offered at the NBBO ask price, and T is the total time of one intraday segment (10 minutes). $AskDpth_k$ is the displayed ask depth for exchange k. Following Madhavan (2012) *Qfrag* is then one minus the average as the ask and bid Herfindahl Indexes; $Qfrag_{it}=1-(H^a+H^b)/2$. Higher levels of *Qfrag* indicate more quote based market fragmentation and hence more intermarket competition.

[13]McInish and Wood (1992) also include the level of their risk and trade size measures. The levels of these measures are not in this specification because they are highly correlated with the deviation measures.

4.5 Descriptive statistics

Table 1 shows descriptive statistics for the sample. The mean of each variable is shown with the standard deviation in parenthesis. The values are conditioned on trade intensity. Market capitalization is determined on the first trading day of 2012 and expressed in millions of dollars. As we expect, firm size is increasing in trade intensity. The average number of trades per day runs from a minimum of 4,713 to a maximum of 21,196.

Quote Intensity (*QI*), quote fragmentation (*Qfrag*), and volume fragmentation (*Vfrag*) are based on the 10 minute intraday segments. As we expect, *QI* is increasing in the trade intensity of the stock. This implies that AT's are more competitive as trading intensity increases. However, quote fragmentation is relatively consistent between the low, medium, and high trade intensity stocks. This implies that intermarket competition is also relatively constant. Volume fragmentation is increasing in trade intensity. The standard deviations of all variables indicate that there is substantial variability in the measures.

Table 2 shows correlations, which we separate by trading intensity groupings, between the independent variables. Overall the independent variables have low correlations indicating that they are measuring different aspects of market conditions. For example, the maximum correlation between *Vfrag* and *Qfrag* is for the low trade intensity group with a correlation of 0.264. This indicates that quote and volume fragmentation represent different aspects of the market liquidity environment. *QiDev* and *MktDev* also have a relatively low correlation, with the highest correlation at 0.433 for high trade intensity stocks. The variables with the highest correlations are *Vfrag* and *SqrNtrd*. In the medium trade intensity group this correlation is 0.500.[14]

5. Results

5.1Intraday NBBO spreads and display depths

Figure 2 shows an intraday plot of time weighted percentage spreads, in basis points, and NBBO display depth, in round lots. The mean of both values are plotted for each minute of the trading day. Spreads are highest at the open and decrease throughout the trading day, reaching a minimum value towards the end of the trading day. NBBO depth has an inverse relationship with spreads, with low depth at the open and increasing depth over the trading day. Depth reaches a maximum at the end of the trading day. Though not shown to conserve space, the same general relationship holds when the plots are

[14]In unreported regression results *Vfrag* and *SqrNtrd* were orthogonalized with no significant change in results indicating that multi co-linearity of these variables has limited impact on the regression results.

segmented based on trade frequency rank. The most liquid time of the trading day, from a quote based perspective, is at the market close.

The intraday pattern in spreads is in contrast with earlier literature on intraday spreads for NYSE listed stocks (McInish and Wood (1992), Lee, Mucklow, and Ready (1993), Chan, Chung, and Johnson (1995), Chung, Van Ness, and Van Ness (1999), Ranaldo (2004), and Vo (2007) all find a U-shaped intraday pattern of spreads), but is consistent with the findings of Barclay et al. who examine NASDAQ stocks after the Order Handling Rules. The decline is spreads at the end of the day is also consistent with the findings of Chan, Christie, and Schultz (1995) who examine NASDAQ stocks prior to the Order Handling Rules and tick size changes. Chan, Christie, and Schultz speculate that the reduction in spreads at the market close is an attempt by NASDAQ dealers to control overnight inventory positions.

The high liquidity at the market close is also consistent with an inventory argument in a market with high AT and HFT participation. The SEC description of HFT's states that HFT's attempt to 'end the day in as close to a flat position as possible' (SEC 2010, p.45). Menkveld (2013), in a study of HFT trading on the Chi-X and Euronext exchanges, finds that HFT's have a zero net inventory position at the start and end of the trading day. Menkveld (2013) calls HFT's the new market makers. In effect, we believe HFT's may be trading extensively at the end of the trading day in order to achieve a zero or close to a zero inventory position, decreasing spreads and increasing display depth. This high liquidity at the end of the trading day can have a number of beneficial results. First, it can reduce price volatility and price impact of trading at the end of the day because the higher posted depth and narrower spreads will create greater resiliency in the book. Second, the high liquidity will reduce potential end of day price dislocation because larger order sizes will be required to move prices, making an attempt at price dislocation more costly. Third, it reduces transaction cost in a period of high volume demand because of the lower spreads. Finally the high end of day liquidity will benefit institutional traders looking to complete large orders for liquidity needs.

5.2 Historical Analysis of Percentage Spread

We extend our analysis of intraday spreads in an attempt to identify when the U-shaped patterns of spreads change to an S-shaped pattern for NYSE stocks. Using Monthly Trade and Quote data (MTAQ) from January 3, 2009 through April 29, 2011 we calculated the time weighted percent spread for each minute of the trading day.[15] We calculate the average for each minute for each six month period (only 4 months in 2011 due to data limitations), and plot the results in Figure 3

[15] The NBBO must be estimated with the MTAQ data. If the ask price or ask depth is less than or equal to zero the ask price is not considered as part of the NBBO estimate. If the bid price or bid depth is less than or equal to zero the bid price is not considered for inclusion in the NBBO. Zero or negative depths or prices indicate that the market center is not offering an NBBO eligible quote on that side of the market.

There is a monatomic decrease in percentage spread over this historical analysis, reflecting the large increases in stock prices from early 2009 through 2011. In the first six months of 2009 the spread pattern clearly follows the typical U-shaped pattern identified in prior research. During roughly the last 10 minutes of trading percentage spreads increase from approximately 0.32 basis points to 0.6 basis points. Figure 3 indicates that as time moves forward, the upturn in percentage spreads decreases. In the first four months of 2011, the increase in percentage spreads is very slight and does not start the upturn until the last 3 minutes of the trading day. While the U-shaped pattern is identifiable over the historical analysis period, it is transforming to the S-shaped pattern shown in Figure 2. We do not plot NBBO depth in Figure 3 to maintain clarity. However, as the spreads increase at the end of the trading day, the depth decreases. As the upturn becomes less in the later periods, 2011 for example, the depth reduction becomes much smaller.

5.3 Volume and Messaging

It is possible that the change in the intraday NBBO spreads and depth is a reaction to a change in trading. Figure 4 shows the intraday mean number of quote updates and the mean volume per minute. Both plots show a general U-shaped pattern.[16]

For the first thirty minutes of trading, the quote count is low relative to the 10:00 am mark. This deviation from the U-shaped pattern is driven by the high and medium trade intensity stocks in the sample. Low trade intensity sample stocks have a strictly U-shaped pattern, without the deviation in the first 30 minutes of trading. In unreported results, a detailed examination of quote traffic for high trade intensity stocks in the first 30 minutes of trading shows that the lower quote traffic is consistent for the full sample period. Several macroeconomic announcements occur at 10:00 am during the trading day, possibly leading to the low quote traffic prior to the announcements; however, no economically significant drop in quote traffic is observed on announcement days. High trade intensity stocks have higher market capitalization and are in the S&P500 as well in various ETF products such as DIA (the DOW Thirty) and SPY (the S&P500). The lower quote traffic in the morning period may reflect an interaction between option markets, future markets, ETF's, and the underlying stocks in the sample. While the lower quote count in the first 30 minutes of trading is an interesting observation, it is not the focus of this analysis.

Trading volumes follow a U-shaped intraday pattern, with high volume at the open and close and lower trading volume during the middle of the trading day.[17]Transaction volume increases substantially in the last 30 minutes of trading; corresponding to the decrease in spreads and the increase in displayed

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[16] As noted in footnote 9, quote updates that result from trade execution at the posted price are removed from the quote count for the market. If these quotes are included in the analysis the plot remains identical.
[17] The same pattern occurs if trade counts are used rather than transaction volume.

depth. Although not included to save space, the volume plot is U-shaped for each trade intensity group and by listing exchange. The volume pattern is consistent with previous studies on intraday liquidity, although a visual comparison suggests a higher percentage of volume tends to execute at the end of the day in this study compared to Chan, Chung, and Johnson (1995, p337, Figure 1).

Both the U-shaped pattern of quotes and volume are consistent with prior research that find a U-shaped pattern in intraday spreads. Chung, Van Ness, and Van Ness (1999, p263, Figure 1) shows a U-shaped pattern of quote updates and a U-shaped pattern for volume (p277, Figure 3), yet they also find a U-shaped pattern for spreads. Similarly, Chan, Chung, and Johnson (1995) find U-shaped patterns for stock volume and stock spreads. Thus, the finding in this research of a decreasing, S-shaped pattern of spreads is likely linked to other structural changes in the market, rather than the consistent quote and volume patterns seen in this and previous studies.

5.4 2SLS regression results

The 2SLS estimation requires instrumental variables in the estimation process. A natural candidate for the instruments is the lagged values of the independent variables. However, it is well known that intraday liquidity measures are serially correlated (McInish, Ord, and Wood, 1985). Thus, a liquidity shock to the market can propagate through various liquidity components of the market.[18] Using simple lagged values of the independent variables incorporate this propagation in the first stage of the 2SLS regression and can lead to the independent variables being correlated with the error term in the second stage regression.

To address this issue an Auto Regressive regression is estimated for each of the independent variables, for each stock, over the sample period.[19] The AR regression is estimated for lags of one, two, and three. The lag that minimizes the Akaike Information Criteria is then used.[20] The instrument is then the expected value, from the AR regression for the previous (lagged) period. Thus a shock in period t-1 is not incorporated into the instrument, terminating the propagation of the shock to period t, yet the evolution of shocks from previous periods is incorporated into the estimation of the first stage regression. In addition, lagged intraday dummy variables are incorporated to maintain the identification of the regression.

[18] A recent example of such a liquidity shock occurred on April 23, 2013 when the AP twitter feed was hacked and a fake message that the White House was bombed was transmitted. The market quickly dropped 130 points only to recover minutes later when the hack was discovered. For additional information on the event see http://www.cbc.ca/news/business/fake-white-house-bomb-report-causes-brief-stock-market-panic-1.1352024.

[19] An AR(3) represents 30 minutes of trading and is selected to control for the slow decay of autocorrelation identified in McInish, Ord, and Wood (1985). The AIC is minimized with the AR(3) regression for a majority of equities in the sample.

[20] We wish to thank Bidisha Chakrabarty for this recommendation.

5.4.1 Interpretation

The results of the 2SLS estimation are shown in Table 3. To conserve space, the discussion is confined to the hypothesis variables *QiDev*, *Qfrag*, *Vfrag*, and *MktDev*. For the Composite Liquidity (CL) measure the coefficients for *QiDev* and *MktDev* are negative and significant. In addition, the coefficient for *Qfrag* is negative and significant. Our interpretation of these results is as follows. As quote message traffic, both from a stock specific level and market wide level, increases above the expected value, additional communications band width is consumed for intermarket communications. The higher band width consumption increases the risks of managing resting orders and AT's reduce quote based liquidity to compensate for the increase in risk. In addition, higher quote fragmentation indicates a higher risk of Thor® trade adversely selecting resting orders across markets. AT's decrease liquidity to compensate for this risk. These results support Hypotheses H2A (an increase in AT competition decreases market liquidity) and H2B (an increase in cross market quote competition decreases market liquidity). In addition, the coefficient for *Vfrag* is positive and significant for the CL regression, which supports Hypothesis H3 (an increase in volume fragmentation increases market liquidity).

The percentage spread regression results indicate that *QiDev* is insignificant. However, *MktDev* is positive and significant, consistent with H2A (an increase in AT competition decreases market liquidity). The coefficient for *Qfrag* is positive and significant, indicating that as quoted depth fragments, percentage spreads increase. This again supports Hypothesis H2B (an increase in cross market quote competition decreases market liquidity). The coefficient of *Vfrag* is negative and significant, again supporting the H3 hypothesis (an increase in volume fragmentation increases market liquidity). Under the latency risk hypothesis, as quote traffic increases, AT's management of posted liquidity becomes more risky because of potential time delays in managing resting orders and acquiring cross market price and trade information. Liquidity suppliers thus reduce liquidity to reduce the value at risk. Similarly, as depth fragments across exchanges, intermarket management of resting orders becomes more of an issue. This increases the latency risk, reducing liquidity. Even if an AT is posting resting orders on a single market center, their algorithms should consider the contribution of the resting order to the total posted depth at NBBO prices. As the NBBO depth increases more depth is available to be captures by a Thor® type router, increasing the potential for adverse selection.[21] AT's increase the price of liquidity to compensate for the increase in potential adverse selection.

[21] In section 5.5 we show that an increase in *Qfrag* is positively related to an increase in quoted NBBO depth and positively related to an increase in percent quoted spread.

The interpretation of the coefficient of *Vfrag* is straight forward. Volume fragmentation is an ex-post measure and is best interpreted as a conditional measure. Given that volume is fragmented, AT liquidity suppliers compete for trade execution of the fragmented order flow at each market center, reducing spreads and increasing display depth. The finding and interpretation is consistent with the predictions of Foucault and Menkveld (2008). Specifically Foucault and Menkveld (2008) find "fragmentation of order flow can enhance liquidity supply", and propositions 2 and 3 of their model (pgs 127 and 130, respectively) support this finding.

5.5 Trading intensity and liquidity

Our sample has considerable cross sectional variation in quote and trade intensity. To investigate whether our results are driven by this cross sectional variation we estimate the CL and percent quoted spread regressions for High, Medium, and Low trade intensity stocks separately. Table 4 presents results for the CL and percentage quoted spread regressions segmented by trade intensity. Panel A shows the results for the CL regression. All coefficients have the same sign and maintain significance as in the regression results of Table 3. Our results on the CL measure do not appear to be driven by the trading intensity of the sample stocks.

Table 4 Panel B details the results of the percentage quoted spread regression. Two variables, *QiDev* and *Vfrag*, indicate that some of the spread results are impacted by trading intensity. For *QiDev*, in the full sample results of Table 3, the coefficient is insignificant. However, Panel B indicates that for the low trade intensity stocks, *QiDev* is positive and significant at the 10% level. In addition, *Vfrag* is negative and significant for the low trade intensity stocks, but insignificant for the medium and high trade intensity groups. For the full sample regression this coefficient is negative and significant. One possible explanation for the trading intensity effect on percentage quoted spreads is that as trading intensity increases, absolute spreads will tighten and possibly be bound at the minimum tick of one cent. If the absolute spread is bound, liquidity suppliers can only manipulate the posted liquidity to change the value at risk. Thus, low intensity stocks are more sensitive to the explanatory variables for quoted percentage spread because their spreads are less often constrained at the minimum tick. The coefficients of *Qfrag* and *MktDev* have the same sign and significance as in the regression of Table 3 for all trade intensity groups. *MktDev* proxies for the total band width consumption of the intermarket communication linkages. This result indicates that total band width consumption has a stronger impact of latency risk than the stock level consumption of band width. However, AT's may allocate smaller amounts of computational band width to low trading intensity stocks, making these stocks more sensitive to abnormal increases in message traffic and increasing latency risk.[22]

5.6 System of equations

When liquidity suppliers post limit orders there are several choices that are made simultaneously; price, size, and on which market center the order will be place.[23] In the prior regression analyses, the simultaneous nature of the price and size variable is controlled for by combining them into the single variable CL. In this section we estimate a system of equations with NBBO depth and percentage spreads as endogenous variables. A two-stage least squares method is applied. We include contemporaneous NBBO depth and percentage quoted spread, *Rsprd*, in the equation system to allow for a more complex relationship between the price and size choices than is contained in the CL metric. Specifically, while the CL measure assesses the combined liquidity impact of depth and spread, the system of equations estimation will allow the evaluation of the separate impact of our explanatory variables on the individual liquidity measures of spread and depth.

For the system of equations to be identified, one variable must be excluded from each of the regression equations. In the percentage spread regression *SzDev* is excluded. *SzDev* is selected because it is not significant in the prior regressions of percent quoted spread. In the NBBO depth regression *SqrNtrd* is excluded. *SqrNtrd* is excluded for several reasons. First, *SqrNtrd* has an average correlation with *Vfrag* of roughly 0.5. By removing *SqrNtrd* a source of multi co-linearity is removed from the system. Second, as noted in O'Hara, Yao, and Ye (2014), odd lot trades are not included in the DTAQ database for our sample period. This will induce a bias to our trade count, underestimating the actual value. O'Hara et al. show that wider spreads are positively related with higher percentage of odd lot trades relative to total trades (Table V); however, as long as the use of odd lot trades is positively correlated with the total number of trades, *SqrNtrd* should be an effective measure for the quoted spread regression. This may not be true for the NBBO depth regression because only round lot sizes of quoted depth are reported. An odd lot trade of one share traded against one round lot of posted liquidity will result in a decrease of one round lot from total aggregate NBBO depth. Although the bias introduced from the lack of odd lot reporting impacts both the NBBO depth and spread regressions, the authors believe

[22] Computational band width can be easily seen on the Windows operating system by starting the task manager and viewing the processes tab. If a new program is started, the other processes do not simply stop while the new program is loading. Rather the operating system allocates processing band width to the new programing while reserving computational band width for the other processes to continue running. In the context of an AT, computational band width is allocated based on trade intensity or some other metric. Thus an increase in message traffic for a low trade intensity stock may consume the computational band width allocated to it, reducing the system's ability to quickly manage new quote and trade updates.
[23] Liquidity suppliers may also select special order conditions. However the DTAQ database does not contain this information.

there is less of an impact on the percentage quoted spread regression. The lagged value instruments associated with these variables are also excluded.

The results of the system of equations estimation are shown in Table 5. The coefficient for *QiDev* is negative and significant at the 1% level in the NBBO depth regression supporting the latency risk hypothesis. As quote traffic increases AT's reduce the depth posted in the market to compensate for the greater risk of liquidity being captured at multiple markets at the same time. The coefficient for *QiDev* in the percentage spread regression is negative and significant at the 10% level. This result supports the traditional view of competition stated in hypothesis 1, that an increase in competition will increase liquidity, and fails to support the latency risk hypothesis. Although greater competition between AT's reduces spreads, this competition also results in a reduction of posted depth. Based on the results of Table 3, where the coefficient of *QiDev* is negative and significant at the 1% level for the CL measure, the reduction in depth dominates the liquidity change related to higher quote traffic.

The *Qfrag* variable, a proxy for intermarket competition, is positive and significant in the NBBO regression, but also positive and significant in the percentage spread regression. These results indicate the as quoted depth becomes more fragmented across exchanges there is a positive contribution to the market depth aspect of liquidity and also an increase in quoted spreads which represents a decrease in liquidity. Based on the CL regression of Table 3, where *Qfrag* is negative and significant, the increase in spread associated with more intermarket competition dominates the liquidity change related to intermarket competition. Although AT's may increase the depth as new orders are submitted across exchanges, they post these orders at higher spreads to compensate for the increase in latency risk.

The coefficient of *Vfrag* is positive and significant in the NBBO depth regression and negative and significant in the percentage spread regression. Higher volume fragmentation unambiguously increases the liquidity of the market. These results are fully consistent with those obtained from the regression reported in Table 3. An increase in volume fragmentation indicates that trades are occurring on multiple market centers. AT's at these market centers compete for the arriving order flow inside the market center by decreasing spreads and increasing posted depth. One can interpret the realization of volume fragmentation as resolving the uncertainty regarding the direction of trading using Thor® or equivalent routing techniques. The removal of this uncertainty allows AT's to reduce spreads and increase depths.

The coefficient of *MktDev* is insignificant in the NBBO depth regression but positive and significant in the percentage spread regression. *MktDev* is our proxy for the total consumption of communications bandwidth for intermarket communications. As *MktDev* increases, based on the latency risk hypothesis, AT's will decrease liquidity to compensate for higher adverse selection costs. For the CL regression in Table 3, we show that increases in *MktDev* decrease market liquidity, supporting the results from the system of equations.

We note that *RskDev* also unambiguously decreases market liquidity with a significant and negative coefficient in the NBBO depth regression and a significant and positive coefficient in the percentage spread regression, confirming theoretical predictions and prior empirical findings. The coefficient of *SzDev* in the NBBO depth regression is positive and significant consistent with the CL regression of Table 3. *SqNtrd* is negative and significant in the percentage spread regression as it was in previously presented results. The coefficient for *Rsprd* in the NBBO depth regression is negative and significant indicating that as spreads widen quoted depth decreases. However, the coefficient of NBBO depth in the percentage spread regression is not significant.

The results from the system of equations estimation complement our earlier findings for quote based market liquidity. Under the context of the latency risk hypothesis, we interpret our findings of the system of equations regression as follows. In the fragmented market structure of the U.S. equity market, AT's, or perhaps more accurately the algorithmic programs used by AT's, must incorporate the latency risk associated with the fragmented architecture of the U.S. market. In addition, although the U.S. markets are 'fast', the speed of the market varies over time.[24] Even as competition between AT's, as proxied by *QiDev,* decreases quoted spread, the algorithmic programs also decrease quoted depth, reducing the value at risk of the resting orders. If an AT's program increases NBBO depth by posting orders at market centers that were previously not at best prices, increasing *Qfrag*, aggregate depth increases but spreads also increase to compensate for the additional risk from a Thor® type router. Or equivalently, when spreads are wide, AT's are willing to post liquidity on additional markets because they are compensated for the additional risk associated with Thor® type routers. In addition, as market wide message traffic increases above expected levels, consuming additional intermarket bandwidth, spreads widen. The increase in market wide message traffic, above the expected value, consumes intermarket communications bandwidth and can slow communications, increasing latency risk.[25] Each of these results, coupled with the results from the previous regressions, supports the latency risk hypothesis.

5.7 Trade execution quality

[24] As an extreme example, according to the CFTC/SEC report on the Flash Crash, quote and NBBO feeds for some stocks were delayed by 5 seconds or more (page 77).

[25] As an additional example of latency risk, the IEX market center has a 350 microsecond delay in order updates to allow the markets matching engine to incorporate changes in NBBO prices. Although, in general, the matching engine can actually calculate the new NBBO under 350 micro seconds, IEX selected 350 microseconds (roughly 1/3 of a millisecond) to 'ensure' that the matching engine can have the new NBBO before outside participants can act on the new information. This indicates that extremely small delays in intermarket communications can have an impact on trade routing, order cancelation, and order submission actions.

We have presented results that indicate that AT's reduce market liquidity in response to latency risk in the market. However, our analysis has exclusively focused on quote based liquidity. In this section of the paper we evaluate the execution quality of trades. He, Odders-White, and Ready (2006) argue that effective spreads and realized spreads are poor measures of execution quality because they do not take into account the role of information asymmetry. For example, informed traders may be happy to pay higher spreads to trade now, prior to the realization of information to the market. He, Odders-White, and Ready (2006) introduce the Preferencing Measure, PM, defined as the ratio of realized spread to effective spread. They argue that this measure is more appropriate when comparing execution across stocks and across exchanges, which is an implicit part of our analysis. Higher values of PM represent low trade execution quality. Effective spreads are calculated against the prevailing NBBO quote. The realized spread is measured against the prevailing NBBO quote midpoint five minutes after the trade or the end of the intraday 10 minute time segment.[26] Trade inference is based on Lee and Ready (1991) method using the contemporaneous NBBO quote. Trade weighted and volume weighted effective and realized spreads are estimated. The PM is then the ratio of realized to effective spreads for each time segment.

Our expectation is that the variables associated with decreases in market liquidity, *QiDev*, *Qfrag*, and *MktDev* will be related with decreases in trade execution quality. Variables associated with increases in market liquidity, specifically *Vfrag*, will be related with increases in trade execution quality. The regression results for the Preferencing Measure are shown in Table 6. We present results for both the trade weighted and volume weighted PM measure of trade execution quality. The empirical techniques applied in the previous regressions are also applied here.

The regression results of the trade weighted and volume weighted measures of PM are very similar, with the exception of the *Qfrag* measure. We believe that the volume weighted results are most relevant since trade execution quality is more important when there is a high amount of trading occurring; thus we confine our discussion to the volume weighted results. The coefficient of *QiDev* is positive and significant at the one percent level, indicating that as message traffic increases trade execution quality decreases. The coefficients of *Qfrag* and *MktDev* are also positive and significant at the one percent level. *QiDev* and *Qfrag* are proxies for competition between AT's, yet our results indicate that as this competition increases, not only does quote based market liquidity decrease, but also there is a decrease in the execution quality of trades. *MktDev* measures the consumption of intermarket communications bandwidth. As more bandwidth is consumed message speed can decrease. While this impacts AT's supplying liquidity, increasing the risk of managing resting orders, it also can give liquidity demanders a

[26] Realized spreads are not calculated with a continuous moving 5 minute period since a trade at the end of period t will have a reference quote midpoint in period t+1. This future midpoint will be influenced by the independent variables in period t+1 inducing a potential artificial serial correlation in the error terms.

stale picture of the liquidity environment of the market, making routing decisions more complex and delay executions or decrease execution probabilities for liquidity demanders.

The coefficient of *Vfrag* is negative and significant indicating that as volume fragments across exchanges, trade execution quality improves. While an increase in volume fragmentation has a positive impact on quote based market liquidity, it also improves the execution quality of trades. The improvement in execution quality with higher volume fragmentation does not appear to be driven simply by higher trading. We find that the coefficient of *SqrNtrd* is positive and significant at the one percent level, indicating that more trading is associated with lower execution quality.

We also note that the coefficient of *RskDev* is negative and significant indicating that an increase in risk increases execution quality. *RskDev* will increase when prices change rapidly. Our liquidity regressions indicate that spreads widen and depth decreases with an increase in *RskDev*; however if informed traders are moving prices they will be willing to pay higher spreads to trade now before prices move in the direction of their information. *SzDev* is not significant in this regression.

We are not asserting that AT's purposefully manipulate quote fragmentation or message traffic to decrease trade execution quality in the market. Rather we believe that liquidity supplying AT's are making rational choices to receive reasonable compensation for the liquidity supplying role they engage in. We are simply investigating the impact of these rational choices on trade execution quality.

6. Conclusion:

Using a sample of NYSE stocks in the first quarter of 2012 this study examines liquidity. We find that the intraday pattern of spreads has changed from the U-shaped pattern identified in earlier studies of NYSE listed stocks, to an S-shaped pattern with high spreads in the morning and the lowest spreads at the end of the trading day. National Best Bid and Offer (NBBO) depth follows an inverse pattern with low depth in the morning and high depth at the market close. In today's market the most liquid period of the day is at the market close.

While the average speed of markets has increased over the past ten years, at any given point in the trading day market speed can deviate from the average and become faster or slower, as communications bandwidth is consumed. When markets become slower, Algorithmic Traders (AT), of which High Frequency Traders (HFT) are a subset, will have more difficulty in managing resting orders across various market centers. We term this risk as Latency Risk. As intermarket communications slow due to high utilization or if market NBBO display depth becomes more fragmented, the increase in Latency Risk may reduce market liquidity. Practitioners recognize latency risk and RBC Capital Markets developed a smart router known as Thor® which times the submission of trades across multiple market centers so all trades arrive at the same time, minimizing latency based information leakage.

Market quote fragmentation is measured by assessing the time weighted average Herfindahl Index of NBBO quoted depth. This measure proxy's for intermarket competition. Latency Risk will also increase if intermarket bandwidth communications become stressed. Bandwidth use is evaluated using the standardized quote traffic volume for an intraday period. These measures are labeled as *QiDev, MktDev,* and *Qfrag* respectively, where *QiDev* measures stock level quote intensity, *MktDev* measures market wide quote intensity, and *Qfrag* measures the stock level distribution of quoted depth. For all measures we show that market liquidity decreases as quote fragmentation increases and as quote traffic increases over average levels. Market liquidity is measured by percentage spreads, composite liquidity (NBBO Depth/percentage spreads), and NBBO display depth.

Traditionally, market fragmentation refers to the fragmentation of transaction volume. Foucault and Menkveld (2008) model a multimarket limit order trading structure and show that higher volume fragmentation improves market liquidity. Volume fragmentation is measured as the Herfindahl Index of transaction volume over the exchanges listed in the Daily Trade and Quote database, including the Finra Trade Reporting Facility (exchange D). This analysis supports the predictions of the model. We find that increased volume fragmentation correlates with increased market liquidity; lower spreads and increased NBBO depth.

We also evaluate the execution quality of trades. We find that execution quality decreases with increases in *QiDev*, *Qfrag*, and *MktDev*. We also find that trade execution quality improves with higher volume fragmentation, *Vfrag*, in the market. Our analysis indicates that higher market competition, either between markets as proxied by *Qfrag*, or between AT's, as proxied by *QiDev* and *MktDev*, decreases market quality, while higher volume fragmentation improves market quality.

As markets, worldwide become more fragmented both in terms of quote fragmentation and volume fragmentation, Latency Risk of liquidity suppliers is likely to increase. Our findings indicate that practitioners and market regulators should have keen awareness of excess message traffic, increases in quote fragmentation, and increases in volume fragmentation. We show these metrics have significant impacts on market liquidity even after controlling for other known variables that effect market liquidity. Our analysis compliments other research showing the impact of multimarket trading and AT on market liquidity.

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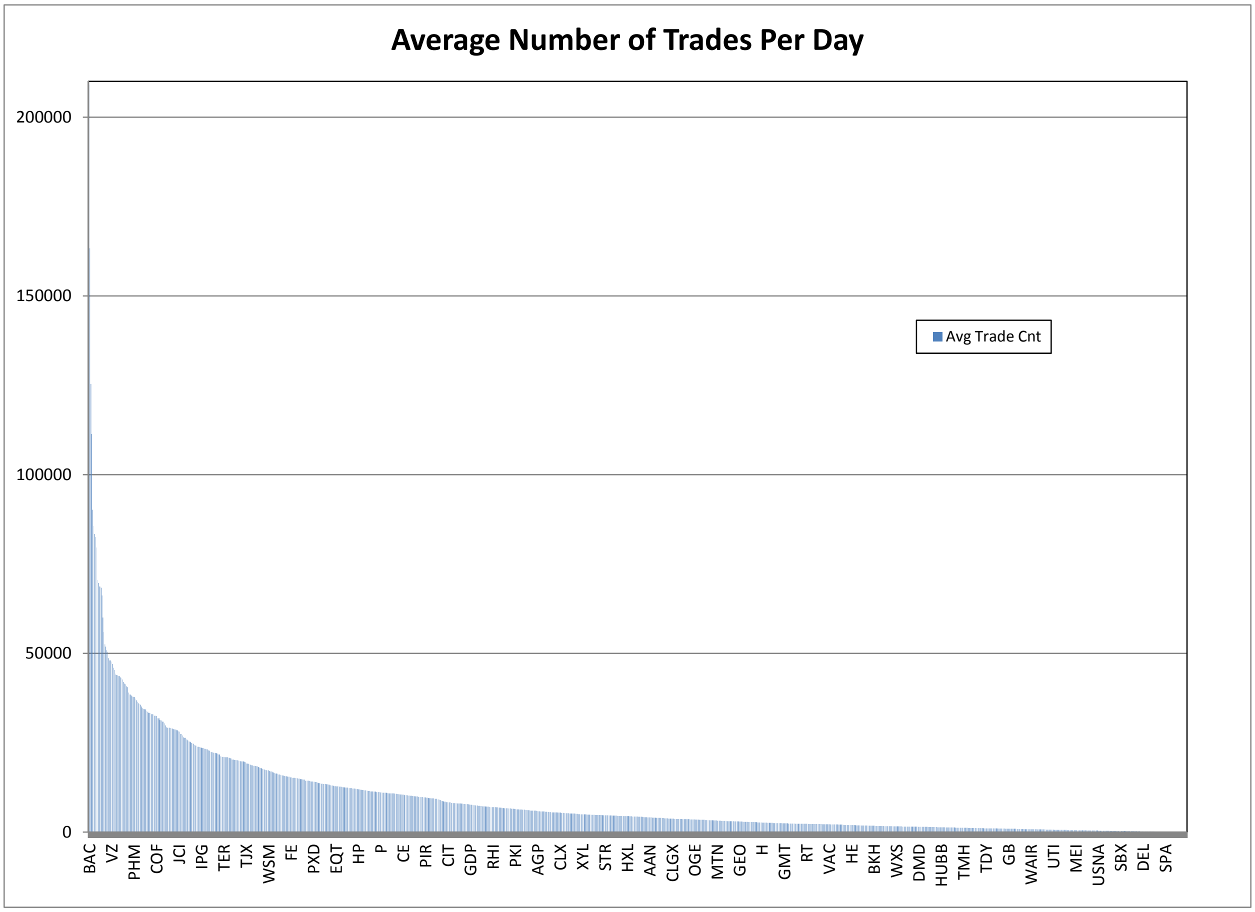

Figure 1. The average number of trades per day for the sample period, January 3 through March 30 of 2012 is shown. All common stocks NYSE listed securities in the Daily Trade and Quote file with an average price between $5 and $200 are included in this plot.

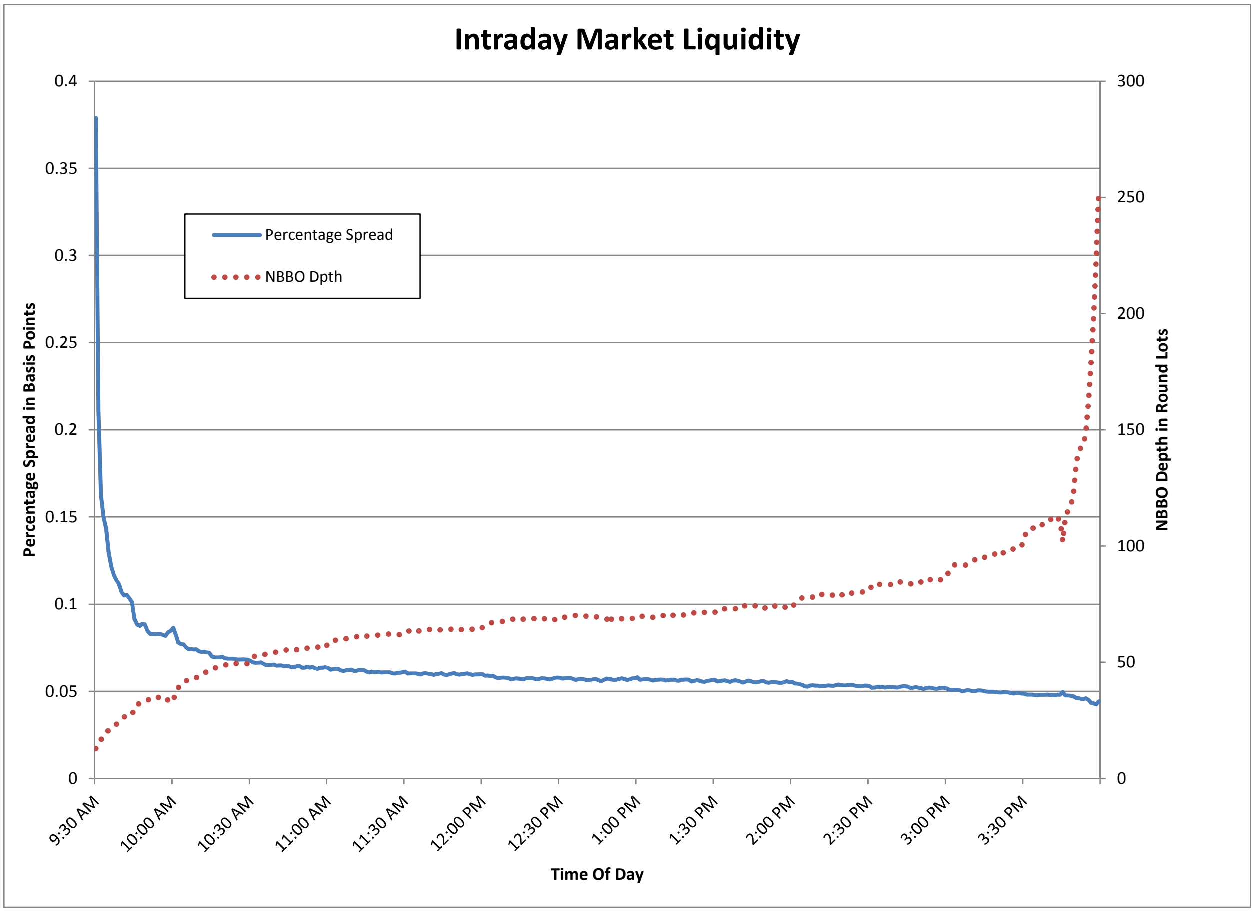

Figure 2. The time weighted average Percentage Spread and National Best Bid and Offer Depth is plotted for each minute of the trading day. Percentage Spread is shown in basis points on the left axis and NBBO Depth is shown in round lots on the right axis. The sample period is from January 3, 2012 through March 31, 2012.

Historic Intraday Percentage Spread

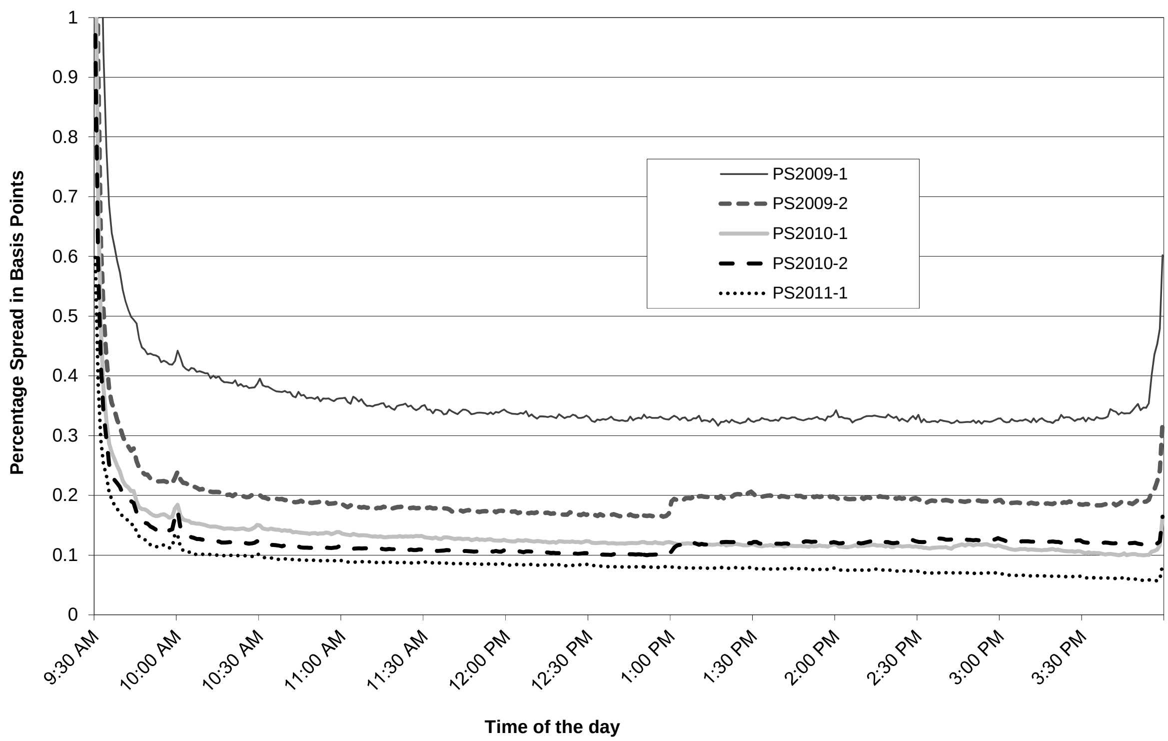

Figure 3: Percentage spreads are plotted from January 2009 through April 2011. PS2009-1 is for the first six months of 2009. PS2009-2 is for the second six months of 2009. PS2010-1 and -2 are for the first and second six month periods of 2010. PS2011-1 is for the first four months of 2011.

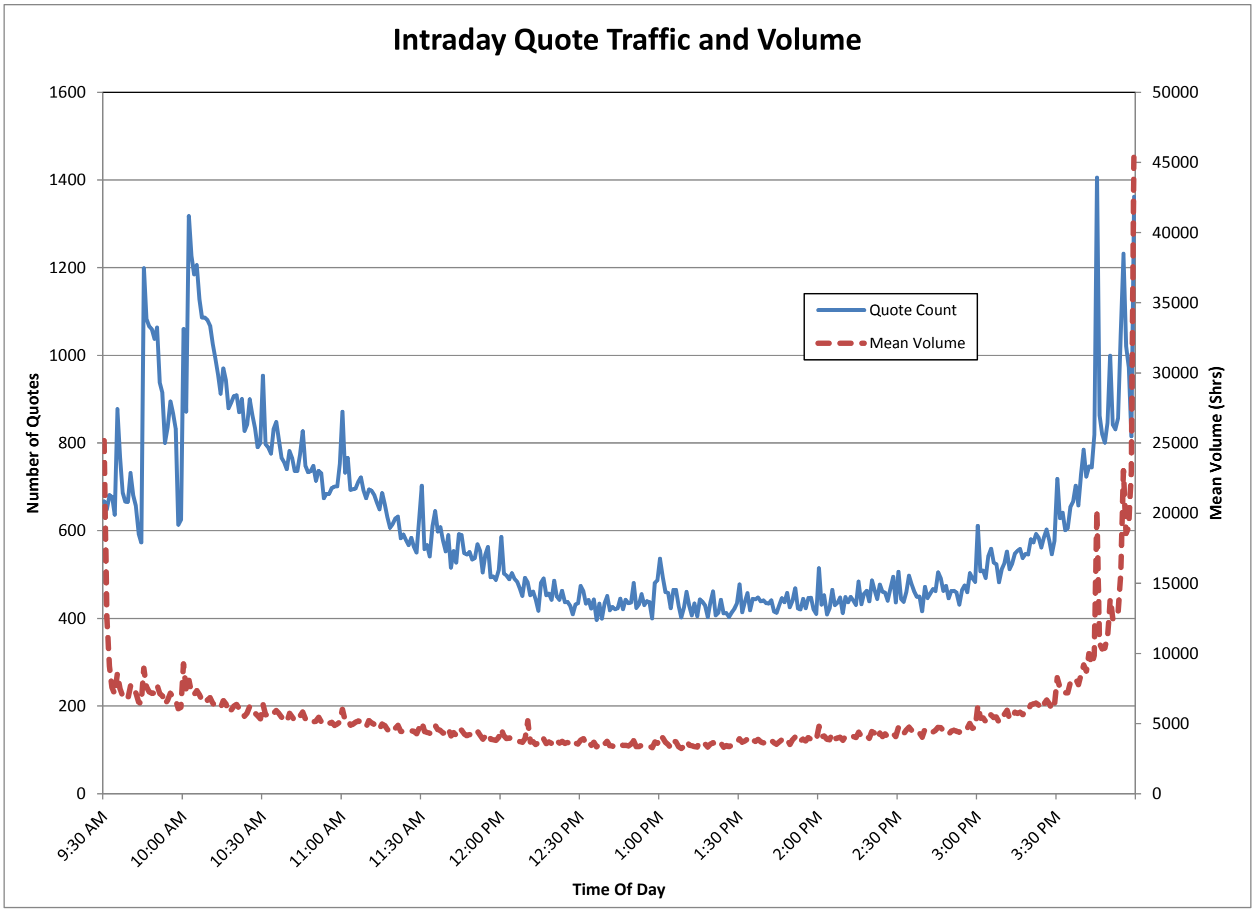

Figure 4. The average number of quote updates from all exchanges per minute of trading is plotted against the left axis and the average transaction volume is plotted against the right axis. The sample period is from January 3, 2012 through March 31, 2012.

Table 1

Descriptive statistics

Selected descriptive statistics of the sample are presented. The mean value is presented for each variable with the standard deviation displayed in parenthesis under the mean value. There are 600 NYSE listed common stocks in the sample equally divided between each trade intensity group. Market capitalization is based on the first trading day of 2012. Market capitalization is expressed in millions of dollars. The average daily number of trades is based on the trade count between 9:30 am and 4:00 pm. *QI* is the Quote Intensity and represents the average (standard deviation) of the number of quotes per 10 minute intraday segment. *QI* is equal to the number of quotes, from all exchanges, minus the number of trades since a new quote is generated for each trade executing against posted liquidity. *Qfrag* is the time weighted inverse Herfindahl Index (1-Herfindahl) of NBBO display depth. The value is separately calculated for ask and bid sides of the market and then averaged for the 10 minute segment value. *Vfrag* is the inverse Herfindahl Index of volume fragmentation. For each 1 minute interval in a 10 minute segment buy and sell Herfindahl indexes are calculated. Trade inference is based on Lee and Ready (1991). Next, for each one minute interval, buy and sell Herfindahl indexes are averaged. Finally, the 1 minute intervals are used to produce a volume weighted volume fragmentation measure for each 10 minute segment. Trades reported to the Finra Trade Reporting Facility (exchange D in the DTAQ database) are included in the calculation. The results are conditioned on the trade intensity grouping.

			By 10 minute segment		
Group	Market Capitalization (Millions $)	Daily Number of Trades	QI	Qfrag	Vfrag
Low Trade Intensity	3,959	4,713	2,341	0.739	0.537
	(3,344)	(826)	(2,444)	(0.074)	(0.123)
Medium Trade Intensity	7,775	9,572	4,850	0.759	0.607
	(7,396)	(2,017)	(4,232)	(0.059)	(0.107)
High Trade Intensity	19,127	21,196	10,883	0.786	0.658
	(24,133)	(6,069)	(9,233)	(0.048)	(0.096)

Table 2
Correlation Table
The correlation matrix for explanatory regression variables is presented. All correlations are significant at the 1% level. *QiDev* is the standardized measure of the number of quotes from all exchanges, *Qfrag* is the inverse Herfindahl index of the NBBO ask and NBBO bid depth, *Vfrag* is the inverse Herfindahl index of volume fragmentation. Increasing *Qfrag* and *Vfrag* indicates increased fragmentation. *MktDev* is the standardized measure of the number of quotes from all NYSE stocks and all exchanges. *RskDev* is the standardized measure of NBBO quote midpoint volatility, *SzDev* is the standardized measure of the average trade size, and *SqrNtrd* is the square root of the number of trades in the period. Results are conditioned on the trade intensity ranking.

	Variable						
Variable	QiDev	Qfrag	Vfrag	MktDev	RskDev	SzDev	SqrNtrd
Panel A: Low Trade Intensity							
QiDev	1.000	0.093	0.231	0.277	0.350	0.060	0.334
Qfrag		1.000	0.264	0.018	0.095	-0.072	0.118
Vfrag			1.000	0.108	0.214	-0.217	0.565
MktDev				1.000	0.238	0.006	0.126
RskDev					1.000	0.071	0.308
SzDev						1.000	0.185
SqrNtrd							1.000
Panel B: Medium Trade Intensity							
QiDev	1.000	0.075	0.273	0.352	0.367	0.033	0.381
Qfrag		1.000	0.235	0.001	0.079	-0.068	0.117
Vfrag			1.000	0.121	0.207	-0.313	0.500
MktDev				1.000	0.222	-0.006	0.133
RskDev					1.000	0.074	0.328
SzDev						1.000	0.178
SqrNtrd							1.000
Panel C: High Trade Intensity							
QiDev	1.000	0.069	0.288	0.433	0.382	0.024	0.394
Qfrag		1.000	0.160	0.016	0.056	-0.081	0.130
Vfrag			1.000	0.138	0.203	-0.340	0.426
MktDev				1.000	0.230	-0.024	0.145
RskDev					1.000	0.091	0.335
SzDev						1.000	0.177
SqrNtrd							1.000

Table 3

Two Stage Least Squares Liquidity Regression

For the 600 firms in the sample a 2SLS regression is estimated. Parameter estimates are aggregated based on the framework proposed in DuMouchel (1994). T-statistics are adjusted for cross-correlation in the residuals following the method of Cordia, Roll, and Subrahmanyam (2005). Two measures of market liquidity are used. Composite Liquidity (CL) is the ratio of NBBO depth to the NBBO percentage spread. Percentage spread is the $(NBBO_{ask}-NBBO_{bid})/NBBO_{Midpoint}$. *QiDev* is the standardized measure of the number of quotes from all exchanges, *Qfrag* is the average inverse Herfindahl index of the NBBO ask and NBBO bid depth, *Vfrag* is the volume weighted inverse Herfindahl index of volume fragmentation. An increase in *Qfrag* or *Vfrag* indicates an increase in fragmentation. *MktDev* is the standardized measure of the number of quotes from all NYSE stocks and all exchanges. *RskDev* is the standardized measure of NBBO quote midpoint volatility, *SzDev* is the standardized measure of the average trade size, and *SqNtrd* is the square root of the number of trades in the period. Dummy variables are included in the regression to control for time of day affects. Variables are aggregated over 39 ten minute intraday segments per stock day.

Variables	Composite Liquidity	Percentage Spreads
QiDev	-0.3088***	-0.0001
(t-stat)	(-5.98)	(-0.70)
Qfrag	-4.5288***	0.0140***
(t-stat)	(-7.00)	(6.97)
Vfrag	6.4403***	-0.0050***
(t-stat)	(8.02)	(-2.48)
MktDev	-0.1811***	0.0004***
(t-stat)	(-8.51)	(5.62)
RskDev	-0.9684***	0.0011***
(t-stat)	(-15.24)	(6.31)
SzDev	0.5437***	0.0001
(t-stat)	(7.10)	(0.49)
SqrNtrd	0.1561***	-0.0001***
(t-stat)	(10.81)	(-3.50)
Intercept	-0.1752	0.0315***
(t-stat)	(-0.43)	(18.76)

* 10% significance
** 5% significance
*** 1% significance

Table 4

2SLS by trading intensity

For the 600 firms in the sample a 2SLS regression is estimated. The results are then conditioned based on trading intensity. Parameter estimates are aggregated based on the framework proposed in DuMouchel (1994). T-statistics are adjusted for cross-correlation in the residuals following the method of Chordia, Roll, and Subrahmanyam (2005). Two measures of market liquidity are used. Composite Liquidity (CL) is the ratio of NBBO depth to the NBBO percentage spread. Percentage spread is the $(NBBO_{ask}-NBBO_{bid})/NBBO_{Midpoint}$. *QiDev* is the standardized measure of the number of quotes from all exchanges, *Qfrag* is the average inverse Herfindahl index of the NBBO ask and NBBO bid depth, *Vfrag* is the volume weighted inverse Herfindahl index of volume fragmentation. An increase in *Qfrag* or *Vfrag* indicates an increase in fragmentation. *MktDev* is the standardized measure of the number of quotes from all NYSE stocks and all exchanges. *RskDev* is the standardized measure of NBBO quote midpoint volatility, *SzDev* is the standardized measure of the average trade size, and *SqNtrd* is the square root of the number of trades in the period. Dummy variables are included in the regression to control for time of day affects. Variables are aggregated over 39 ten minute intraday segments per stock day. Panel A shows the results for the Composite Liquidity measure while Panel B shows the results for the percent quoted spread.

Variables	Low Trade Intensity	Medium Trade Intensity	High Trade Intensity
Panel A: Composite Liquidity			
QiDev	-0.2611***	-0.3076***	-0.4837***
(t-stat)	-3.30	-4.02	-3.23
Qfrag	-3.6477***	-5.2951***	-12.6959***
(t-stat)	-4.80	-3.83	-4.71
Vfrag	5.5268***	6.7006***	13.5862***
(t-stat)	5.60	4.27	4.64
MktDev	-0.1413***	-0.2173***	-0.3624***
(t-stat)	-5.36	-5.15	-5.18
RskDev	-0.7474***	-1.1304***	-1.8125***
(t-stat)	-9.19	-9.49	-9.25
SzDev	0.3866***	0.6474***	1.0263***
(t-stat)	3.90	4.35	4.97
SqrNtrd	0.1242***	0.1657***	0.1890***
(t-stat)	5.38	6.54	6.96
Intercept	-0.0224	-0.7104	-0.9056
(t-stat)	-0.05	-0.73	-0.44

Table 4 Continued

Panel B: % Quoted Spread

Variables	Low Trade Intensity	Medium Trade Intensity	High Trade Intensity
QiDev	0.0010*	-0.0001	-0.0003
(t-stat)	1.82	-0.31	-1.44
Qfrag	0.0371***	0.0162***	0.0107***
(t-stat)	4.91	4.15	4.33
Vfrag	-0.0331***	-0.0047	-0.0033
(t-stat)	-3.26	-1.42	-1.25
MktDev	0.0013***	0.0005***	0.0003***
(t-stat)	4.26	3.78	3.30
RskDev	0.0043***	0.0015***	0.0006***
(t-stat)	5.87	4.65	3.06
SzDev	0.0002	0.0000	0.0001
(t-stat)	0.26	-0.07	0.54
SqrNtrd	-0.0011***	-0.0002***	-0.00005**
(t-stat)	-4.52	-3.27	-2.04
Intercept	0.0530***	0.0336***	0.0258***
(t-stat)	11.08	11.09	11.56

* 10% significance
** 5% significance
*** 1% significance

Table 5

System of Equations

For the 600 firms in the sample a 2SLS regression system is estimated. Parameter estimates are aggregated based on the framework proposed in DuMouchel (1994). T-statistics are adjusted for cross-correlation in the residuals following the method of Chordia, Roll, and Subrahmanyam (2005). Two measures of market liquidity are used. NBBO Depth is the aggregate depth from all exchanges matching the NBBO price. Percentage spread is the $(NBBO_{ask}-NBBO_{bid})/NBBO_{Midpoint}$. *QiDev* is the standardized measure of the number of quotes from all exchanges, *Qfrag* is the average inverse Herfindahl index of the NBBO ask and NBBO bid depth, *Vfrag* is the volume weighted average inverse Herfindahl index of volume fragmentation. An increase in *Qfrag* or *Vfrag* represents an increase in fragmentation. *MktDev* is the standardized measure of the number of quotes from all NYSE stocks and all exchanges. *RskDev* is the standardized measure of NBBO quote midpoint volatility, *SzDev* is the standardized measure of the average trade size, and *SqNtrd* is the square root of the number of trades in the period. To estimate the system of equations, *SqNtrd* is excluded from the NBBO Depth equation and *SzDev* is excluded from the percentage spread equation. *Rsprd* is the percentage quoted spread and *NBBOdpth* is the aggregate depth at the NBBO quote. Dummy variables are included in the regression to control for time of day affects. Variables are aggregated over 39 ten minute intraday segments per stock day.

Variable	NBBO Depth	Percentage Spread
QiDev	-0.802***	-0.0004*
(t-stat)	(-8.41)	(-1.73)
Qfrag	6.263***	0.0156***
(t-stat)	(5.43)	(5.74)
Vfrag	3.770***	-0.0024***
(t-stat)	(7.06)	(-3.56)
MktDev	-0.059	0.0005***
(t-stat)	(-1.29)	(5.31)
RskDev	-0.399***	0.0015***
(t-stat)	(-3.64)	(4.86)
SzDev	2.089***	
(t-stat)	(16.67)	
SqNtrd		-0.0001***
(t-stat)		(-3.12)
Rsprd	-55.933***	
(t-stat)	(-8.79)	
NBBO Dpth		0.0000
(t-stat)		(-0.93)
Intercept	5.726***	0.0291***
(t-stat)	(7.23)	(14.25)

* 10% significance
** 5% significance
*** 1% significance

Table 6

Two Stage Least Squares Trade Execution Quality Regression

For the 600 firms in the sample a 2SLS regression is estimated. Parameter estimates are aggregated based on the framework proposed in DuMouchel (1994). T-statistics are adjusted for cross-correlation in the residuals following the method of Chordia, Roll, and Subrahmanyam (2005). The dependent variable is either the trade weighted Preference Measure or the volume weighted Preference Measure. The Preference Measure, proposed by He, Odders-White, and Ready (2006), is defined as the ratio of realized to effective spreads. The effective spread is measured against the prevailing NBBO quote. The realized spread is measured against the prevailing NBBO quote midpoint 5 minutes after the trade or the end of the intraday 10 minute time segment. *QiDev* is the standardized measure of the number of quotes from all exchanges, *Qfrag* is the average inverse Herfindahl index of the NBBO ask and NBBO bid depth, *Vfrag* is the volume weighted inverse Herfindahl index of volume fragmentation. An increase in *Qfrag* or *Vfrag* indicates an increase in fragmentation. *MktDev* is the standardized measure of the number of quotes from all NYSE stocks and all exchanges. *RskDev* is the standardized measure of NBBO quote midpoint volatility, *SzDev* is the standardized measure of the average trade size, and *SqNtrd* is the square root of the number of trades in the period. Dummy variables are included in the regression to control for time of day affects. Variables are aggregated over 39 ten minute intraday segments per stock day.

Variables	Trade Weighted Preference Measure	Volume Weighted Preference Measure
QiDev	0.1045***	0.1168***
(t-stat)	(8.95)	(9.67)
Qfrag	0.1407	1.0473***
(t-stat)	(1.08)	(7.29)
Vfrag	-0.9024***	-1.1479***
(t-stat)	(-5.35)	(-6.60)
MktDev	0.0219***	0.0242***
(t-stat)	(4.47)	(4.75)
RskDev	-0.3909***	-0.3560***
(t-stat)	(-27.44)	(-23.69)
SzDev	-0.0598***	-0.0211
(t-stat)	(-4.65)	(-1.56)
SqrNtrd	0.0206***	0.0198***
(t-stat)	(10.06)	(9.24)
Intercept	-0.0991	-0.5271***
(t-stat)	(-1.03)	(-5.03)

* 10% significance
** 5% significance
*** 1% significance