

Information Contents in Trades at Steps away from BBO: Evidence from Tokyo Stock Exchange

Ying Huang
The University of Manitoba
Winnipeg, MB R3T 6C4, Canada
Phone: 204-396-4691
Email: yhuang.huang@umanitoba.ca

Thomas H. McInish
Professor and Wunderlich Chair of Finance
Department of Finance, Insurance and Real Estate
Fogelman College of Business and Economics
The University of Memphis
Memphis, TN 38152
Voice: 901-277-9202
Fax: 901-678-3006
Email: tmcinish@memphis.edu

Pankaj K. Jain
Suzanne Downs Palmer Professor
Associate Professor of Finance
Department of Finance, Insurance & Real Estate
425 Fogelman Admin Building
The University of Memphis
Memphis, TN 38152, USA
Phone: 901-678-3810
Email: pjain@memphis.edu

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ABSTRACT

We investigate the information contents imbedded in trades at steps away the best bid and offer (BBO) using Tokyo Security Exchange tick-by-tick daily trading data. We found that trades that traded at inferior steps to BBO as measured by strings carry significant amount of information. Strings are a series of trades each of which is at a price that is inferior to or equal to the price of the previous trade in the series. The number of the strings is ubiquitously invariant across trading days, while remarkably variant across securities. The variations of the aggregated depth and the time measured in minutes for the completion of the strings, however, are found to be moderate and large respectively across trading days. Moreover, these characteristics of the strings are positively correlated with return volatility of strings. We are the first to show that the information content is a significant determinant of the return for trades beyond BBO by using the LOB slope, the beginning price, the beginning volume, the beginning spread, and the duration of strings as proxies for the measure of the informative-ness in the LOB.

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1. Introduction

Since the shifting from firm-specific liquidity to common determinants of liquidity started nearly a decade ago, this line of microstructure research has investigated the prevalent traits of trading activities relevant to the market-wide co-movement of liquidity (Kamara, Lou and Sadka (2008), Coughenour and Saad (2004), and Aitken, et al. (2007)), in addition to the systematic common movement of liquidity (Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Kempf and Mayston (2008), Amihud (2002), and Korajczyk and Sadka (2008)). Among these studies, most majorities focus on the commonality in liquidity at or within best bid and offer (BBO). The existence and extent beyond the BBO and the aspects of the liquidity beyond the BBO, however, remain unexplored. In addition, it is unknown as to how the LOB status affects the return of the trades that walk up/down the LOB.

We investigate the existence and extent and liquidity beyond the BBO by using daily trading data of Tokyo Security Exchange (TSE). Bid and ask spread in various forms has been a primary measure of liquidity and liquidity commonality within and beyond the BBOs in prior research. In this paper, rather than using conventional various spread measures, we employ string which is defined as a series of trades each of which is at a price that is inferior to or equal to the price in the series to explore the liquidity of orders that walk up/down the limit order book (LOB). In addition, we gauge the properties of three aspects of liquidity, i.e., width, depth, and immediacy by examining the number of different types of string, the aggregated volume, and the

duration measured in minutes elapsed to complete trades in the series of strings. We found that there is a uniform co-movement of liquidity beyond the BBO. The liquidity beyond the BBO is ubiquitously invariant across trading days, while remarkably variant across securities. The variations of depth and immediacy needed for the common movement of liquidity, however for the first time, are found substantially large across trading days. Moreover, all three aspects of the liquidity beyond the BBO are found to be positively correlated with return volatility of strings. Finally, we show that the state of LOB, i.e., the slope, the beginning price, the beginning spread, and the beginning volume, and the duration of strings are significant determinants of the return of trades that beyond BBO.

The remainder of the paper is organized as follows. Section 2 presents theoretic considerations and development of our empirical hypotheses. In section 3, we provide a detailed description of our methodology. Section 4 shows the development of our hypotheses. Data and empirical design are described in Section 5. Section 6 reports the empirical results. The concluding section contains a summary of findings and the implications.

2. Theoretical Considerations

It is a common knowledge that small trades executed at or within BBO are mostly from small order proprietary traders. The available depths at BBO are sufficiently large to have these traders' orders filled due to their relative small demand in size. For large trades, normally placed by institutional traders and rich individuals, however, walk up/down the LOB by default trading rules when volume is too large to be filled by insufficient available depth at BBO. The related frequencies regarding large orders placed by rich individuals is not available, while there are

summary figures about proportion of institutional traders, although not very precise. Prior empirical studies assert that institutional traders comprise a significant portion of the trading volume on a number of exchanges such as NYSE, London Security Exchange and the Tokyo Security Exchange (Chan and Lakonishok (1993); Gompers and Metrick (2001)). Additionally, Chan and Lakonishok (1993) and Kamara, Lou, and Sadka (2008) demonstrate that there is a substantial increase in institutional investing and index trading over the years. Therefore, the extent of the systematic movement of liquidity beyond the BBO, if any, is non-trivial and important. In line with the finding of Kempf and Mayston (2008), we conclude that there is a common existence of liquidity beyond the BBO in TSE, which as with NYSE and other exchanges being examined in prior studies. Moreover, the liquidity beyond the BBO constitutes a substantially large proportion trading activities for institutions traders (Hong and Rady, 2002). In addition, we examine and provide for the first time a conclusive evidence of little or lack co-variation in two liquidity dimensions: depth and immediacy, while in the meantime the third dimension of liquidity: width, co-moves across trading days. Lastly, the three dimensions of the liquidity beyond the BBO are positively correlated with return volatility of strings. Our study is the first, to the best of our knowledge, to show that the information content is a significant determinant of the return for trades beyond BBO by using the LOB slope, the beginning price, the beginning volume, the beginning spread, and the duration of strings as proxies for the measure of the informative-ness in the LOB.

Using the evidence from Australian Security Exchange, Domowitz, Hansch, and Wang (2005) show that there is a linkage between the liquidity commonality and security returns. However, their main focus of the liquidity commonality is at the best bids and offers. The

relationship between the liquidity commonality and return beyond the BBO is unknown. In contrast, our focus of liquidity common movement is on the series of trades where the volume of large orders is too big to be executed by the best bid or the best offer and the remaining unexecuted portion of the order walks up/down the limit order book. As a result, as we conjectured, the beginning price, beginning spread, beginning volume are significant determinants of the number of trades in the series and the duration of strings, thus the return of strings.

3. Method

We employ a distinct approach which differs from previous empirical studies in three ways. First, without access to and relying on price steps of the complete limit order book, we are able to test the proposition that there is a co-variation in liquidity beyond the BBO as advanced by Kemptf and Mayston (2008). The data that provided to us contain no information pertaining order entries such as cancellations, revisions, executions, and expirations as the data used in Kemptf and Mayston's study. The NEEDS data of TSE are typical tick-by-tick trading data with anonymous trades and quotes records and the associated depths and time stamps precision in minutes.

Second, the typical liquidity proxy measures such as various types of bid-ask spreads are not used as our analytical tool because they are more relevant to the cost of demanding for immediacy for small trades. Additionally, liquidity measures of bid-ask spread ignore the liquidity demand and supply at multiple steps by disregarding the price concession in the later steps for large orders. Thus, the number of price steps of large orders walking up/down the book

is used as an alternative measure of liquidity for large trades. Clearly, the motive and widely usage of bid-ask spread as liquidity measure for commonality in liquidity at BBO is due to the fact that permanent component, the information contents of the spread can be factored into common market movement. For large trades, however, the information contents can be revealed by price premium or discount, in our study the price steps, that large buy or sell order traders yield to the liquidity suppliers. As a result, this price concession manifested through the willingness that the large order traders to trade against standing limit orders with more aggressive prices creates a serial consecutive trades that eat up the standing orders in LOB, which could not be taken into account by using the bid and ask spread at the BBO. Further, similar to the information content embedded in the bid and ask spread, these price steps are a proxy for a cost of creating informative prices for large orders. To make these price concession steps concrete, we identify trade patterns as described above and characterize them into string 2, string 3,, String 9 based on the number of price concessions and form five categories as following:

1. String 2: a series of trades each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, two successively higher/lower prices.
2. String 3: a series of trades each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, three successively higher/lower prices.

3. String 4: a series of trades each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, four successively higher/lower prices.
4. String 5: a series of trades each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, five successively higher/lower prices.
5. String “other”: a series of trades (more than five) each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, a total of five, six, seven, eight, or nine successively higher/lower prices.

Third, in addition to the common movement in liquidity supply beyond the BBO, the co-variation of depth and immediacy of liquidity beyond the BBO is investigated, which to our knowledge, has received little attention. We show that the variation in three dimensions of liquidity i.e. width, depth, and immediacy deviates from each other. Our empirical evidence shows that volume that it takes large orders to co-move does not necessarily co-vary over time. Additionally, the immediacy of execution of large orders over multiple steps varies significantly through time. These aspects of co-movement of liquidity beyond the BBO are relatively new territories in the microstructure literature. By exposing these features concerning large orders, we hope that these findings shed light on the trading strategies that large order trades could employ to minimize their trading costs using appropriate timing and sizes to maximize their returns and minimize the risks.

4. Hypotheses

In order-driven market, commonality in liquidity at or within BBO arises when continuous interactions of both the small order liquidity suppliers and liquidity demanders co-move with market or industry. We believe that, further, there is a systematic co-movement beyond the BBO. As documented by Aitken et al. (2007) in their study of liquidity supply in electronic markets, the institutional investors simultaneously and aggressively supply liquidity at multiple price steps in LOB although the degree of price aggressiveness varies by institutional investors' type. That is liquidity supply is undoubtedly non-negligible at price steps inferior to BBO. Additionally, Keim and Madhavan (1995) state that either due to the fear of high opportunity costs resulting from failing to trade timely or because of the belief that their information is short-lived, institutional traders show a surprisingly strong demand for immediacy. As a result, institutional traders trade aggressively by gradually placing orders inferior to BBO. When large order demanders or suppliers price their order aggressively and continuously and when this strong immediacy demand and supply is consistently inter-temporal invariant, rather than a temporal phenomenon, we are expecting a co-movement of liquidity beyond the BBO. Kempf and Mayston (2008) analyze this co-movement using LOB of Xetra of Frankfurt Security exchange and unsurprisingly conclude that the commonality in liquidity outside of BBO is larger than that of inside BBO. We believe that this commonality is not a unique case of Frankfurt Security exchange due to its relative small market size, yet it is a distinguishable feature of any rapid-paced market. Accordingly, we advance our first hypothesis upon which the consequent hypothesis is built.

Hypothesis 1: There is a strong evidence of the existence of liquidity beyond the BBO across trading days for large orders that walk up/down the LOB. In addition, the related aspects

of liquidity, i.e. the width, the depth and the immediacy beyond the BBO have various variability across trading days.

We believe that although there is liquidity beyond the BBO, in particular, a common movement in liquidity beyond the BBO. It takes considerably variant volume and the immediacy in order executions across the trading days to achieve the co-movement. Thus, in addition to the width, aspects of liquidity including the size of large orders, i.e. depth and how quickly trader's trading desire is fulfilled, i.e. immediacy do not necessary co-vary through time.

The consumption of available depths of standing limit orders parallels the immediacy of the execution of trades in strings. Or, the aggressiveness of price steps and the available liquidity supplied jointly determine the immediacy of large order executions. Thus, intuitively, immediacy as the third dimension of the liquidity beyond the BBO varies by its own across the trading days as set forth by our first hypothesis. Keim and Madhavan (1995) show that large orders spread over a long time period in order to be filled i.e., the larger quantities, the longer of trading durations. Based on the unique settings of various tick size and different trading units in Tokyo Security Exchange, we believe that the duration of strings being executed increases with tick size, MTU, and the combination of ticker size and MTU. That is, more specifically, it takes longer duration for large orders walking up/down the LOB for firms that trade at higher tick size, higher MTU, or the combination of higher values in ticker size and MTU.

Amihud and Mendelson (1986) and Datar et al. (1998) show that liquidity plays a significant role in explaining security returns. We conjecture that liquidity beyond the BBO positively correlates with the return volatility and hence affects the return of orders that walk

up/down the book. As formulated in the previous session, strings are a series of trades resulting from the most aggressive order that walks up/down the book. By definition, the most aggressive order is a “large buy” to buy or a “large sell” to sell a larger quantity than that is available at the best bid and offer (Biais, Hillion, and Spatt, 1995). Secondly, the informative traders and their observers and followers give rise to the series of trades in strings by placing a sequence of new orders at or away from the best bid and offer. Consequently, given a considerable liquidity supply/demand beyond the BBO and significant amount of information contained in the series of trades, we believe that the return and the volatility of strings are directly related to the state of the LOB at the beginning of strings. The LOB slope, the beginning volume, the beginning price, and the beginning spread are our measures of state of the LOB. The beginning volume and the beginning price of strings are significant determinants of the return and return volatility of strings because both the beginning volume and the beginning price determine the price steps that strings contain and determine the duration for the series of trades being executed. In addition, we conjecture that the beginning spread of strings which may reflect significant amount of private information of strings has significant role in determining the returns for large trades. Thus, we develop our second hypothesis as following.

Hypothesis 2: The state of LOB, such as the slope, the beginning price, the beginning volume, the beginning spread, and the duration of strings are significant determinants of the return and return volatility of strings.

Thus, we investigate the existence of common movement of liquidity beyond the BBO and the aspects associated with the liquidity beyond the BBO. In addition, the state of the LOB at

the beginning of strings such as the LOB slope, beginning price, beginning spread, beginning volume, and the duration are significant determinants of the return and return volatility of strings. In the next section, we present the description of our data and the methodology.

5. Data and Methodology

5.1 Data

The data are obtained from TSE, a purely order-driven market without designated market maker or specialist. There are some special features about the TSE that differentiate it from other security markets around the world. The TSE includes three different security types (sections): first, second and mothers. The first section, also referred to as “Blue Chips” is primarily for the largest and successful companies, while the second section is mainly for investors interested in smaller firms and trades in lower trading volumes relative to the first section. The third, also the mothers, not available until November of 1999 trades both domestic and foreign newer and innovative venture enterprises. The trading comprises two sessions with standard trading hours starting from 9am to 11am in the morning session and from 12:30pm to 15:00pm in the afternoon session. Consequently, there are two opening and two closing periods. The security price formation in these periods is different from that of the regular trading hours. Accordingly, there are two distinct methods: Itayose (single price auction method) and Zaraba (continuous auction method) to determine security prices. The former is primarily used to form the opening and closing prices for each of the trading sessions and the latter is to determine the trading prices in the continuous auction trading right after the opening and before the closing of the trading sessions. One essential feature of the Zaraba method is that it allows large order to walk up the

limit order book if the volume is greater than the depth available at the best quote. As is the same in most order-driven markets, the price takes higher precedence over time in order matching process. However, there are four special features pertaining to the TSE market. In contrast to other order-driven markets around the world, the TSE allows 11 different tick sizes, specifically 1, 5, 10, 50, 100, 500, 1,000, 5,000, 10,000, 50,000, and 100,000 Japanese Yen based on various price ranges. Second, to protect the investor from the excess volatile price changes, daily price limits are set by limiting the maximum range of price fluctuation in accordance to 29 price ranges. Third, unlike other markets around the world where a variety of types of orders are permitted, only two types of order are allowed in TSE market: market order and limit order. As a result, there are only two types of trader, who either provides immediacy or demands immediacy. All trades are computerized. Lastly, perhaps most relevant to our investigation, the trading units can vary. Although trading units can vary from 1 share, 10 shares, 50 shares, 100 shares, 500 shares, 1,000 shares to 3,000 shares, most majority of domestic securities trade in 1,000 trading unit. These tiered tick sizes and trading units, while facilitating the trading activities, are ideal natural breaking points in our research design and analyses.

The sample period is the month June of 2008, which includes a total of 21 trading days. In addition to the records of each trade and quote in the normal trading hours, the data include pre-opening quotes in the period prior to the opening auction, which is specifically from 8:20am till 9:00am for the morning session and from 12:05pm till 12:30pm for the afternoon session. These pre-opening quotes are excluded from our study. For each trade and quote, it includes time stamp, price, and volume as well as best bid, best ask, bids and asks inferior to BBO up to 5 cumulative tick sizes, and the associated depth. In our sample, the blue-chip securities trading

activity accounts for nearly 95% of total trading activity, while second section securities trading activity takes up about 1.42% and mothers section securities 3.84% of total trading activity, both of which trade in trading unit of 1,000 shares or less. We apply three filters to finalize our sample. We limit our analyses to securities that (i) have traded without changing in tick size but allowing various trading units, (ii) have at least 15 trades per firm and per trading day, and (iii) have continuously traded for 21 days in June, 2008. As a result, there are a total of 1,899 distinct securities in our final sample. Of these, 1,608 are “Blue Chips”, 150 are small securities, and 141 securities are from the mothers market.

5.2 Methodology

In order to measure the common movement of strings, we investigate the co-variations of the number of strings, of the aggregated volume of strings, and of the average duration of strings per trading day across trading days and the co-variations of the number of strings, of the aggregated volume, and of the duration of strings per security across securities. For the former, the total number of strings, the aggregated volume, and the average duration is computed across the securities within one trading day regardless of the string types. Similarly, for the latter the number of strings, the aggregated volume, and the average duration is totaled for each security across trading days with string types disregarded. The variability for each of three aspects of liquidity is measured by the Intra-class Correlation Coefficient (ICC), which differs from Pearson correlation coefficient in that it deals with observations with same metric (McGraw and Wong, 1996). The ICC is a measure of the proportion of a variance that is attributable to objects of measurement (Shrout & Fleiss, 1979). In this study, the single score ICC for two-way random

effects model is applied to measure the variations with respect to the total number of strings across the trading days and across securities. In the case of measuring the variability across trading days, the trading day is regarded as the column effect and the firm as the row effect. Both the row and column effects are deemed random, i.e. exchangeable. The row and column effects are transposed for the case of measuring the variability across securities. Note that ICC can be used to measure either consistency or agreement, although the only difference resides computationally in the denominator of ρ in the equation (1). In the case of consistency, it is used to infer the inter-rater reliability in most cases. For the purpose of this study, the ICC for degree of absolute agreement among measurements as shown in the equation below is used, which is formulated based on the mean squares derived from analysis of variance (McGraw and Wong, 1996).

$$\rho = \frac{MS_R - MS_E}{MR_R + (k-1)MS_E + \frac{k}{n}(MS_C - MS_E)} \quad (\text{McGraw and Wong, 1996}) \quad (1)$$

Where MS_E is the mean square error, MS_C is the mean square for columns and MS_R is the mean square for rows; k denotes the total number of days (the row effect) and n is the total number of firms (the column effect). The associated F-test and confidence interval is as the following.

$$F = \frac{MS_R}{MS_E} * \frac{1 - \rho_0}{1 + (k-1)\rho_0} \quad \text{with degrees of freedom of } (n-1) \text{ and } (n-1)(k-1) \quad (2)$$

$$\text{Lower Confidence Interval Limit} = \frac{F_L - 1}{F_L + (k - 1)} \quad (3)$$

$$\text{Upper Confidence Interval Limit} = \frac{F_U - 1}{F_U + (k - 1)} \quad (4)$$

Where $F_L = F_{obs} / F_{tabled}$ and $F_U = F_{obs} * F_{tabled}$. F_{obs} are the row effects of F from two-way Analysis of Variance (ANOVA). F_{tabled} denotes the (1-0.5a)100th percentile of the F distribution with n-1 numerator degrees of freedom and (n-1)(k-1) denominator degrees of freedom.

Next, we use the LOB norm slope as the measure for the degree of agreement/disagreement on securities' valuation among traders. The LOB slope is based on the immediate quotes before the first trade in the string and the computation of the slope is following Næs and Skjeltorp (2006). First, we compute the absolute average slope for the immediate quotes before the first based on the equations (5) and (6) for ask side (absSE) and bid side (absDE) respectively.

$$absSE_{i,t} = \frac{1}{N_A} \left\{ \frac{RV_1^A}{abs(p_1^A / p_0^A - 1)} + \sum_{\tau=1}^{N_A} \frac{RV_{\tau+1}^A / RV_{\tau}^A - 1}{abs(p_{\tau+1}^A / p_{\tau}^A - 1)} \right\} \quad (5)$$

$$absDE_{i,t} = \frac{1}{N_B} \left\{ \frac{RV_1^B}{abs(p_1^B / p_0^B - 1)} + \sum_{\tau=1}^{N_B} \frac{RV_{\tau+1}^B / RV_{\tau}^B - 1}{abs(p_{\tau+1}^B / p_{\tau}^B - 1)} \right\} \quad (6)$$

Where N is the total number of ask prices (tick levels) and τ is the tick level; the subscript 0 represents the inner quote; thus p_0^A and p_0^B denotes the bid-ask midpoint; p_1^A and p_1^B are the best ask and best bid respectively. As a result, $\tau=0$ is the bid-ask midpoint and $\tau=1$ represents the best

ask or bid quote. For both ask and buy side, the RV_{τ}^A is the fraction of the total volume at snapshot s at price level τ . V_{τ}^A is the natural logarithm of accumulated total volume at each tick level τ . The fraction is computed for each level as the equation below by following the appendix of Næs and Skjeltorp (2006).

$$RV_{\tau}^A = V_{\tau}^A / \sum_{\tau} V_{\tau}^A \quad (7)$$

Then we normalize the order book at each snapshot relative to the total number of shares supplied in the order book at the snapshot. We average the slope for security i at time t as

$$Slope_{i,t} = \frac{1}{2} \left(\frac{absSE_{i,t} + absDE_{i,t}}{2} \right) \quad (8)$$

6. Empirical Results

6.1 Univariate Results

We identify a sequence of consecutive trades as strings that are a series of trades each of which is at a price that is inferior to or equal to the previous price to measure the liquidity common movement beyond the BBO. Strings are classified into 5 categories: string of 2, 3, 4, 5, and other. A “string 2” has a series of trades each of which is at a price that is inferior to or equal to the previous price in the series, in which there are a total of two distinct successively higher/lower prices. Similarly, a “string 3” has a series of trades each of which is at a price that is inferior to or equal to the previous price in the series, among which, there are three distinct successively higher/lower prices. Strings with names “strings 4”, “string 5”, and “string other” are formed in the similar fashion. The descriptive statistics of strings for both the buy and sell

side are delineated in the Table 1. For string 2 there are five average numbers of consecutive trades and for string 9 there are an average of 11 numbers of consecutive trades. However, the kurtosis is very high and is in an approximately descending order from string 2 to string 9. It indicates that the distribution of string 2 has a higher peakiness or is more heavily tailed relative to strings of higher number. Or simply put, more of the variance is due to infrequent extreme deviations for string 2 than other types of strings.

The frequencies of strings, average duration of strings, and LOB slopes are presented in Table 2 for both buy and sell sides. The buy side has slightly lower frequencies for strings with length greater than 2 than its sell side counterparts, while the buy side has higher frequencies relative to that of the sell side except for strings 2. Overall, strings compose a little over 14% of all trades on both the buy side and the sell side with most majorities in string 2. Moreover, for both buy and sell side, the general trend is that the proportion decreases when the number of the trades in the string series increases. Moreover, strings with more than 5 trades make up about only 0.10% on both sides. We report the average and the standard deviation of the duration in columns (3) and (4) for buy and sell side respectively. The durations of strings are computed by taking the difference of the minutes between the first trade and the last trade within the string. The duration is the total minutes that consumed to complete the series of trades in the strings. As seen in the Table 2, the duration is longer for the sell side than the buy side market. It seems that the more trades in the string series there are, the more minutes are needed for the completion of the entire strings series. This is opposite to the order in the frequencies of strings, i.e. the more trades in the string, the less proportion in the whole sample. Additionally, string 5 takes the longest duration to complete among all types of string. The descriptive statistics of slope is

reported in column (5). It appears that the lower number of trades in the string, the more gentle the slopes are. In other words, the aggressive traders complete their orders in small number of trades when there is a widely dispersed belief on securities' valuation among investors.

In Table 3, descriptive statistics by tick size and MTU combinations are presented for the frequencies of strings, the average duration of strings, and average aggregated volume of strings by string types. For the same combination of the tick size and the MTU, strings with more trades in the series are associated with longer duration, the same general trend observed in the Table 2. Moreover, across different string types, the average duration of strings and the average aggregated volume of strings generally increase with the MTU regardless of the tick size. Lastly, it is generally true that for the same combination of tick size and MTU, strings that are associated with more trades have higher volumes.

6.2 Multivariate Results

If there is a common movement in liquidity beyond the BBO, as we conjectured, there will be little variation in liquidity measure, in our case, the number of strings over time. Table 4 reports the co-variation of number of strings measured by ICC across trading days and across securities by combinations of tick size and MTU. The ICC is viewed as the proportion of relevant variance that is associated with differences among measured objects or persons. The closer to the unity the ICC is the smaller degree of variability it represents. Conversely, it shows a strong variability if ICC approaches zero. Panel A of Table 4 reports the ICC for the number of strings across trading days. The ICCs are significant at 99% confidence level in nearly all cases. Consistent with our expectation, ICCs are of large size or close to the unit and are indicative of

small degree or lack of variation in the number of strings across the trading days. Clearly, there is a pervasively strong co-movement of liquidity beyond the BBO, confirming our first hypothesis. In contrast, the panel B, reporting the ICCs across securities, reveals a pronouncedly strong degree of variation. The less degree or absent of co-movement in liquidity across securities is not abnormal as firms inherently differ. Note that similar sized ICCs across different combinations of the tick size and the MTU in panel A and panel B respectively are indicative of little cross-sectional variation in the intensity of liquidity beyond the BBO.

Given strongly significant evidence of common movement of liquidity, broader questions related to liquidity are asked. Do other aspects of liquidity exhibit same level of variation? Does it take similar length of time to complete the string 2 to that of string “other”? Does it consume similar amount of volume for the completion of different string types or it varies? Liquidity is commonly known to have at least three dimensions: width, depth, and immediacy. As with width, we proceed to examine the variation over depth and immediacy across trading days and across securities. The depth is measured by the aggregated volume and the immediacy is essentially how quickly the series of trades within the string are executed and is measured in minutes, which is termed as the duration of strings in our study. The empirical results are displayed in columns 8 through 11 for trading volume and columns 12 through 15 for duration accordingly. For aggregated trading volume, the variability across trading days is considerably stronger relative to that of the number of strings, supportive of our first hypothesis. Moreover, the ICCs are in within a wider range: 0.1 to 0.8 than the ICCs for the number of strings: 0.4 to 0.9, indicating there is a considerably large variation in the aggregated volume by various combinations of the tick size and the MTU. Further, no evidence of strong variation across securities is detected. To test the

first hypothesis, similarly, we compute and report the ICCs by duration across trading days and across securities. Our evidence provides strong support for the hypothesis 1. The ICCs reported are in a range less than that of number of strings, suggesting a high level degree of variation in the durations of the completion of the series of trades in strings across trading days. Most majority ICCs are significant at the 0.01 level in panel A.

The variation across securities is mostly insignificant as shown in Panel B, similar to the results of the aggregated volume of strings. The higher degree of variation in duration of strings in Panel B as represented by smaller values in ICCs relative to that of in Panel A for the number of strings and the aggregated trading volume of strings is consistent with the univariate results illustrated in Table 2 and Table 3 respectively.

In Table 5, we report the correlation between the return volatility of strings (squared returns) and the aspects of the liquidity beyond the BBO. As can be seen in both panels for buy and sell side of market respectively, the return volatility of strings is positively associated with all aspects of liquidity beyond the BBO. More specifically, there is a higher risk in the return of strings when there is higher number of price concession steps in the strings, when higher volume is demanded, and when longer duration is required to complete the series of trades in the string. Notably, the aspects of the liquidity beyond the BBO are positively correlated with each other at 0.01 alpha level.

Indeed, the information content of large orders that can significantly affect the return of for large orders. How does the informativeness resided in the LOB affect the return and volatility of strings? We probe into this question by first examining the information content of strings

using the beginning spread, the beginning price, the beginning volume of the first trade in the series as well as the duration of strings. We investigate their relation by regressing the return and return volatility of strings on the beginning price, the beginning volume, the beginning spread, and the duration of strings (measured in minutes). We also include 4 dummy coded variables in the regression representing string types from 2 to 5 by treating strings that have at least 6 trades in the series as the reference group. As revealed in Panel A of Table 6, for buy side market, the higher beginning price is associated with the lower return of strings, because for buyers the buying price is one of the key determinants of their goal of maximizing returns. On the contrary, the beginning price is positively related to the return of strings for the sell side market, i.e., the higher selling price to start with, the higher return of strings for sellers. The beginning spread, however, has completely opposite direction with the return of strings to that of the relationship between the beginning price and the return of strings. For the buy side, higher return of strings is significantly associated with wider beginning spread, while for the sell side, it is associated with narrower beginning spread. In other words, the less information content in the beginning spread (Easley and O'Hara, 1987), the buyers have higher return. This is consistent with Hasbrouck's (1991) finding that wide spreads have larger price impacts. Both the volume and the duration of strings seem to be positively related with the return of strings for the buy side market and negatively related with the return of the strings for the sell sides of the markets. On the other hand, for the buy side market, strings that have more number of trades in the series have higher returns compared to strings have less number of trades in the series. This is the consistent with the effect of duration on string return. The effect is reversed for the sell side market. Collectively,

the evidence shows that the return is higher when the traders sell the series of the trades more quickly and in a smaller number of trades.

The results for return volatility of the strings are displayed in the Panel B of Table 6. The directions of the control variable are consistent for both the buy and sell side market. In summary, the return volatility of strings is inversely related to the beginning price and beginning volume, however positively related to the beginning spread and the duration of the strings. In addition, the negative coefficients for string dummy variable indicate that strings with more than 6 trades in the series are more risky than other string types. Intuitively, it is because the longer the duration or the more trades in the strings incurs higher uncertainty of the price concessions and price steps.

Second, we use the slope of the beginning quote of strings as a proxy for informativeness in the LOB. A gentle slope represents a wide dispersed belief of traders in security's valuation (Næs and Skjeltorp, 2006). Thus, it is believed that when traders have different private information about a security which leads to high level of uncertainty of the value of the security, the slope of the LOB is more gentle than the slope when there is a homogeneous belief among traders. We report our results in the Table 7. As shown in columns (1) and (2), return is higher when slope is steeper, while return volatility increases as slope is more gentle, consistent with the findings of Næs and Skjeltorp (2006). We include the interaction term of slope and string in the regression to investigate the mediation effect of slope by string types and report the results in columns (3) and (4). Clearly, the linear line of return of strings by the number of trades in the series is steeper if the LOB slope increases one unit. That is the slope of the return on the number

of trades increases as heterogeneous belief in securities valuation increases. Conversely, the slope of the return volatility on the number of trades decreases as heterogeneous belief in securities valuation increases. In columns (5) and column (6), we report the similar regression results by including interaction of slope by string dummy variables. The variables of interests are the interaction terms and the LOB slope. For instance, the interaction term slope*string 2 represents the return for the string 2 while the slope represents the return for the reference group, the string with more than 6 trades in the series. All the interaction terms are negative in the return regression and positive in the volatility of return regression. Thus, we conclude that the wider dispersed belief in traders' valuation on the securities the higher return for strings with more than 6 trades in the series relative to strings with fewer than 6 trades in the series. That is, for block trades that walk up/down the book, the return is higher when less private information in the order flow. This result is in line with the results for trades within the BBO. As can be seen in column (6), this effect is reversed for return volatility.

7. Summary and Conclusions

By the end of 2008, according to the report of World Federation of Exchanges, the TSE ranked the second in terms of market capitalization around the world. Its fast-paced trading activities make our results applicable to most major exchanges and markets around the world. Using tick-by-tick trading data of the TSE in June of 2008, we first examine the existence and extent of liquidity beyond the BBO by identifying strings which by definition are a series of trades each of which is at a price that is greater than or equal to the previous price in the series. We are able to capture the co-variation of liquidity beyond the BBO without relying on the complete LOB. We show that ICC that is the measure of variability among the number of strings

is prevalently close to unity across various combinations of tick size and MTU. As a result, we conclude that there is a systematic co-movement in liquidity beyond the BBO. In addition to the empirical evidences of common liquidity or common movement of strings beyond the BBO, we also examine the degrees of the co-variation of the depth and immediacy, the other two properties of liquidity beyond the BBO. We show that co-variation of the duration of strings, in contrast to that of the number of strings is relatively high and to a lesser degree the co-variation of the depth is moderate across trading days. Therefore, we conclude that there is extensive liquidity beyond the BBO, however, the related aspects of liquidity, i.e. the width, the depth and the immediacy beyond the BBOs have various variability across trading days.

Not surprisingly, each of three properties of liquidity beyond the BBO is positively correlated with string return and volatility of the string return. Further, our analysis shows that the return of strings and return volatility of strings have direct relationship with the beginning prices, the beginning spread, the beginning volume, and the duration of strings. Specifically, the beginning spread, the beginning volume, and the duration of the strings has a positive relationship with the return of strings for buy side and an inverse relationship with the return of strings for sell side. On the contrary, the higher beginning price reduces the return of strings for the buy side while improves the return of strings for the sell side. The return volatility increases as the number of trades in the string series increases and when the beginning price decreases. Moreover, the return volatility is higher when the beginning spread is wider and the duration is longer. We also examine the effect of the slope on the return and return volatility of the strings. We conclude that when traders have heterogeneous belief in securities' valuation, it increases return and decreases the volatility of the string return for strings with more than 6 trades in the

series relative to strings with less than 6 trades in the series. Slope by itself is negatively related to the return volatility and positive related to the return, which is consistent with the prior research.

Thus, we find conclusive evidence in supporting of our hypothesis that the information significant affect block trades' return and volatility by using the LOB slope and the state of the LOB as our proxies for the measure of the informative-ness in the LOB. To the best of our knowledge, we are the first to show that the private information has significant impact on the return of the block trades that walk up/down the LOB, which is consistent with the evidence for trades within the BBO.

References

- Aitken, M., N. Almeida, F. H. deB. Harris, T. H. McInish, 2007, Liquidity supply in electronic markets, *Journal of Financial Markets* 10, 144–168.
- Amihud, Y., and H. Mendelson, 1986, Liquidity and security returns, *Financial Analysts Journal* 42, 43-48.
- Anshuman, V. R. and A. Kalay, 2002, Can splits create market liquidity? Theory and evidence, *Journal of Financial Markets* 5, 83-125.
- Barlay, M. J., R. H. Litzenberger, J. B. Warner, 1990, Private information, trading volume, and security-return variances, *The Review of Financial Studies* 3, 233-253.
- Bæs, Randi and Johannes A. Skjeltorp, 2006, Order book characteristics and the volume-volatility relation: Empirical evidence from a limit order market, *Journal of Financial Markets* 9, 408-432.
- Biais, B., P. Hillion, C. Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *The Journal of Finance* 50, 1655-1689.
- Chan, L. K.C. and J. Lakonishok, 1993, Institutional trades and intraday security price behavior, *Journal of Financial Economics* 33, 173-199.
- Chordia, T., R. Roll, and A. Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3-28.
- Coughenour, J. F., and M. M. Saad, 2004, Common market makers and commonality in liquidity, *Journal of Financial Economics* 73, 37-69.
- Datar, V. T., N. Y. Naik, R. Radcliffe, 1998, Liquidity and security returns: An alternative test, *Journal of Financial Markets* 1, 203-219.
- Domowitz, I., O. Jansch, X. Wang, 2005, Liquidity commonality and return co-movement, *Journal of Financial Markets* 8, 351-376.
- Easley, D. and M. O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 18, 69-90.
- Gompers, P. A. and A. Metrick, 2001, Institutional investors and equity prices, *The Quarterly Journal of Economics* 1, 229-259.
- Hasbrouck, J. and D. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Journal*

- of Financial Economics* 59, 383-411.
- Hasbrouck, J. 1991, Measuring the information content of security trades, *The Journal of Finance* 46, 179-207.
- Hong, H. and S. Rady, 2002, Strategic trading and learning about liquidity, *Journal of Financial Markets* 5, 419-450.
- Kamara, A., X. Lou, and R. Sadka, 2008, The divergence of liquidity commonality in the cross-section of Securities, *Journal of Financial Economics* 89, 444-466.
- Keim, D. B. and A. Madhavan, 1995, Anatomy of the trading process: Empirical evidence on the behavior of institutional traders, *Journal of Financial Economics* 37, 371-398.
- Kempf, A. and D. Mayston, 2008, Liquidity commonality beyond best prices, *Journal of Financial Research* 1, 25-40.
- Korajczyk, R. A. and S. Ronnie, 2008, Pricing the commonality across alternative measures of liquidity, *Journal of Financial Economics* 87, 45-72.
- Lin, J. C., A. J. Singh, and W. Yu, 2009, Security splits, trading continuity, and the cost of equity capital, *Journal of Financial Economics* 93, 474-489.
- McGraw, K. O. and S. P. Wong, 1996, Forming inferences about some intraclass correlation coefficients, *Psychological Methods* 1, 30-46.
- Næs, R. and J.A. Skjeltorp, 2006, Order book characteristics and the volume-volatility relation: Empirical evidence from a limit order market, *Journal of Financial Market* 9, 408-432.
- Shrout, P. E. and J. L. Fleiss, 1979, Intraclass correlation: Uses in assessing rater reliability, *Psychological Bulletin* 86, 420-428.

Table 1

Descriptive Statistics of Number of Trades in the Strings

We define the string based on number of price concession steps. For example, string 2 is a series of trades each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, two successively higher/lower prices. Similarly, string 3 is a series of trades each of which is at a price that is inferior to or equal to the previous price in the series and there are, among these trades, three successively higher/lower prices. Similarly, string 9 is a series of trades each of which is at a price that is inferior to or equal to the previous price in the series. There are, among these trades, a total of nine successively higher/lower prices.

	Buy side				Sell side			
	Mean	STD	Skewness	Kurtosis	Mean	STD	Skewness	Kurtosis
String 2	5.16	6.37	19.92	1048.1	4.95	5.59	19.18	966.4
String 3	6.08	5.40	12.12	322.3	5.85	5.30	25.67	1729.5
String 4	7.00	4.86	10.72	219.8	6.90	4.82	11.00	216.3
String 5	7.93	4.36	8.35	126.1	7.88	5.56	20.79	819.1
String 6	8.81	3.94	7.79	111.5	8.83	4.17	7.68	99.61
String 7	9.88	5.10	18.22	614.2	9.81	5.28	12.79	250.7
String 8	10.65	3.65	8.85	149.2	10.47	2.77	4.24	29.84
String 9	11.49	3.00	4.78	36.1	11.39	3.51	13.02	299.8

Table 2

Frequencies and Descriptive Statistics of Number of Strings and Duration of Strings

Strings are classified into 5 different types depending on the number trades at successively higher/lower prices in the series. For example, string 2 is a series of trades each of which is at a price that is inferior to or equal to the previous price in the series and there are two trades, among the series of trades, at successively higher/lower prices. The “other” category includes strings of a series of 6, 7, 8, or 9 such trades. The LOBSlope is the LOB slope computed using the immediate quotes before the first trade in the series. The frequency and the percentage (in parenthesis) are reported in the columns (1) and (2) for buy and sell sides respectively. The average duration of strings (in minutes) and the standard deviation (in parenthesis) are reported in the columns (4) and (5) for buy and sell sides respectively. Column (5) reports the average and standard deviation of the LOB slope.

String Type	Frequency of strings (%)		Average duration of strings (SD)		LOBSlope (5)
	(1) Buy	(2) Sell	(3) Buy	(4) Sell	
String 2	714,789 (11.31)	602,009 (11.27)	0.78 (1.80)	0.93 (2.02)	2,797 (1,770)
String 3	66,931 (1.94)	105,053 (1.97)	1.18 (2.32)	1.37 (2.61)	3,056 (1,914)
String 4	18,432 (0.53)	28,708 (0.54)	1.45 (2.70)	1.65 (2.86)	3,159 (1,972)
String 5	5,595 (0.16)	9,161 (0.17)	1.62 (2.90)	1.86 (3.09)	3,217 (2,010)
String “Other”	3,333 (0.10)	5,782 (0.11)	1.39 (3.03)	1.66 (3.06)	3,074 (2,023)
All	484,660 (14.04)	750,713 (14.05)	1.28 (31.03)	1.40 (32.85)	2,853 (1,807)

Table 3

Descriptive Statistics of Duration and Aggregated Volume of Strings by Combination of Tick Size and MTU and by String Type

Tick Size	MTU	String Type	Frequencies of Strings		Average Duration of Strings (SD)		Average Aggregated Volume (SD)	
			Buy	Sell	Buy	Sell	Buy	Sell
<i>Panel A - Combination of Tick Size and MTU for String of Length 2</i>								
1	1	2	2,071	2,188	0.25 (0.47)	0.24 (0.49)	88 (311)	99 (211)
1	10	2	1,221	2,642	0.43 (1.05)	0.43 (0.92)	521 (847)	735 (4347)
1	50	2	4,048	5,507	0.34 (0.89)	0.40 (0.96)	2318 (3216)	2338 (5981)
1	100	2	122,605	197,789	0.62 (1.56)	0.76 (1.75)	4980 (24149)	3791 (17245)
1	500	2	6,408	11,547	0.88 (1.79)	0.93 (1.84)	18462 (77047)	17372 (84325)
1	1000	2	148,962	242,096	0.90 (2.02)	1.08 (2.28)	15758 (61360)	15585 (55682)
5	50	2	196	411	1.30 (1.79)	1.82 (2.61)	403 (428)	490 (487)
5	100	2	18,755	28,495	1.04 (1.95)	1.23 (2.11)	3881 (9064)	3471 (7382)
5	1000	2	5,802	6,914	0.71 (1.21)	0.92 (1.61)	19109 (23305)	19878 (62976)
10	1	2	5,781	6,493	0.56 (1.52)	0.61 (1.54)	22 (52)	25 (88)
10	10	2	10,761	11,014	0.43 (0.87)	0.53 (1.06)	785 (1903)	714 (2443)
10	50	2	2,187	2,319	0.60 (1.31)	0.89 (1.76)	1837 (2456)	1615 (2986)
10	100	2	29,644	47,403	0.84 (1.73)	0.98 (1.84)	5313 (42587)	5534 (28292)
10	500	2	132	268	1.93 (3.14)	2.80 (4.49)	6436 (7537)	21773 (256702)
10	1000	2	374	675	1.55 (3.14)	1.77 (2.91)	12289 (13356)	13092 (14544)
50	1	2	2,632	4,192	0.38 (0.90)	0.42 (1.17)	102 (238)	133 (271)
50	10	2	48	137	3.40 (5.02)	3.65 (5.03)	31 (16)	32 (18)
100	1	2	5,208	6,130	0.72 (1.60)	0.85 (1.98)	17 (21)	16 (23)
1000	1	2	23,454	25,680	0.84 (2.06)	0.98 (2.23)	61 (238)	54 (187)
10000	1	2	80	109	1.92 (3.33)	1.91 (3.17)	210 (267)	1.91 (3.17)
<i>Panel B - Combination of Tick Size and MTU for String of Length 3</i>								
1	1	3	473	575	0.40 (0.55)	0.36 (0.58)	174 (281)	210 (328)
1	10	3	246	661	0.51 (0.94)	0.64 (1.39)	1036 (1164)	1216 (1451)
1	50	3	972	1,376	0.48 (1.10)	0.60 (1.30)	4329 (4971)	4301 (5159)
1	100	3	27,219	45,728	1.05 (2.15)	1.21 (2.34)	6194 (26850)	5145 (18649)
1	500	3	863	1,557	1.37 (2.29)	1.52 (2.41)	13512 (26781)	19032 (68492)
1	1000	3	23,625	38,399	1.40 (2.61)	1.63 (2.95)	21450 (43174)	21095 (63715)
5	50	3	32	52	1.50 (1.57)	1.83 (2.03)	942 (574)	862 (592)
5	100	3	1,843	2,714	1.71 (3.08)	1.95 (2.94)	5175 (13096)	5075 (9336)
5	1000	3	422	442	1.19 (1.47)	1.40 (1.72)	40268 (32319)	42771 (49657)
10	1	3	1,646	1,872	0.82 (1.88)	0.78 (1.90)	38 (58)	41 (59)
10	10	3	2,015	1,982	0.47 (0.77)	0.67 (1.10)	1155 (2254)	949 (1650)
10	50	3	272	252	0.77 (1.38)	1.41 (2.68)	4720 (4540)	3951 (3647)
10	100	3	3,033	4,686	1.32 (2.30)	1.52 (2.63)	4570 (8168)	5884 (62617)
10	500	3	12	9	2.33 (2.87)	4.22 (3.67)	10375 (6169)	10944 (5276)
10	1000	3	27	19	1.56 (1.95)	3.32 (3.76)	34444 (22752)	19947 (14845)
50	1	3	499	673	0.77 (1.50)	0.82 (1.56)	167 (326)	134 (301)
50	10	3	9	37	4.33 (4.95)	5.16 (5.62)	50 (13)	69 (41)
100	1	3	922	1,210	1.09 (2.44)	1.41 (3.11)	40 (42)	31 (44)
1000	1	3	2,800	2,807	1.22 (2.31)	1.34 (3.08)	47 (182)	54 (190)
<i>Panel C - Combination of Tick Size and MTU for String of Length 4</i>								
1	1	4	138	194	0.43 (0.61)	0.44 (0.65)	222 (228)	337 (414)
1	10	4	101	203	0.60 (1.19)	0.45 (0.64)	1778 (2856)	1899 (2318)
1	50	4	332	426	0.49 (0.83)	0.79 (1.66)	6687 (7055)	6926 (8634)
1	100	4	8,171	13,787	1.34 (2.58)	1.51 (2.52)	8196 (31020)	7470 (68836)
1	500	4	217	379	1.44 (2.14)	1.69 (2.17)	15664 (36056)	33161 (194163)
1	1000	4	6,093	9,641	1.80 (3.14)	1.98 (3.31)	27613 (51601)	27040 (75922)
5	50	4	5	12	2.40 (1.95)	3.50 (4.64)	2130 (1526)	1112 (597)

Table 3 (Cont.)

Descriptive Statistics of Duration of Strings and Aggregated Volume by Combination of Tick Size and MTU and by String Type

Tick Size	MTU	String Type	Frequencies of Strings		Average Duration of Strings (SD)		Average Aggregated Volume (SD)		
			Buy	Sell	Buy	Sell	Buy	Sell	
5	100	4	336	521	1.93 (2.57)	2.46 (3.63)	6400 (12256)	6098 (18488)	
5	1000	4	65	76	1.20 (1.62)	1.72 (2.22)	66154 (70372)	50237 (54794)	
10	1	4	546	661	0.89 (1.68)	1.10 (2.85)	55 (75)	67 (96)	
10	10	4	600	630	0.59 (0.76)	0.83 (1.32)	1274 (1848)	1391 (2335)	
10	50	4	51	51	1.37 (2.42)	1.27 (1.47)	6079 (7948)	6288 (4485)	
10	100	4	625	1,020	1.54 (2.57)	1.78 (2.83)	5128 (10705)	5339 (9150)	
10	500	4	2	3	2.00 (1.41)	5.67 (5.69)	20250 (4596)	10000 (1500)	
10	1000	4	4	1	2.00 (1.41)	Na	54750 (71369)	97667 (49541)	
50	1	4	118	155	0.66 (1.36)	1.05 (1.85)	211 (580)	185 (448)	
50	10	4	4	10	5.50 (10.34)	7.70 (14.02)	43 (29)	81 (21)	
100	1	4	280	312	1.27 (2.77)	1.49 (2.63)	65 (75)	49 (94)	
1000	1	4	744	624	1.38 (2.63)	1.54 (3.15)	48 (143)	54 (173)	
<i>Panel D- Combination of Tick Size and MTU for String of Length 5</i>									
1	1	5	67	102	0.51 (0.61)	0.44 (0.65)	419 (417)	495 (530)	
1	10	5	29	96	0.38 (0.56)	0.69 (1.27)	2825 (3016)	3314 (4351)	
1	50	5	120	171	0.57 (0.92)	0.91 (1.56)	9623 (10593)	8440 (8280)	
1	100	5	2,689	4,518	1.52 (2.86)	1.78 (2.87)	9876 (35669)	8596 (21845)	
1	500	5	54	117	1.72 (2.66)	2.07 (2.65)	34926 (67161)	52611 (305814)	
1	1000	5	1,668	2,937	2.04 (3.18)	2.31 (3.64)	33260 (59812)	36797 (154110)	
5	100	5	78	124	2.82 (5.09)	2.72 (4.72)	5685 (7046)	7389 (13066)	
5	1000	5	10	14	1.70 (2.06)	1.50 (2.35)	33400 (35994)	65571 (74728)	
10	1	5	176	241	1.36 (2.14)	0.99 (1.47)	82 (200)	87 (98)	
10	10	5	222	204	0.72 (1.07)	0.78 (1.01)	1719 (2171)	1375 (1165)	
10	50	5	12	10	0.75 (0.75)	1.20 (1.40)	5521 (3651)	5960 (4579)	
10	100	5	137	263	1.37 (2.08)	2.02 (3.25)	6482 (10395)	4665 (7405)	
50	1	5	43	57	0.63 (0.79)	0.58 (0.82)	208 (449)	537 (1607)	
50	10	5	2	3	1.50 (2.12)	2.33 (4.04)	100 (14)	167 (119)	
100	1	5	82	110	1.71 (4.25)	1.50 (2.88)	82 (81)	76 (73)	
1000	1	5	206	193	1.86 (2.78)	1.10 (1.70)	25 (36)	76 (392)	
<i>Panel E - Combination of Tick Size and MTU for String of Length Other</i>									
1	1	Other	90	104	0.34 (0.52)	0.28 (0.49)	323 (526)	404 (537)	
1	10	Other	43	89	0.35 (0.53)	0.44 (0.54)	1836 (2384)	2737 (3216)	
1	50	Other	67	138	0.42 (0.70)	0.64 (1.16)	9996 (14468)	9624 (11311)	
1	100	Other	1,563	2,891	1.30 (2.50)	1.66 (2.97)	11290 (28520)	9198 (23914)	
1	500	Other	30	50	1.30 (1.91)	1.86 (2.35)	23633 (33127)	25130 (28711)	
1	1000	Other	911	1,700	1.82 (3.46)	2.06 (3.49)	35527 (56433)	36941 (74811)	
5	100	Other	26	56	1.62 (2.47)	2.98 (3.80)	5238 (7963)	6379 (9544)	
5	1000	Other	1	6	4.00 (Na)	1.83 (1.17)	11000 (Na)	52500 (34274)	
10	1	Other	160	212	1.48 (4.91)	0.96 (1.58)	85 (105)	108 (156)	
10	10	Other	151	142	0.57 (0.81)	0.64 (0.96)	1657 (2702)	1465 (1618)	
10	50	Other	6	4	0.83 (0.41)	0.50 (0.58)	12350 (9689)	8463 (5271)	
10	100	Other	76	111	1.83 (2.12)	2.21 (4.90)	4784 (5069)	3999 (9272)	
50	1	Other	23	46	1.13 (2.67)	0.54 (1.17)	364 (842)	182 (412)	
100	1	Other	64	65	1.14 (2.96)	1.37 (3.00)	100 (156)	70 (104)	
1000	1	Other	121	167	1.76 (5.85)	1.05 (2.64)	37 (124)	31 (68)	

Table 4

Intra-class Correlation Coefficients

For the 21 trading days in June 2008, for each tick size MTU combination, for buys and sells, in turn, we report intra-class correlation coefficients (ICCs) and the associated F-value across days (Panel A) and across securities (Panel B). We report ICCs for number of strings in columns 3-6, for trading volume in columns 7-10, and for duration in columns 11-14. An ICC close to zero (one) indicates high (low) variability. We report the number of observations in column 15. * and † indicate that we reject the null hypothesis of equality of number of strings at the 0.01 and 0.05 levels, respectively.

<i>Panel A- ICC across Trading Days</i>														
Tick Size	MTU	N	Number of Strings				Trading volume				Duration			
			ICC	F-Value	ICC	F-Value	ICC	F-Value	ICC	F-Value	ICC	F-Value	ICC	F-Value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1	10	21	0.838*	119	0.875*	164	0.224*	7.44	0.258*	8.59	0.601*	30.6	0.382*	14.5
1	50	21	0.788*	81	0.719*	62.8	0.340†	11.8	0.319*	12.1	0.653*	39.7	0.714*	54.9
1	100	21	0.910*	222	0.862*	141	0.787*	78.9	0.384*	113	0.333*	11.8	0.403*	15.5
1	500	21	0.420*	19.0	0.710*	61.3	0.244*	8.31	0.296*	10.1	0.444*	19.2	0.533*	25.4
1	1000	21	0.808*	95.4	0.797*	90.1	0.589†	31.7	0.647*	40.1	0.385*	14.7	0.435*	17.5
5	100	21	0.826*	111	0.697*	52.8	0.572*	30.7	0.668*	44.7	0.392*	15.3	0.430*	17.3
5	1000	21	0.922*	284	0.779*	90.1	0.775*	80.6	0.591*	33.1	0.416*	16.3	0.538*	24.9
10	1	21	0.745*	66.1	0.670*	48.8	0.695*	48.9	0.553*	27.3	0.188*	5.8	0.370*	13.4
10	10	21	0.889*	183	0.825*	110	0.664*	44.7	0.654*	43.6	0.331*	12.7	0.452*	17.9
10	50	21	0.924*	225	0.870*	125	0.787*	76.7	0.794*	81.9	0.507*	22.9	0.646*	42.1
10	100	21	0.786*	83.9	0.826*	110	0.456*	18.7	0.684*	47.7	0.505*	22.8	0.483*	20.9
10	1000	21	0.445*	25.4	0.627*	39.0	0.130	4.12	0.201†	5.69	0.142	4.02	0.388*	13.6
50	1	21	0.849*	132	0.916*	230	0.688*	46.8	0.905*	206	0.528*	24.3	0.636*	35.2
100	1	21	0.724*	62.5	0.744*	64.9	0.534*	26.1	0.595*	33.0	0.369*	13.6	0.392*	14.2
1000	1	21	0.866*	146	0.877*	166	0.720*	56.1	0.826*	102	0.479*	21.2	0.430*	16.9
10000	1	21	0.539*	26.7	-0.024	0.38	0.149†	5.49	0.165†	5.56	-0.029	0.44	0.001	1.02
<i>Panel B - ICC across Securities</i>														
Tick Size	MTU	N	Number of Strings				Trading volume				Duration			
			ICC	F-Value	ICC	F-Value	ICC	F-Value	ICC	F-Value	ICC	F-Value	ICC	F-Value
1	10	2	0.013	1.18	0.012	1.22	0.047	1.13	0.030	1.08	-0.027	0.87	0.021	1.07
1	50	4	0.016	1.42	0.040†	1.87	0.015	1.10	0.067	1.50	-0.083	0.57	-0.039	0.69
1	100	294	0.001*	8.26	0.003*	7.89	0.000	0.078	0.000	1.08	0.020*	9.53	0.022*	13.1
1	500	21	0.069*	4.73	0.042*	4.60	0.041†	2.25	0.025†	1.79	0.016†	1.69	0.009	1.44
1	1000	435	0.004*	10.3	0.007*	14.7	0.000	0.888	0.002*	2.53	0.059*	330	0.007*	6.44
5	100	61	0.004†	2.92	0.019*	5.25	0.017*	3.38	0.007*	2.42	0.023*	3.47	0.008†	1.99

5	1000	10	0.010*	2.57	0.037*	3.02	0.021†	2.13	0.021	1.55	0.011	1.21	-0.012	0.75
10	1	14	0.004	1.23	0.030*	2.54	-0.014	0.369	-0.002	0.94	0.015	1.32	0.025	1.51
10	10	11	0.008†	1.87	0.016†	2.04	0.017	1.59	0.024†	1.76	0.075*	2.38	-0.014	0.76
10	50	3	-0.010	0.648	-0.018	0.63	-0.006	0.922	0.003	1.05	0.008	1.05	0.024	1.22
10	100	84	0.173*	8.26	0.014*	8.77	0.000	1.03	0.008*	3.05	0.014*	3.39	0.003†	1.41
10	1000	2	0.227	1.91	0.026	1.15	-0.006	0.987	-0.102	0.77	-0.131	0.74	-0.036	0.89
50	1	4	0.007	1.27	0.000	1.02	-0.002	0.977	0.002	1.10	-0.013	0.90	-0.026	0.73
100	1	11	0.022†	2.25	0.011	1.51	0.028	1.81	0.014	1.40	0.040	1.69	-0.014	0.76
1000	1	57	0.037*	16.3	0.011*	6.52	-0.003	0.006	0.003†	1.80	0.066*	6.85	0.002†	1.19
10000	1	2	0.020	1.09	0.208	1.51	0.156	1.45	0.074	1.20	-0.66	0.88	-0.133	0.77

Table 5

Correlations Results

This table reports correlations between the liquidity aspects of strings and squared return (a measure of return volatility). Panel A (B) presents the Pearson correlation results for buy (sell) side. * and † indicate that we reject the null hypothesis of equality of number of strings at the 0.01 and 0.05 levels, respectively.

	Return Volatility	String Length	Aggregated Volume	Duration of strings (in Minutes)
Panel A: Buy Side				
Return Volatility	1			
String Length	0.022*	1		
Aggregated Volume	0.020*	0.033*	1	
Duration of strings (in Minutes)	0.035*	0.060*	0.051*	1
Panel B: Sell Side				
Return Volatility	1			
String Length	0.019*	1		
Aggregated Volume	0.016*	0.034*	1	
Duration of strings (in Minutes)	0.015*	0.066*	0.055*	1

Table 6
Regression Outcomes

This table reports regression outcomes for both buy side and sell side using string return and string return volatility as dependent variable in Panel A and panel B respectively. The beginning price, beginning volume, and beginning spread are the price, volume, and spread of the initial trade of the string. The duration of strings is the minutes consumed to complete the series of trades in the string. The t-statistics are bracketed and computed using heteroscedasticity consistent standard errors. * and † indicate that we reject the null hypothesis of equality of number of strings at the 0.01 and 0.05 levels, respectively.

	Panel A: String Return		Panel B: String Return Volatility	
	Buy Side	Sell Side	Buy Side	Sell Side
Constant	0.018* (74.7)	-0.017* (-107.60)	0.0003* (11.49)	0.0002* (14.87)
Log of Beginning Price	-0.002* (-63.8)	0.002* (91.89)	-0.00004* (-10.42)	-0.00002* (-12.62)
Log of Beginning Spread	0.002* (84.1)	-0.002* (-116.47)	0.00003* (11.98)	0.00002* (14.29)
Log of Beginning Volume	0.00003* (6.6)	-0.00004* (-32.56)	-0.0000* (-4.98)	-0.000* (-4.26)
Log of Duration	0.0002* (23.19)	-0.0002* (-32.56)	0.000003* (3.45)	0.0000* (3.36)
String 2 Dummy	-0.005* (-65.8)	0.004* (77.43)	-0.00005* (-25.91)	-0.00005* (-26.79)
String 3 Dummy	-0.003* (-47.1)	0.003* (56.20)	-0.00004* (-21.07)	-0.00004* (-22.17)
String 4 Dummy	-0.002* (-31.1)	0.002* (37.95)	-0.00003* (-15.62)	-0.00003* (-17.01)
String 5 Dummy	-0.001* (-15.9)	0.001* (19.66)	-0.00002* (-9.07)	-0.00002* (-10.95)
No of observation	203,765	346,597	203,765	346,597
Adj. R-squared	0.43	0.46	0.03	0.03

Table 7
Effect of LOB Slope on String Return and String Return Volatility

This table reports regression outcomes using string returns as dependent variable. The LOBSlope is the LOB slope computed using the immediate quotes before the first trade in the series. The beginning price, beginning volume, beginning spread are the respective price, volume, and spread of the initial trade of the string. The string with at least 6 trades in the series is treated as the reference group for the string dummy variables. The t-statistics are bracketed and computed using heteroscedasticity consistent standard errors. * and † indicate that we reject the null hypothesis of equality of number of strings at the 0.01 and 0.05 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Return	Volatility	Return	Volatility	Return	Volatility
Constant	-0.000*** (-6.57)	0.000 (0.98)	-0.000 (-0.16)	-0.000* (-7.10)	-0.002* (-11.52)	0.0001* (28.00)
LOBSlope*String			0.124* (3.06)	-0.026* (-9.12)		
String	-0.0002* (-33.39)	0.00001* (24.81)	-0.0003* (-14.55)	0.00002* (13.25)		
LOBSlope	0.726* (42.97)	-0.040* (-34.24)	0.439* (4.92)	0.021* (3.39)	2.648* (5.93)	-0.192* (-22.23)
LOBSlope*String 2					-1.930* (-4.32)	0.159* (18.18)
LOBSlope*String 3					-2.028* (-4.52)	0.148* (17.09)
LOBSlope*String 4					-2.025* (-4.34)	0.099* (4.83)
LOBSlope*String 5					-1.324* (-2.58)	0.077* (8.28)
String 2 Dummy					0.002* (8.85)	-0.0001* (-24.02)
String 3 Dummy					0.002* (8.00)	-0.0001* (-21.93)
String 4 Dummy					0.002* (6.89)	-0.0001* (-6.81)
String 5 Dummy					0.001* (3.77)	-0.00004* (-10.38)
No of observation	1,198,070	1,198,070	1,198,070	1,198,070	1,198,070	1,198,070
Adj. R-squared	0.005	0.005	0.005	0.005	0.005	0.005