Does trading remove or bring frictions?

William Lin and David Sun and Shih-Chuan Tsai

Kai Nan University

August 2010

Does Trading Remove or Bring Frictions?

William T. Lin
Tamkang University

David S. Sun[a]
Kainan University

Shih-Chuan Tsai[b]
National Taiwan Normal University

(For the special issue of EMFT)

[a] Address correspondences to: David Sun, Kainan University, PO Box 11061, Taipei, Taiwan 100, or davidsun0769@gmail.com

[b] Address correspondences to: Shih-Chuan Tsai, National Taiwan Normal University, or e-mail: Tsai16888@gmail.com

Abstract

We explore in this paper how trading noise, when considered as a market friction, reacts to trading activity. Transactions cost is a good explanation for intraday trading behavior in the market according to our data. Particularly, we show that in general trading brings friction to market. However, trading friction at market open is the lowest during the day, as trading causes less friction then relatively. This is due to the behavioral difference among investors. When market opens, individual trading removes, while institutional trading brings, market friction. Situation in the rest of the day is just the opposite, where individual, instead of institutional, trading brings friction. The uneven behavior of trading noise across investors and time of day makes it a specific, rather than general, transactions cost, as opposed to Stoll (2000). Intraday trading activity suppresses both order width and depth, as proxies for trading intensity, therefore creates more noise or friction in the market. Width and depth contribute to trading noise in a polarized way, so that individual trading hurts friction in small cap stocks at open, but benefits it at close. Institutional trading brings extremely strong friction to large cap stocks, but less so at market close. So trading noise as a specific, rather than general, transactions cost is prominent only to certain investors, at certain time and for certain stocks in the market. Our findings lend itself to the justification of the new financial transactions tax proposed by the European Union.

Keywords: Noise, transaction cost, herding, search model, order book
JEL codes: C14, D82, D83, G12, L11

I. Introduction

Trading in markets involves general transaction costs applicable to the entire market as well as specific costs only born by certain investors. The former acts as a friction in trading, which could be noises as argued in Stoll (2000) or herding out of information cascades (see Nofsinger and Sias (1999), Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Avery and Zemsky (1999, AZ), among others). The latter could also take the form of information asymmetry (as discussed in Diamond and Verrecchia (1981), Glosten and Milgrom (1985), Kyle (1985), Admati (1991), Easley and O'Hara (1992) and Easley, Kiefer, and O'Hara (1997)). This study addresses the role of trading noise as a friction to market participants, especially in the presence of trading concentration. Our interest is in whether trading activity itself adds to or drives down this friction, and how the relationship is affected by investor type, market capitalization of stocks and time of day the trading takes place. If trading brings friction, then our findings provide support to financial transactions tax which encounters much resistance.

We attempt to verify in this study if trading noise really qualifies to be a general transactions cost, or a market-wide friction, in an intraday framework. It has been well documented in Amihud and Mendelson (1987), Stoll and Whaley (1990), and Stoll (2000) that stock return volatility is the highest right after market opens. Stoll (2000) suggests that the high volatility is caused by friction, a general transaction cost for everyone in the market. Alternatively, Lakonishok, Shleifer, and Vishny (1992, LSV) and Wermers (1999) stress that volatility is closely related to information-induced herding behavior. However, Lin, Tsai and Sun (2011) argue that comparative advantage in search cost dictates a polarization of trading activity across investors, firm size and time of day. Based on that notion, an investor can optimize by allocating trades when transaction cost is the most favorable. Hu (2006) applied a return decomposition mechanism to conclude that specific transactions cost causes the market to be the most volatile at open since frictional noises are the smallest during the day. We adopt this concept but attempt to identify its driving factors.

We find in this study that trading activity brings friction to market. However, friction at market open tends to be the lowest during the day, as trading causes less friction relatively at that time. This is due to the behavioral difference among investors. When market opens, individual trading removes, while institutional trading brings, market friction. Situation in the rest of the day is just the opposite, where individual, instead of institutional, trading brings friction. The uneven behavior pattern of trading noise across investors and time of day makes it a specific, rather than general, transactions cost, as opposed to Stoll (2000). We also find that noise component of return volatility is stronger when trading is more concentrated, different from the prediction of Lin, Sanger, and Booth (1995) and Hu (2006). Although in general the time needed to fill an order, or the inverse of the number of orders matched with a certain time window, is inversely related to trading noise, it is quite the contrary at market open. Moreover, we argue that noise is influenced more by trading concentration, at open than at close. We also find that market width of limit order book, which measures how tightly the orders are placed to each other or how closely they are to the mid-quote, affect trading noise. Market depth exhibits similar influence. Response of noise to market width and depth differs by market capitalizations as well as by trading hours. Individual trading aggravates at open, but benefits at close, friction in the trading of small cap stocks. Despite that institutional trading brings extremely strong friction to large cap trading, it still contributes relatively less to trading friction at market close.

We consider in this study trading intensity more in a dynamic sense by measuring order intensity rather than quantity, with sequences of buy or sell runs based on Patterson and Sharma (2006, PS). It captures intraday order flows better than the popular LSV method, which is more suitable for longer time frame. The dynamic trading intensity helps us capturing how ‘friction’ really arises from trades. Although noise proportion of stock returns is high on individual orders and low on institutional orders, its behavior at market open is entirely different from the rest of the day. Noises for small cap stocks, unlike volatilities, are lower than those for large cap stocks. For individuals, noise benefits trading stocks of smaller firms, while for institutional investors it its market width and depth that benefit trading stocks of larger firms. This distinct pattern of trading activity is not compatible with information-based explanation, especially why market width is lower, at market open, when trading is extremely heavy. Institutionals prefer to trade large cap stocks, especially at market close, while individuals are more eager to trade small caps at market open. So trading noise is just a specific transaction cost, as information cost, prominent only to certain investors in the market. If trading noise is not compatible with general market phenomena, then it may not be a general transaction cost as argued in Stoll (2000). Trading noise is just another kind of specific cost, rather than a market-wide friction.

As we find trading brings friction, our findings provide support to the new financial transactions tax proposed by the European Union, which has invited lots of criticism. The results of this study also indicate that uneven trading noise makes market trading polarized. Transactions cost, rather than information dissemination, is the more important factor causing the result. Our study also helps identifying for various types of investors a more cost-efficient time to trade. Both individual and foreign institutional investors (FII’s) in Taiwan bear relatively much lower general transaction cost caused by noise, especially at market open, when there is significantly intensive trading. But foreign institutional benefit more from trading at market close than at market open when trading does not concentrate. A brief literature review and discussion is given in Section II. Data and empirical results are laid out in Section III. Conclusion is given in Section IV.

II. Noise and Trading

Trading noise has long been considered a crucial factor to asset returns. When market trading is more heavily concentrated, noise plays a more important role. Literature has modeled noise as investor irrationality or information barrier, among others. Although the direct effect of noise trading to a securities market seems to be reducing informational efficiency, there are views on the positive side of noise. Greater noise trading induces rational agents to trade more aggressively on their existing information and provides them with incentives to acquire better information. As a result, Grossman and Stiglitz (1980) and Kyle (1985), argue that noise trading does not reduce informational efficiency. Furthermore, Kyle (1985) suggests that noise trading improves informational efficiency.

Various models consider rational agents not being able to fully offset noise traders' demands because of limits to arbitrage. De Long, Shleifer, Summers, and Waldmann (1990) indicate that rational arbitrageurs may magnify demand shocks from noise traders because anticipated worsening mispricing in the short-run. Relative to the issue of trading noise, Bikhchandani and Sharma (2001) classify herding behavior into rational and irrational ones. Rational herding takes place when investors make the same response to a piece of information or when they exhibit similar preference for a stock, while irrational herding occurs as investors ignore their own information but imitate or follow others' trades. These views are not compatible with how noise trading is modeled.

Other than Kyle (1985), many have also studied trading against one's own private information (e.g., Jarrow (1992), Chakraborty and Yilmaz (2004)) in market manipulation, where the informed may trade in a wrong direction to increase noise in trading volume. Herding behavior is also considered a challenge to the efficient market paradigm. At a group level it is considered irrational as it leads to mispricing, but it can be rational at an individual level. Literature argues that the herding arises from agents copying one another in trading decisions. The models of BHW and Bannerjee (1992) consider that individuals make their decisions sequentially at a time, taking into account the decisions of the individuals preceding them. The model proposed by Cont and Bouchaud (2000) consider, instead of a sequential decision process, a random communication structure. Random interactions among agents lead to a heterogeneous market structure. AZ argues, on the other hand, that information cascades that induce herding will be short-lived and fragile as one contrarian trade from the herd can quickly stop an information cascade.

Noise and Information

Following the definition of Hu (2006), we make the following decomposition of the log price of a given stock,

$$P_t = m_t + n_t,\quad E_t[n_{t+j}] = 0, \text{ and } \quad E_t[n_t n_{t+j}] = 0 \text{ as } j \to \infty \tag{1}$$

where m_t is considered as the permanent component of the stock price and follows a random walk process,

$$m_t = m_{t-1} + u_t,\quad E_{t-1}[u_t] = 0,\quad E[u_t^2] = \sigma_u^2, \text{ and } \quad E[u_t n_{t-i}] = 0,\ i=1,2,\ldots \tag{2}$$

Where u_t is a white noise and is orthogonal to m_{t-1}. The other component of P_t, n_t, is a temporary noise which disappears over time. After simple algebra, we would obtain

$$E_t[P_t - P_{t+j}] = n_t \text{ as } j \to \infty$$

The volatility of stock return $Var(P_t - P_{t-1})$ can be decomposed into $Var(u_t)$, $Var(n_t - n_{t-1})$ and $Cov(u_t, n_t - n_{t-1})$. The ratio

$$N_t = \frac{Var(n_t - n_{t-1})}{Var(P_t - P_{t-1})} \tag{3}$$

will be used as a relative measure of noise within stock return volatility subsequently. When noise ratio of the entire market is computed, transactions price is used. But the midpoint of buy and sell order price is used in place of market price when noise ratio of a certain type of investor is to be computed.

Table I reports noise proportion and return volatility computed according to the definition above, by market capitalization and intraday interval. This noise proportion is shown I to be, at any given day, the lowest at market open. Also, noises for small cap stocks, unlike volatilities, are lower than those for large cap stocks, contrary to findings of Stoll (2000). Volatilities and noise proportions of small-cap stocks exhibit in general a U-shaped pattern across a trading day, but noise for large-cap stocks tend to go up from open to close. The intraday distribution of noise ratio for small-caps is consistent with similar friction measures found in Hong Kong by Anh and Cheung (1999).

A measure of herding

We consider trading activity more in an dynamic sense by measuring order intensity not by quantity, but by it sequences based on Patterson and Sharma (2006, PS). It captures intraday order flows better than the popular LSV method, which is more suitable for longer time frame. In the context of investor herding, we adopt a cost-based framework of trading concentration to see how return volatility decomposition should be evaluated. The dynamic trading intensity allows us capturing how 'friction' really arises from trades. As search cost goes up, so does noise. However, search generates less noise at market open than at market close. Therefore, noise is lower when specific search cost prevails, and noise gets higher when general friction rises.

To gauge the extent of trading concentration, we have adopted a dynamic measure specifically for a high frequency trading environment. The common LSV measure computes the proportion of market participants buying or selling within a given period and hence cannot capture dynamic order flows. Its inference relies on conventional *t*-test, making it subject to distributional imperfections especially with high frequency data. As a result, various measures have been proposed lately to overcome its limitations. Radalj and McAleer (1993) noted that the main reason for the lack of empirical evidence of herding may lie in the choice of data frequency, in the sense that too infrequent data sampling would lead to intra-interval herding being missed (at monthly, weekly, daily or even intra-daily intervals). For the purposes of our investigation we used the PS measure, which we consider the most suitable, since it overcomes this problem of intraday data. Constructed from intraday data, it has a major advantage of not assuming herding to vary with extreme market conditions, and considering the market as a whole rather than a just the institutional investors.

PS statistic measures herding intensity in terms of the number of runs. The bootstrapped runs test of PS uses run numbers of buy and sells orders[3]. As our data set contains identification of buy or sell orders, we would not need Lee and Ready (1991) and Finucane (2002) to determine directions of investors' trading directions. If traders engage in systematic herding, the statistic should take significantly negative values, since the actual number of runs will be lower than expected. The standardized and adjusted type *i* runs for stock *j* on day *t* in PS is defined as

$$x(i,j,t) = \frac{(r_i + 1/2) - np_i(1-p_i)}{\sqrt{n}} \qquad i = 1, 2 \tag{4}$$

Where r_i is the actual number of type *i* runs (up runs, down runs or zero runs), *n* is the total number of

[3] The formula of runs is according to Mood (1940), but with non-trading adjustments.

trades executed on asset j on day t, ½ is a discontinuity adjustment parameter and p_i is the probability of finding a type of run i. Under asymptotic conditions, the statistic $x(i, j,t)$ has a normal distribution with zero mean and variance

$$\sigma^2(i, j,t) = p_i(1-p_i) - 3p_i^2(1-p_i)^2 \tag{5}$$

So the herding intensity statistic is expressed as

$$H(i, j,t) = \frac{x(i, j,t)}{\sqrt{\sigma^2(i, j,t)}} \tag{6}$$

which has an asymptotic distribution of $N(0,1)$. Mood (1940) requires state variables to be independent and i.i.d. as well as continuously distributed. As realized transaction price of stock is discrete, $H(i, j,t)$ would have a non-normal distribution and critical values for testing the existence of herding would have to be constructed through bootstrapping the sample.

The distribution of significant herding percentage, as shown in Table II, suggests that intraday trading concentration is heavier in the opening interval. At the 5% significance level, there are 7.35% of the trading days exhibit herding phenomenon in the first half hour of a day's trading session. The percentage falls as with time of day and goes down to only 3.74% for the final half hour of trading. Table III gives the sizes of buy and sell orders, in lots of one thousand shares, for all days where herding is significant at 1%. The average order size at market close is much larger than in other periods. The ratios of average buy orders to average sell orders, for days when herding is significant at 1%, is slightly higher than for the entire period. Among investor types, buy-sell ratios are greater than 1 for all institutionals during days of herding. Looking further into the opening intervals, we find that overall buy-sell ratios during significant herding days are actually *lower* than the entire period. But for the closing interval, not only the ratios are generally higher than those in the opening interval, but those in significant herding days are also higher than in the entire period. This pattern coincides with intraday trading noise, which rises from open to close. If we look at stocks in the top and bottom return deciles, the buy-sell ratios are, as expected, higher in the top return decile. In the bottom return decile, buy-sell ratios are in general smaller than 1. Buy-sell ratios in the closing intervals are uniformly higher, around 20%, than in the opening intervals. Even for the bottom return decile, there appears to be a stronger, about 24% in magnitude, buying force near market close than right after market open.

Market Width

Limit order book dispersion can describe the *tightness* of the book by examining how far apart from each other (or from the midquote) the limit orders are placed in the book. It can also be considered as the width of a market and it captures the execution price innovation expected by the limit order trader when he sacrifices demand of immediacy and instead provides liquidity to the market. Foucault, Kadam, and Kandel (2005) suggest that the limit order book dispersion is linked with the patience of limit order traders and the pick-off risk they face. We adopt the following market width measure by modifying the dispersion measure of Kang and Yeo (2008). The market width of stock *i* in a given day is defined as

$$MW_i = \frac{1}{2}\left[\frac{\sum_{j=1}^{5} w_j^b Dst_j^b}{\sum_{j=1}^{5} w_j^b} + \frac{\sum_{j=1}^{5} w_j^s Dst_j^s}{\sum_{j=1}^{5} w_j^s}\right] \tag{7}$$

where Dst_j^b is the price interval between the *jth* best buy order price and its next better order price, and similarly Dst_j^s is that for the sell order price. The buy and sell price intervals, up to the fifth best limit orders are weighted by w_j^b and w_j^s, the size of the corresponding buy or sell limit orders. For the whole market, transaction prices are used to compute the first price interval, while for each type of investors, average of buy and sell order price at each priority level is used instead. This dispersion, or market width, measure is designed to show how clustered or dispersed the limit orders are in the book. It measures how tightly the orders are placed to each other or how closely they are to the midquote. The higher the dispersion is, the less tight the book is, and the lower amount of liquidity the limit order book provides.

It is a well known fact in Taiwan that, due to funding liquidity, individual investors tend to hold and trade stocks with lower prices, while institutional investors concentrate more on high price stocks. Therefore, Dst_j^b and Dst_j^s in (7) are computed using the raw price distance divided by tick size of the stock, so that only the relative price distance is used, allowing MW_i to be comparable across stocks and various types of investors.

Market Depth

Bloomfield, O'Hara, and Saar (2005) argue that informed traders would submit more limit orders than market orders in an electronic market. McKenzie (2007) argues that in the emerging markets especially the ability to forecast future price movements is related to the depth of those markets. Therefore, beside the tightness measure, limit order book helps examining how well the book handles large volume of market orders. A deep limit order book can absorb a sudden surge in the demand of liquidity without inducing much price deviation. Without the interference of the specialist and before new limit orders can replenish the book, market buy (sell) orders will first be executed against the limit sell (buy) orders at the best offer (bid) quote. If the volume of the market order(s) is larger than the best offer (bid) size, the remainder of the unexecuted market orders will be executed against the limit orders queuing at the next best offer (bid) quote. In other words, large volume of market buy (sell) orders will walk up (down) the limit order book to get filled. The further away the market orders walk up or down the book, the larger the difference between the execution price and the mid-quote is, and therefore the more costly the trading process will be for the market order traders. Motivated by the mechanism described above, we modify the market depth measure of Kang and Yeo (2008), which can be thought of as an enhanced depth measure for the limit order book.

$$MD_i = \frac{\sum_{k=1}^{K} I_k^B (MQ_i - P_k^B) + \sum_{k=1}^{K} I_k^S (P_k^S - MQ_i)}{TNS_i \times MQ_i}, \tag{8}$$

where i=1,2,…,525. MQ_i is the midpoint of the nearest buy and sell quote prices, TNS_i is the total number of shares traded within the time interval of interest, P_k^B is the best bid price, P_k^S is the best offer price and,

$$I_k^B = \begin{cases} Q_j^B & \text{if} \quad TNS > \sum_{j=1}^{k} Q_j^B \\ (TNS - \sum_{j=1}^{k} Q_j^B) & \text{if} \quad TNS > \sum_{j=1}^{k-1} Q_j^B \quad \text{and} \quad TNS < \sum_{j=1}^{k} Q_j^B \\ 0 \quad \text{otherwise} & \end{cases}$$

$$I_k^S = \begin{cases} Q_j^S & \text{if} \quad TNS > \sum_{j=1}^{k} Q_j^S \\ (TNS - \sum_{j=1}^{k} Q_j^S) & \text{if} \quad TNS > \sum_{j=1}^{k-1} Q_j^S \quad \text{and} \quad TNS < \sum_{j=1}^{k} Q_j^S \\ 0 \quad \text{otherwise} & \end{cases}$$

III. Data and empirical results

This study employs intra-day order book data from the Taiwan Stock Exchange starting from March 1st, 2005 to December 31st, 2006, covering stocks of 525 firms over a period of 461 trading days. Excluded from the complete pool of stocks listed on the exchange are those with irregularities and unusual exchange sanctions. As the Taiwan Stock Exchange would only release limit book data two years after an order or trade is realized, the data period the latest we could obtain. Each data record includes date, exact time in hours, minutes and seconds, stock code, price and quantity of all orders, filled or not, submitted during the data period. Individual stock returns, market capitalizations, daily turnover and price-book ratios are obtained from the Taiwan Economic Journal (TEJ) database.

Each daily session is then divided further into 9 intervals between 9:00 AM and 1:30 PM, with 30 minutes in each interval. As our data contains flags identifying each investor as either a proprietary dealer, an investment trust, a FII or an individual, we are able to extend our analysis according to investor types. Over the last ten years, percentages of trades in Taiwan stock market accounted for by FII's have apparently grown much faster than the other two types of local institutionals. As a matter of fact, FII'S owns one third of the total market capitalization and account for one quarter of daily volume as of end of 2009 in Taiwan. On average, about 15% of the daily orders are submitted during the first half hour of a regular four and half hour trading session. In the last half hour period, the percentages range between 9% and 19%. Trading in other periods is usually slower than open and close.

To construct the herding intensity measures required for our study, we begin by sorting the trades for each day (having excluded all those executed outside normal trading hours) by stock code and count the numbers of up and down runs of order prices submitted within a given day, as well as within each of the nine 30-minute intervals. We then compute herding statistic in the respective periods according to PS (2006). The definition (6) usually makes computed herding measures take on negative values. In computing PS herding measures, only the orders actually filled are included in the computation to avoid reporting unrealistic herding phenomenon. The computed daily herding measures in are larger in magnitudes than when they are computed intra-day, consistent with Dorn, Huberman and Sengmueller (2008) which argue that herding measures should rise with length of period. For all and each type of investors, we bootstrapped their 1%, 5% and 10% critical values. Among all types of investors, FII's exhibit the strongest herding behavior in the opening interval, followed by individuals and investment trusts. Herding of proprietary dealers is quite different from the other three types, peaking at mid-day sessions.

We report in Table IV the noise proportion in return volatility in the presence of trading concentration, where trading noise falls from open to close, contrary to Anh and Cheung (1999). We intend to identify possible factor driving trading noise. Does trading noise get heavier when market is extremely active? According to the argument of Hu (2006) and Stoll (2000), a general transaction cost should apply to everyone in the market, regardless of market capitalization of stocks or which trading hour it is. Although noise is high on individual orders and low on institutional orders, it is especially low at market open than in the rest of the day. For individuals, noise rises with significance of herding as shown in Table IV, but not so for institutional investors. So trading noise maybe just a specific transaction cost, as information cost, prominent to only certain investors in the market.

In order to explore the effects of herding alone on noise in trading, we use the model below to see its influences. We perform a panel regression with generalized least squares random effect based on

$$N_{k,t} = \alpha + \beta AH_{k,t} + \varepsilon_{k,t} \tag{9}$$

where N stands for noise as defined in (3), and H is defined according to (6). Also, t=1,…,461 (for trading days) and k=1,…,525 (for stocks) . A greater β in magnitude implies stronger noise is produced by more intensive trading activity. Table V gives the result of this model, where a negative β estimate would indicates that trading activity brings in more trading noise, as herding measure summarized in Table II in general takes on negative values. For the entire observations, the magnitudes of coefficients in general peak at mid-day, with the closing interval having the weakest coefficient. If we narrow the observations down to only those with significant herding at 10%, the magnitudes of coefficients fall by 50%. When market opens, trading brings in the least amount of noise. In another word, although noise does rise with herding, but when herding is very strong, its influence on trading noise is actually smaller. When trading is not heavy, it affects noise more, but not otherwise.

Table V reports the summary statistics of the market width measure, which shows why trading could bring in more friction in the market. *MW* at each intraday interval, for the whole market or various types of investors, is achieved by first subtracting the daily measure and then dividing by it, which assures comparability across investor type. The market width measures are reported with a layout with time-size blocks. As the computed value of measure is affected in practice by the arrival rate of orders within a given time, figures in the table is modified to reflect the percentage each cell in the block is above or below corresponding daily averages. *MW* increases in market capitalization, as various friction measures mentioned in Stoll (2000). Also, it falls roughly from open to close, again consistent with Anh and Cheung (1999), but the difference between open and close decreases with firm size. Intraday trading activity suppresses width of orders submitted, therefore creates more friction in the market. Taking investor type into consideration, we are able to see more prominent northwest-southeast block polarization, with *MW* being polarized the most for individuals and the least for FII's. In fact, order width goes up with firm size on orders submitted by FII's and domestic institutional investors (DII's), contrary to the direction for individuals. The block distribution by investor type in Table VI suggests that, across time of day, order width benefits trading. But in the category of individuals, it benefits more when trading stocks of the smaller firms, while for institutional investors higher dispersion benefits trading stocks of larger firms. This kind of clientele distribution of trading activity is not compatible with information-based explanation, especially why order price dispersion is higher, at market open, when trading is extremely heavy. However, if *MW* is just a form of economic rent imposed by limit order traders to reflect the benefits each trader can enjoy through shorter search time.

According to Table VII, the distribution of market depth, proxied by the depth of a limit order book, is also compatible with our findings in previous tables. *MD* falls in general with both time of day and firm size, uniformly across all types of investors. Order depth across firm size is compatible with what frictions behave in Stoll (2000). The distribution across time of day is also consistent with the findings of Anh and Cheung (1999) on intraday friction measures. Intraday trading activity lowers order depth, and hence elevates market friction. Although stocks of larger firms possess better depth, orders from individuals have on average more depth than those from institutional investors. At market open, this edge is about 2.4 times, and increases to 3.9 times at market close. Along the direction of firm size, individuals' edge in order book depth at market open is 2.1 times on small cap and 2.3 times on large cap, but is 3.7 times and 2.7 times respectively at market close. So the results on market depth measure in Table VII implies that it is in the interest of FII's and DII's to trade large cap stocks, especially at market close. For individuals, order book depth indicated they should make the similar trading decision as the institutional investors to avoid higher execution cost in trading small cap stocks at market open. However, the search cost advantage dominates the execution cost. Apparently, for individuals finding a counterparty to complete an intended trade is more important than walking up a few ticks on the limit order book and paying for a slightly higher transacted price. After all, not being able to submit a market order in the Taiwan market is itself a strong protection against shallow limit order book. Besides, there is also a 7% price limit on either direction. Actual trading intensity may depend in part on the relative strength of search and execution costs.

Based on a framework of time-size block, we show why intraday trading could actually result more friction in a market. The relation is, however, on the level of broad categories. To determine on average what dictates behavior of market friction at every incidence, we need to conduct further point estimations. We use the following model to find out how order width affects actual time it takes to fill a buy order. A fixed effect panel regression is performed on

$$N_{k,t} = \alpha + \gamma_1 MW_{k,t} + \varepsilon_{k,t} \tag{10}$$

where t=1,…,461 and k=1,…,525. Results are estimated using a panel GLS with $AR(1)$[4] adjustments on residuals and reported in Table VIII, which suggests that order width affects market friction in different ways across investor type and time of day. Similar to the previous models, the model for domestic institutional does not pass the validation test again and only results for the largest market capitalization are available for FII's. For FII's dispersion suppresses trading noise significantly except for the first intraday interval. For the individuals, however, dispersion elevates trading noise except for the first intraday interval regardless of market capitalizations. The exact mirror type pattern that distinguish FII's from individuals supports notion that heavy trading of individuals at market open induces noise. For FII's, aggressive order price pattern, or lower dispersion, just produces lower trading noises at market open. In other intraday intervals, only more aggressive order price pattern would produce greater trading noise, confirming the findings of Table VI.

Table IX gives results showing how market depth affects trading noise. The following model is considered for this purpose,

$$N_{k,t} = \alpha + \gamma_1 MD_{k,t} + \varepsilon_{k,t} \tag{11}$$

where t=1,…,461 and k=1,…,525. Results are estimated using a panel GLS with $AR(1)$ adjustments on residuals. Table IX shows a similar pattern to that in Table VIII. Market depth of orders from institutional investors, which is lower than the depth in individuals' orders, contributes to trading noise positively at market open. However, for the rest of the day, market depth of institutionals' orders tends to suppress trading noise. The relation between trading noise and market depth is the opposite of that at market open. For the institutional investors, market depth affects noise only weakly on small cap stocks. Results from Tables VIII and IX validate the pattern of noise across a day, as reported in Table IV. When the market is very active, in width or depth, trading noise of investors actually benefit from heavy trading. This is especially true for individual investors at market open, when poor width and depth actually hurts the institutional investors in bearing higher trading noise.

[4] We have verified that the model with AR(1) residuals are supported by the SBC criterion.

IV. Conclusion

This study examines intra-day order book data to study whether trading activity incites or suppresses certain market friction, particularly when trading is heavy. We adopt a measure of trading concentration specifically ideal for high frequency data. The measure is not only constructed on a daily level, but also within intra-day time intervals. Trading concentration is found to bring in noise or friction to the market. As we find trading brings friction, our findings provide support to the new financial transactions tax proposed by the European Union, which has invited lots of criticism.

We have also introduced measures on width and depth of a limit order book to explain why market friction reacts to trading activity as we find it. We find strong evidences against the idea of trading noise being a general transaction cost, or a general friction in market trading. Specifically, trading noise behaves, and reacts to market width and depth, differently across investor type, market capitalization and time of day. Trading noise is just a specific transaction cost, as information cost, prominent at certain aspect in the market.

Although this noise is high on individual orders and low on institutional orders, its behavior at market open is entirely different from the rest of the day. Noises for small cap stocks, unlike volatilities, are lower than those for large cap stocks. Intraday trading activity suppresses width, as well as depth, of orders submitted, therefore creates more noise in the market. At market open, behaviors of noise from institutional and individual orders are opposite to each other, but they switch positions in the rest of the day. Noise from high-cap stocks is actually more responsive than that from low-cap ones across investors. So trading noise is a specific transactions cost, prominent to only certain investors, at certain time and for certain stocks in the market, rather than a general market friction as argued in Stoll (2000). This transactions cost is inversely related to order width and depth, which depends on investor, trading hour of day and market capitalization of stocks.

Although we have presented valid arguments regarding the central issue of this study, there are areas yet to be worked on. We have to investigate further behavior of trading noise and its interaction with investors. Other analysis, such as trading motives of investors, evidence on sequence or development of trading concentration and the dynamics of trading noise need to be added to the current model as well.

References

1. Admati, A. R., (1991), “The Informational Role of Prices,” *Journal of Monetary Economics* 28,347-361.
2. Ahn, H. and Cheung, Y.. (1999), “The intraday patterns of the spread and depth in a market without market makers: The Stock Exchange of Hong Kong,” *Pacific-Basin Finance Journal* 7, 539-556.
3. Amihud, Y. and Mendelson, H.. (1987), “Trading mechanism and stock returns: An empirical investigation,” *Journal of Finance* 42, 533-553.
4. Avery, C. and Zemsky, P.. (1998), “Multidimensional uncertainty and herd behavior in financial markets,” *American Economic Review* 88, no. 4, 724-748.
5. Banerjee, A.. (1992), “A Simple Model of Herd Behavior,” *Quarterly Journal of Economics* 107, 797-817.
6. Bikhchandani, S.; Hirshleifer, D.; Welch, I.. (1992), “A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades,” *Journal of Political Economy* 100, 992-1026.
7. Chang, E. C.; Cheng, J. W.; Khoran, A., (2000), “An examination of herd behavior in equity markets: An international perspective,” *Journal of Banking and Finance* 24, no. 10, 1651-1699.
8. Chakraborty, A. and Yilmaz, B., (2004), "Manipulation in market order models," *Journal of Financial Markets* 7(2), 187-206.
9. Cont, R. and Bouchaud, J. P.. (2000), “Herd Behavior and Aggregate Fluctuations in Financial Markets,” *Macroeconomic Dynamics* 4, 170-196.
10. De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann, (1990), “Positive Feedback Investment Strategies and Destabilizing Rational Speculation,” *Journal of Finance* 45(2), 374-397.
11. Diamond, D. W., and Verrecchia, R. E., (1981), “Information Aggregation in a Noisy Rational Expectations Economy,” *Journal of Financial Economics* 9, 221-235.
12. Dorn, D.; G. Huberman; P. Sengmueller. 2008. “Correlated Trading and Returns.” *Journal of Finance* 58, no. 2: 885-920.
13. Easley, D., Kiefer, N. M., and O’Hara, M., (1997), “One Day in the Life of a Very Common Stock,” *Review of Financial Studies* 10, 805-835.
14. Easley, D., and O’Hara, M., (1992), “Time and the Process of Security Price Adjustment,” *Journal of Finance* 47, 577-605.
15. Finucane, T. J.. (2002), “A Direct Test of Methods for Inferring Trade Direction from Intra-day Data,” *Journal of Financial and Quantitative Analysis* 35, 553-557.
16. Foucault, T., Kadam, O., and Kandel, E., (2005), “Limit Order Book as a Market for Liquidity, ” *Review of Financial Studies* 18, 1171-1218.
17. Glosten, L. R. and Milgrom, P. R., (1985), “Bid, ask and transaction prices in a specialist market with heterogeneously informed traders,” *Journal of Financial Economics*, Vol. 14(1), 71-100.
18. Grossman, S. J., and Stiglitz, J. E., (1980), “On the Impossibility of Informationally Efficient

Markets," *American Economic Review* 70(3), 393-408.

19. Hu, S.. (2006), "A Simple Estimate of Noise and Its Determinant in a Call Auction Market," *International Review of Financial Analysis* 15, 348-362.
20. Jarrow, R.. (1992), "Market manipulations, bubbles, corners and short squeezes," *Journal of Financial and Quantitative Analysis* 27, 311-336.
21. Kang, W., and Yeo, W., (2008), "Liquidity beyond the Best Quote: A Study of the NYSE Limit Order Book," Working Paper, National University of Singapore.
22. Kyle, A. S., (1985), "Continuous Auctions and Insider Trading," *Econometrica* 53, 1315-1335.
23. Lakonishok, J.; Shleifer, A.; Vishny, R. W., (1992), "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics* 32, 23-43.
24. Lee, C. M. C., and Ready, M. J., (1991), "Inferring Trade form Intraday Data," *Journal of Finance* 46, 733-746.
25. Lin, J., Sanger, G. C., and Booth, G. G., (1995). "Trade size and components of the bid-ask spread," *Review of Financial Studies* 8, 1153−1183.
26. Lin, W. T., Tsai, S. C., and Sun, D. S., (2011), "Search Costs and Investor Trading Activity: Evidences from limit order book," Forthcoming, *Emerging Markets Finance and Trade*.
27. McKenzie, M.D. (2007). Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises, *Emerging Markets Finance and Trade*, 43, 46-73.
28. Mood, A., (1940), "The distribution theory of runs," *Annals of Mathematical Statistics* 11, 367-392.
29. Nofsinger, J. R., and Sias, R.W.. (1999), "Herding and Feedback Trading by Institutional and Individual Investors," *Journal of Finance* 54, 2263-2295.
30. Patterson, D., and Sharma, V.. (2006), "Do Traders Follow Each Other at the NYSE?" Working Paper, University of Michigan-Dearborn.
31. Radalj, M., and McAleer, M.. (1993). "Herding, information cascades and volatility spillovers in futures markets," Working Paper, University of Western Australia, Perth, Australia.
32. Stoll, H.R.. "Friction," *Journal of Finance* 55 (2000), 1479-1514.
33. Stoll, H. R., and R. E. Whaley, (1990), "Stock market structure and volatility," *Review of Financial Studies*, Vol. 3, pp.37−71.
34. Wermers, R.. "Mutual Fund Herding and the Impact on Stock Prices," *Journal of Finance*, 54 (1999), 581-622.

Table I Noise as Proportion of Stock Returns by Market Capitalization and Intraday Interval

Averaged across 525 firms and over 461 days

		9:00~9:30	**9:30~10:00**	**10:00~10:30**	**10:30~11:00**	**11:00~11:30**	**11:30~12:00**	**12:00~12:30**	**12:30~13:00**	**13:00~13:30**	**all day**
MV10*	Noise Ratio	0.342278	0.349138	0.351538	0.353061	0.353678	0.353752	0.353574	0.35327	0.350522	0.346329
	Volatility	2.94E-06	2.04E-06	1.89E-06	1.83E-06	1.82E-06	1.87E-06	1.87E-06	1.90E-06	2.28E-06	2.06E-06
MV9	Noise Ratio	0.299264	0.306318	0.309945	0.310761	0.312009	0.31237	0.311695	0.311612	0.308912	0.301522
	Volatility	5.31E-06	3.48E-06	3.17E-06	3.06E-06	2.98E-06	3.19E-06	3.10E-06	3.10E-06	3.71E-06	3.46E-06
MV8	Noise Ratio	0.312762	0.31705	0.318713	0.320591	0.319912	0.320309	0.320878	0.321037	0.318995	0.310814
	Volatility	7.03E-06	4.61E-06	4.15E-06	3.98E-06	3.84E-06	4.23E-06	3.95E-06	4.04E-06	4.93E-06	4.51E-06
MV7	Noise Ratio	0.265489	0.270462	0.273346	0.273981	0.274287	0.272752	0.274185	0.274522	0.27341	0.262707
	Volatility	7.94E-06	4.99E-06	4.35E-06	4.16E-06	4.08E-06	4.93E-06	4.17E-06	4.32E-06	5.33E-06	4.93E-06
MV6	Noise Ratio	0.273087	0.276788	0.279308	0.279894	0.279174	0.278379	0.279982	0.279452	0.279812	0.268396
	Volatility	8.75E-06	5.54E-06	4.84E-06	4.51E-06	4.61E-06	5.38E-06	4.63E-06	4.73E-06	5.74E-06	5.44E-06
MV5	Noise Ratio	0.267541	0.269733	0.272056	0.270965	0.271129	0.27107	0.27164	0.273007	0.273653	0.260174
	Volatility	1.10E-05	6.86E-06	5.83E-06	5.65E-06	5.60E-06	6.40E-06	5.60E-06	5.78E-06	7.18E-06	6.71E-06
MV4	Noise Ratio	0.275499	0.275677	0.277627	0.276941	0.276011	0.276052	0.275425	0.278486	0.280638	0.264206
	Volatility	1.38E-05	8.78E-06	7.43E-06	7.32E-06	6.88E-06	8.01E-06	6.98E-06	7.10E-06	8.90E-06	8.41E-06
MV3	Noise Ratio	0.253431	0.255456	0.257726	0.260689	0.259907	0.258176	0.259207	0.259522	0.259299	0.242237
	Volatility	1.59E-05	1.00E-05	8.39E-06	7.94E-06	7.76E-06	8.81E-06	7.60E-06	8.11E-06	1.01E-05	9.56E-06
MV1	Noise Ratio	0.266264	0.268133	0.269037	0.266463	0.27026	0.264406	0.26723	0.267985	0.270713	0.25229
	Volatility	2.00E-05	1.29E-05	1.11E-05	1.03E-05	1.02E-05	1.11E-05	9.99E-06	1.02E-05	1.31E-05	1.21E-05
MV1	Noise Ratio	0.282314	0.280608	0.281831	0.283886	0.281262	0.279193	0.280412	0.282529	0.282901	0.264302
	Volatility	3.37E-05	2.24E-05	1.87E-05	1.77E-05	1.73E-05	1.64E-05	1.65E-05	1.71E-05	2.14E-05	2.04E-05

* MV10 denotes the decile containing stocks with the largest market capitalization.

Table II Bootstrapped Intra-day Critical Values and Herding Significance Percentages
by Intraday Intervals and Investor Type, Averaged across 525 firms and over 495 days

Significance	Critical Values	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30
All Investors										
1%	-9.182	1.70%	1.29%	1.01%	0.94%	0.82%	0.82%	0.79%	0.85%	0.72%
5%	-5.080	7.35%	6.28%	5.26%	4.93%	4.50%	4.37%	4.09%	4.31%	3.74%
10%	-3.676	13.90%	12.38%	10.75%	10.00%	9.21%	8.89%	8.18%	8.66%	7.76%
Proprietary Dealers										
1%	-5.528	0.81%	1.03%	1.15%	1.17%	1.13%	1.13%	1.08%	1.05%	0.81%
5%	-3.497	5.72%	4.63%	5.11%	4.95%	4.55%	5.61%	4.89%	5.04%	3.98%
10%	-3.676	11.80%	9.44%	10.09%	9.27%	9.69%	10.88%	9.87%	10.16%	7.93%
Investment Trusts										
1%	-6.084	1.42%	0.90%	0.77%	0.82%	0.98%	0.99%	1.07%	1.16%	0.49%
5%	-4.264	6.88%	4.75%	4.34%	4.56%	4.82%	4.94%	5.51%	5.17%	3.00%
10%	-3.463	13.31%	10.01%	9.12%	9.23%	9.82%	10.05%	10.95%	10.45%	6.28%
FII's										
1%	-12.073	1.85%	1.02%	0.83%	0.81%	0.81%	0.80%	0.90%	1.05%	0.84%
5%	-8.068	7.06%	5.10%	4.43%	4.50%	4.63%	4.48%	4.84%	5.27%	4.36%
10%	-6.347	13.23%	10.11%	9.18%	9.18%	9.40%	9.35%	9.65%	10.40%	8.92%
Individuals										
1%	-9.627	1.55%	1.22%	1.01%	0.97%	0.87%	0.86%	0.83%	0.92%	0.73%
5%	-5.093	7.17%	6.10%	5.23%	4.90%	4.50%	4.43%	4.22%	4.48%	3.82%
10%	-3.645	13.93%	12.17%	10.52%	9.84%	9.11%	8.80%	8.31%	8.85%	7.97%

Table III Daily and Intra-day Buy and Sell Orders, All Days and When Herding Is Significant at 1%

By Investor Type

In thousand shares

Investor Type	9:00~9:30				13:00~13:30				All Day			
	All days		Days when herding is significant at 1%		All days		Days when herding is significant at 1%		All days		Days when herding is significant at 1%	
	Ave. buy orders per lot	Ave. sell orders per lot	Ave. buy orders per lot	Ave. sell orders per lot	Ave. buy orders per lot	Ave. sell orders per lot	Ave. buy orders per lot	Ave. sell orders per lot	Ave. buy orders per lot	Ave. sell orders per lot	Ave. buy orders per lot	Ave. sell orders per lot
	All Stocks											
All	14.19	14.24	15.09	18.33	19.92	18.07	22.82	18.53	8.50	8.45	9.64	9.56
Proprietary Dealers	29.77	24.81	68.96	15.11	23.37	25.39	26.57	19.69	21.66	22.17	26.22	8.61
Investment Trusts	41.53	31.41	56.62	29.49	31.58	27.62	66.09	53.32	28.68	25.34	13.77	12.88
FII's	27.12	26.18	43.95	25.22	69.19	59.72	130.17	26.60	17.10	17.34	14.05	12.39
Individual	10.54	11.12	10.05	22.82	9.76	10.18	9.66	17.31	7.29	7.36	7.02	7.67
	Top Stock Return Decile											
All	5.43	5.24	6.46	5.87	5.67	5.29	7.15	5.65	5.44	5.28	5.99	5.96
Proprietary Dealers	17.95	15.20	6.36	12.28	11.91	12.60	9.25	12.80	14.96	14.39	6.49	5.33
Investment Trusts	25.99	17.91	25.48	18.95	22.56	17.95	14.28	5.22	19.33	16.13	11.66	11.08
FII's	7.93	6.76	4.73	3.95	13.30	12.61	5.88	4.24	7.52	7.06	4.28	3.90
Individual	5.02	4.95	5.47	5.32	5.00	4.83	3.00	3.07	5.02	4.94	5.18	5.33
	Bottom Stock Return Decile											
All	10.81	10.64	15.53	13.06	12.39	12.39	18.76	12.67	10.53	10.85	10.17	12.83
Proprietary Dealers	32.68	31.13	34.55	20.14	26.12	29.81	56.59	37.77	25.82	28.30	31.04	12.15
Investment Trusts	58.67	46.06	180.25	24.81	41.04	31.32	45.81	56.36	39.80	34.26	14.58	13.49
FII's	18.88	18.87	19.95	6.95	45.79	46.07	39.87	42.69	20.61	20.84	18.02	10.53
Individual	10.22	9.98	12.58	12.53	9.92	10.18	9.35	10.77	9.64	9.91	8.64	10.71

Table IV Noise as Proportion of Stock Returns by Herding Significance

Averaged across 525 firms and over 495 days

Significance	All Day	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30
All Investors										
1%	0.3242	0.2718	0.3010	0.3082	0.3183	0.3161	0.3122	0.3144	0.3162	0.3066
5%	0.2981	0.2651	0.2833	0.2918	0.2972	0.2995	0.2984	0.2970	0.2957	0.2944
10%	0.2916	0.2678	0.2816	0.2880	0.2929	0.2958	0.2944	0.2949	0.2924	0.2943
Proprietary Dealers										
1%	0.2977	0.2467	0.2462	0.2557	0.2791	0.2822	0.2973	0.3038	0.3349	0.3206
5%	0.3144	0.2624	0.2822	0.3006	0.3082	0.2957	0.3253	0.3101	0.3165	0.3036
10%	0.3144	0.2705	0.2849	0.3056	0.3031	0.3076	0.3304	0.3205	0.3187	0.3017
Investment Trusts										
1%	0.2751	0.1924	0.2358	0.2688	0.2456	0.2773	0.2862	0.2736	0.2778	0.2861
5%	0.2602	0.2042	0.2429	0.2583	0.2573	0.2675	0.2758	0.2774	0.2870	0.2917
10%	0.2581	0.2118	0.2410	0.2554	0.2570	0.2673	0.2729	0.2737	0.2805	0.2873
FII's										
1%	0.3067	0.2766	0.3084	0.3100	0.3214	0.3166	0.3217	0.3224	0.3218	0.3215
5%	0.3098	0.2968	0.3099	0.3158	0.3205	0.321	0.3241	0.3211	0.3198	0.3192
10%	0.3136	0.305	0.3153	0.3188	0.3200	0.3241	0.325	0.3217	0.3224	0.3224
Individuals										
1%	0.3387	0.2855	0.3129	0.3212	0.3268	0.3294	0.3291	0.3336	0.3383	0.3346
5%	0.3030	0.2703	0.2871	0.2964	0.3006	0.3011	0.3016	0.3044	0.3037	0.3050
10%	0.2926	0.2703	0.2837	0.2885	0.2939	0.2959	0.2947	0.2969	0.2959	0.2992

Table V Effects of Herding on Noise in Panel Regression

Intraday Intervals

In order to explore the effects of trading concentration alone on trading noise, we use the model below to see what could have influenced noise. We performed a panel regression with generalized least squares random effect based on

$$N_{k,t} = \alpha + \beta H_{k,t} + \varepsilon_{k,t}$$

where N stands for noise as defined in (3), and H is defined according to (6). Also, t=1,…,461 (for trading days) and k=1,…,525 (for stocks) . A greater β in magnitude implies stronger noise is produced by more intensive trading activity.

Intraday interval	β (x100)	No of obs.
	All days	
9:00-9:30	-1.32(0.0128)***	222,711
9:30-10:00	-1.21(0.0140)***	217,529
10:00-10:30	-1.34(0.0153)***	213,436
10:30-11:00	-1.45(0.0161)***	209,637
11:00-11:30	-1.53(0.0168)***	206,076
11:30-12:00	-1.59(0.0170)***	202,803
12:00-12:30	-1.56(0.0173)***	202,750
12:30-13:00	-1.30(0.0166)***	208,049
13:00-13:30	-0.98(0.0161)***	222,387
	Days when herding is significant at 10%	
9:00-9:30	-0.25(0.0128)***	22,298
9:30-10:00	-0.45(0.0140)***	21,815
10:00-10:30	-0.62(0.0153)***	21,402
10:30-11:00	-0.79(0.0161)***	20,944
11:00-11:30	-0.83(0.0168)***	20,650
11:30-12:00	-0.85(0.0170)***	20,416
12:00-12:30	-0.86(0.0173)***	20,464
12:30-13:00	-0.74(0.0166)***	20,959
13:00-13:30	-0.54(0.0161)***	22,497

1. Standard deviations are in the parentheses.
2. *: Significant at 10%; **: Significant at5%; ***: Significant at1%.

Table VI Summary Statistics of Intraday Market Width Relative to Daily Average

525 firms and over 461 days

The dispersion measure of stock i in a given day is defined as

$$MW_i = \frac{1}{2 \times Tick_i} \left[\frac{\sum_{j=1}^{n} w_{ij}^B D_{ij}^B}{\sum_{j=1}^{n} w_{ij}^B} + \frac{\sum_{j=1}^{n} w_{ij}^S D_{ij}^S}{\sum_{j=1}^{n} w_{ij}^s} \right]$$

where i=1,2,⋯,525 and $Tick_i$ is the tick size of the respective stock. $D_{ij}^B = (Bid_{i,j-1} - Bid_{ij})$, which is the price interval between the jth best bid order price and the next better quote, whereas $D_{ij}^S = (Offer_{i,j-1} - Offer_{ij})$, which is the price interval between the jth best offer order price and the next better quote, with w_{ij} being the size of the corresponding bid or offer order. For the whole market, transaction prices are used to compute the first price interval, while for each type of investors, average of buy and sell order price at each priority level is used instead. As the computed value of measure is affected in practice by the arrival rate of orders within a given time, figures in the table is modified to reflect the percentage each cell in the block is above or below corresponding daily averages.

Market Caps*	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30
				All Investors					
All	20.50%	5.63%	0.72%	-1.74%	-3.46%	-4.51%	-5.33%	-5.78%	-6.03%
1	30.57%	10.19%	2.16%	-2.22%	-5.19%	-`7.18%	-8.59%	-9.56%	-10.18%
2	25.19%	7.16%	0.98%	-2.15%	-4.45%	-5.66%	-6.63%	-7.16%	-7.38%
3	20.35%	5.04%	0.40%	-1.80%	-3.36%	-4.35%	-5.15%	-5.47%	-5.66%
4	17.03%	4.04%	0.18%	-1.59%	-2.86%	-3.55%	-4.18%	-4.45%	-4.62%
5	9.36%	1.71%	-0.13%	-0.95%	-1.52%	-1.81%	-2.11%	-2.25%	-2.30%
				Individuals					
All	20.20%	5.79%	0.85%	-1.64%	-3.39%	-4.43%	-5.28%	-5.83%	-6.26%
1	30.40%	10.18%	2.21%	-2.19%	-5.16%	-`7.15%	-8.59%	-9.59%	-10.11%
2	24.95%	7.21%	1.06%	-2.08%	-4.28%	-5.60%	-6.64%	-7.23%	-7.41%
3	19.87%	5.12%	0.52%	-1.67%	-3.26%	-4.23%	-5.04%	-5.49%	-5.81%
4	16.16%	4.17%	0.38%	-1.37%	-2.70%	-3.35%	-3.99%	-4.41%	-4.88%
5	9.62%	2.27%	0.09%	-0.88%	-1.57%	-1.82%	-2.17%	-2.46%	-3.08%
				FII's					
All	8.97%	3.38%	0.82%	-0.66%	-1.78%	-2.53%	-3.08%	-3.03%	-2.09%
1	0.22%	0.09%	-0.00%	-0.04%	-0.05%	-0.08%	-0.10%	-0.08%	0.04%
2	0.90%	0.46%	0.16%	-0.01%	-0.19%	-0.31%	-0.39%	-0.39%	-0.24%
3	3.00%	1.38%	0.49%	-0.09%	-0.60%	-0.97%	-1.24%	-1.20%	-0.77%
4	7.73%	3.36%	1.12%	-3.63%	-1.52%	-2.39%	-2.97%	-2.99%	-1.20%
5	32.97%	11.62%	2.31%	-2.80%	-6.53%	-8.90%	-10.69%	-10.52%	-7.47%
				DII's					
All	11.41%	3.72%	0.46%	-1.22%	-2.46%	-3.18%	-3.40%	-2.81%	-2.53%
1	1.17%	0.52%	0.15%	-0.06%	-0.18%	-`0.29%	-0.29%	-0.23%	-0.80%
2	3.25%	1.37%	0.33%	-0.25%	-0.78%	-1.04%	-1.04%	-0.76%	-1.09%
3	7.54%	2.73%	0.41%	-0.83%	-1.76%	-2.26%	-2.45%	-1.80%	-1.57%
4	15.09%	5.47%	0.97%	-1.42%	-3.25%	-4.37%	-4.79%	-4.11%	-3.59%
5	30.02%	8.55%	0.46%	-3.57%	-6.33%	-7.95%	-8.43%	-7.16%	-5.60%

* Firms with the lowest market capitalization is assigned with 1, while the largest firms are assigned with 5.

Table VII Summary Statistics of Intraday Market Depth

Across 525 firms over 461 trading days

$$MD_i = \frac{\sum_{k=1}^{K} I_k^B (MQ_i - P_k^B) + \sum_{k=1}^{K} I_k^S (P_k^S - MQ_i)}{TNS_i \times MQ_i},$$

where i=1,2,⋯,525. MQ_i is the midpoint of the nearest buy and sell quote prices, TNS_i is the total number of shares traded within the time interval of interest, P_k^B is the best bid price, P_k^S is the best offer price and,

$$I_k^B = \begin{cases} Q_j^B & \text{if} \quad TNS > \sum_{j=1}^{k} Q_j^B \\ (TNS - \sum_{j=1}^{k} Q_j^B) & \text{if} \quad TNS > \sum_{j=1}^{k-1} Q_j^B \quad \text{and} \quad TNS < \sum_{j=1}^{k} Q_j^B \\ 0 & \text{otherwise} \end{cases} \quad I_k^S = \begin{cases} Q_j^S & \text{if} \quad TNS > \sum_{j=1}^{k} Q_j^S \\ (TNS - \sum_{j=1}^{k} Q_j^S) & \text{if} \quad TNS > \sum_{j=1}^{k-1} Q_j^S \quad \text{and} \quad TNS < \sum_{j=1}^{k} Q_j^S \\ 0 & \text{otherwise} \end{cases}$$

Market Caps*	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30
					All Investors (x1000)				
All	13.0079	9.8449	8.6888	8.1036	7.6669	7.3865	7.1746	7.0736	6.9958
1	17.8589	14.1373	12.5737	11.7438	11.1532	10.7470	10.4468	10.1948	9.9790
2	14.1931	10.6952	9.4177	8.7636	8.2676	7.9675	7.7290	7.6085	7.5207
3	12.3820	9.2101	8.0962	7.5566	7.1474	6.8688	6.6576	6.5776	6.5194
4	11.4488	8.4558	7.4450	6.9397	6.5596	6.3176	6.1297	6.0875	6.0521
5	9.1591	6.7281	5.9134	5.5160	5.2082	5.0333	4.9114	4.9011	4.9092
					Individuals (x1000)				
All	13.3955	10.4136	9.2868	8.7193	8.2999	8.0390	7.8118	7.6603	7.5285
1	18.0690	14.3891	12.8305	11.9916	11.3952	10.9884	10.6776	10.4073	10.2155
2	14.2668	10.8553	9.5973	8.9522	8.4784	8.1937	7.9314	7.7879	7.7046
3	12.6287	9.5807	8.4841	7.9552	7.5623	7.2972	7.0700	6.9430	6.8464
4	11.9329	9.2087	8.2513	7.7756	7.4143	7.2065	7.0072	6.9023	6.7844
5	10.0826	8.0364	7.2727	6.9234	6.6509	6.5103	6.3740	6.2626	6.0931
					FII's (x1000)				
All	31.6742	30.7326	30.2594	29.9569	29.6639	29.4932	29.3019	29.3110	29.4198
1	38.2287	38.1884	38.1322	38.0976	38.0382	38.0152	38.0066	38.0051	38.0210
2	38.4410	38.2997	38.2193	38.1541	38.0731	38.0783	37.9811	37.9710	38.0837
3	30.5419	30.2111	30.0790	30.0179	29.8711	29.7989	29.7067	29.7387	29.9595
4	25.5691	25.8143	25.3715	25.1059	24.8172	24.6598	24.4530	24.4801	24.8677
5	24.5935	21.1536	19.4991	18.4132	17.5244	16.9181	16.3665	16.3646	16.1717
					DII's (x1000)				
All	35.3645	32.8618	31.9597	31.4973	31.0950	30.8792	30.8544	31.1076	30.5155
1	49.1130	48.7376	48.5554	48.3584	48.2354	48.1506	48.1809	48.2515	47.0022
2	38.9963	38.0760	37.6922	37.4903	37.2298	37.1191	37.1422	37.3311	36.4473
3	33.0821	31.3160	30.5527	30.2103	29.8196	29.6622	29.6451	29.9616	29.5253
4	30.7961	27.2124	25.8983	25.2023	24.6050	24.2437	24.0973	24.4305	24.1344
5	24.8420	18.9749	17.1083	16.2339	15.5939	15.2289	15.2152	15.5719	15.4765

* Firms with the lowest market capitalization is assigned with 1, while the largest firms are assigned with 5.

Table VIII Effects of Market Width on Noise

Foreign Institutional and Individual Investors, by Market Caps

To explore the effects of search motive on trading noise on an intraday level, we use the model below to see what could have influenced noise. We performed a panel regression with generalized least squares random effect based on

$$N_{k,t} = \alpha + \gamma_1 MW_{k,t} + \varepsilon_{k,t} \quad \text{with} \quad MW_i = \frac{1}{2\times Tick_i}\left[\frac{\sum_{j=1}^{n} w_{ij}^B D_{ij}^B}{\sum_{j=1}^{n} w_{ij}^B} + \frac{\sum_{j=1}^{n} w_{ij}^S D_{ij}^S}{\sum_{j=1}^{n} w_{ij}^s}\right]$$

and t=1,…,461 and k=1,…,525. $MW_{k,t}$ follows the same definition as in (7). Results are estimated using a panel GLS with $AR(1)$ adjustments on residuals.

Intraday interval	*FII's*		*Individuals*	
	γ_1 (x1000)	*No. of Obs.*	γ_1 (x100)	*No. of Obs.*
		Smallest Market Caps		
9:00-9:30			-1.67(0.23)***	34,016
9:30-10:00			-0.93(0.36)***	30,295
10:00-10:30			3.08(0.48)***	27,200
10:30-11:00			5.24(0.78)***	24,886
11:00-11:30			5.05(0.58)***	22,835
11:30-12:00			7.11(0.63)***	21,360
12:00-12:30			6.80(0.60)***	20,936
12:30-13:00			6.97(0.51)***	23,243
13:00-13:30			5.31(0.32)***	34,183
		Middle Market Caps		
9:00-9:30			-2.44(0.40)***	44,497
9:30-10:00			1.34(0.63)**	45,936
10:00-10:30			8.56(0.82)***	43,296
10:30-11:00			17.00(0.92)***	42,194
11:00-11:30			20.95(1.01)***	41,344
11:30-12:00			25.95(1.01)***	40,481
12:00-12:30			23.28(0.98)***	40,388
12:30-13:00			24.45(0.85)***	41,653
13:00-13:30			16.12(0.65)***	45,273
		Largest Market Caps		
9:00-9:30	0.56(0.11)***	34,166	-1.20(0.47)***	48,159
9:30-10:00	-0.48(0.13)***	32,370	1.79(0.74)***	47,914
10:00-10:30	-0.62(0.16)***	30,476	3.04(0.90)***	47,595
10:30-11:00	-0.65(0.19)***	30,213	10.77(1.07)***	47,329
11:00-11:30	-0.57(0.20)***	29,797	17.84(1.20)***	47,050
11:30-12:00	-0.58(0.19)***	30,258	23.59(1.21)***	46,864
12:00-12:30	-0.24(0.19)***	30,549	23.13(1.15)***	46,846
12:30-13:00	-0.40(0.17)**	32,114	20.38(1.00)***	47,239
13:00-13:30	-0.36(0.10)***	38,055	11.99(0.82)***	48,091

1. Standard deviations are in the parentheses.
2. *: Significant at 10%; **: Significant at5%; ***: Significant at1%.

Table IX Effects of Market Depth on Noise

Foreign Institutional and Individual Investors, by Market Caps

To explore the effects of search motive on trading noise on an intraday level, we use the model below to see what could have influenced noise. We performed a panel regression with generalized least squares random effect based on

$$N_{k,t} = \alpha + \gamma_1 MD_{k,t} + \varepsilon_{k,t} \quad \text{with} \quad MD_k = \frac{\sum_{i=1}^{I} I_i^B (MQ_k - P_i^B) + \sum_{i=1}^{I} I_i^S (P_i^S - MQ_k)}{TNS_k \times MQ_k}$$

and t=1,…,461 and k=1,…,525. Results are estimated using a panel GLS with $AR(1)$ adjustments on residuals.

Intraday interval	*FII's*		*Individuals*	
	γ_1(x10)	*No. of Obs.*	γ_1	*No. of Obs.*
		Smallest Market Caps		
9:00-9:30	0.09(0.03)**	34,016	-0.54 (0.12)***	34,016
9:30-10:00	-0.07(0.04)**	30,295	0.61(0.15)***	30,295
10:00-10:30	-0.13(0.06)**	27,200	0.82(0.16)***	27,200
10:30-11:00	-0.14(0.07)*	24,886	4.45(0.21)***	24,886
11:00-11:30	-0.11(0.07)	22,835	5.00(0.22)***	22,835
11:30-12:00	-0.15(0.08)	21,360	7.29(0.26)***	21,360
12:00-12:30	-0.04(0.03)	20,936	6.92(0.25)***	20,936
12:30-13:00	-0.07(0.05)**	23,243	4.11(0.20)***	23,243
13:00-13:30	-0.05(0.02)**	34,183	3.37(0.19)***	34,183
		Middle Market Caps		
9:00-9:30	0.18(0.03)***	44,497	-0.62(0.16)***	44,497
9:30-10:00	-0.14(0.04)***	45,936	0.77(0.22)***	45,936
10:00-10:30	-0.20(0.06)***	43,296	1.31(0.27)***	43,296
10:30-11:00	-0.22(0.08)**	42,194	5.09(0.21)***	42,194
11:00-11:30	-0.16(0.07)*	41,344	7.58(0.35)***	41,344
11:30-12:00	-0.19(0.08)*	40,481	9.87(0.40)***	40,481
12:00-12:30	-0.06(0.03)*	40,388	8.47(0.52)***	40,388
12:30-13:00	-0.12(0.05)**	41,653	6.33(0.31)***	41,653
13:00-13:30	-0.09(0.03)***	45,273	4.08(0.22)***	45,273
		Largest Market Caps		
9:00-9:30	0.29(0.06)***	34,166	-0.65(0.17)***	48,159
9:30-10:00	-0.23(0.05)***	32,370	0.89(0.25)***	47,914
10:00-10:30	-0.29(0.06)***	30,476	1.66(0.31)***	47,595
10:30-11:00	-0.35(0.08)***	30,213	5.33(0.26)***	47,329
11:00-11:30	-0.29(0.07)***	29,797	8.12(0.47)***	47,050
11:30-12:00	-0.30(0.09)***	30,258	10.44(0.57)***	46,864
12:00-12:30	-0.14(0.04)***	30,549	10.95(0.61)***	46,846
12:30-13:00	-0.24(0.06)**	32,114	8.60(0.49)***	47,239
13:00-13:30	-0.17(0.04)***	38,055	5.13(0.39)***	48,091

1. Standard deviations are in the parentheses.
2. *: Significant at 10%; **: Significant at5%; ***: Significant at1%.