Searching out of Trading Noise:

A Study of Intraday Transactions Cost

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Abstract

We attempt to identify in this paper the role of trading noise as a transactions cost to market participant in the sense of Stoll (2000), especially in the presence of trading concentration. Applying the measures of Hu (2006) and Kang and Yeo (2008), we analyze the noise proportion in intraday stock returns and its interaction with investor herding and search cost. 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. We also found that noise relates positively to trading volume, but inversely to holdings and turnover ratio of institutional investors. Responses from institutional and individuals are quite the opposite. The noise proportion generated by individual order rises with institutional turnover and search cost encountered, while that of institutional order behaves just oppositely. At market open, behaviors of noise from institutional and individual orders just switch mutually, and then switch back afterwards. Also, 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 search costs encountered in trading, which depends on investor, trading hour of day and market capitalization of stocks.

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 take the form of either 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)) or search cost as modeled in Vayanos and Wang (2007, VW). This study addresses the role of trading noise as a transactions cost to market participant, especially in the presence of trading concentration. Specifically, we attempt to verify if trading noise really qualifies to be a general transactions cost, or a market friction, in an intraday framework.

It has been well document 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) suggested that the high volatility is caused by friction, a general transaction cost for everyone in the market. Alternatively, Lakonishok, Shleifer, and Vishny (1992, LSV), Choe, Kho and Stulz, (1998), Wermers (1999) as well as Bowe and Domuta (1998) stressed that volatility is closely related to information-induced herding. However, VW and Lin, Tsai and Sun (2010) argue that price variations from trading concentration should be considered as a specific, rather than general, transaction cost. Based on that notion, an investor can optimize by allocating trades over when transaction cost specific to the investor is the most favorable. Hu (2006) applied a return decomposition mechanism to conclude that specific transaction cost causes the market to be volatile at open since frictional noises are the smallest during the day. We adopt this concept but attempt to identify its driving factor, as how Lin, et *al*. (2009) analyses factors behind trading concentration.

We found that noise component of return volatility is stronger when trading is more concentrated, suggesting a different perspective from Lin, Sanger, and Booth (1995) and Hu (2006). Although the time needed to fill an order, or the inverse of the number of orders matched with a certain time window, produces less noise, it is quite the contrary at market open. Moreover, we argue noise is influenced more by trading concentration, at open, when search cost prevails in market transaction, than at close. We also found that limit order book dispersion, which measures how tightly the orders are placed to each other or how closely they are to the midquote, affect trading noise. But the pattern for foreign institutional is just the opposite to that for individual investors. Response of noise to order dispersion, or search cost, differs by market capitalizations as well as by trading hours.

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, one more suitable for longer time frame. In the context of investor herding, we adopted a cost-based framework of trading concentration to see how return volatility decomposition should be evaluated. The dynamic trading intensity helps us capturing how ‘friction’ really arise 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.

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. We also found that noise relates positively to trading volume, but inversely to holdings and turnover ratio of institutional investors. Nnot only falls when herding is the most significant, but also inversely related to search cost proxies. Over an intraday session, although noise increases over time, it is influenced less and less by investor herding. Moreover, trading noise is also found to be sensitive to only certain investors in the market when they trade heavily. Only investors with lower search cost drives up market noise in heavy trading. Trading noise maybe just a specific transaction cost, as information cost, prominent to only 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 could well be just another kind of specific cost, rather than a market friction.

Our study helps identifying for various types of investors a more cost-efficient time to trade. Both individual and foreign institutional investors (FII’s), although facing higher search cost, 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 do not concentrate. The results of this study contribute highly to the understanding of search cost and its influence on noise. 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 heavily concentrated, noise plays a more important role. Literatures have 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, standard models feature strong countervailing effects. 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), argued that noise trading does not reduce informational efficiency. Furthermore, Kyle (1985) suggested that noise trading improves informational efficiency.

However, competing models contend that rational agents do not fully offset noise traders' demands because of various limits to arbitrage. De Long, Shleifer, Summers, and Waldmann (1990) indicated rational arbitrageurs sometimes reinforce demand shocks from noise traders because they anticipate mispricing will worsen in the short-run. Bikhchandani and Sharma (2001) classified 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.

Many have studied situations of trading against one's own private information (e.g., Jarrow (1992), Allen and Gale (1992), Allen and Gorton (1992), Chakraborty and Yilmaz (2004a)) in the analysis of market manipulation, where the informed may trade in a wrong direction to increase noise in trading volume. They tend to adopt models other than Kyle (1985). There are several studies modeling trading manipulation with variations of Kyle (1985), such as Chakraborty and Yilmaz (2004) and Huddart, Hughes, and Levine (2001). 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. Literatures argue that the herding arises from the interaction among agents as they copy each other's decisions. The models of BHW and Bannerjee (1992) considered 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) considered, instead of a sequential decision process, a random communication structure. Random interactions between agents lead to a heterogeneous market structure. AZ argues that information cascades 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,

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

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

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

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

$$E_t[P_t - P_{t+j}] = n_t \text{ as j}\rightarrow\infty \tag{3}$$

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

$$\frac{Var(n_t - n_{t-1})}{Var(P_t - P_{t-1})}$$

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. 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. 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. We also found that noise relates positively to trading volume, but inversely to holdings and turnover ratio of institutional investors.

We found that noise proportion of stock returns not only falls when herding is the most significant, but also inversely related to search cost proxies. Over an intraday session, although noise increases over time, it is influenced less and less by investor herding. Moreover, trading noise is also found to be sensitive to only certain investors in the market when they trade heavily. Only investors with lower search cost drives up market noise in heavy trading. Trading noise maybe just a specific transaction cost, as information cost, prominent to only 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 could well be just another kind of specific cost, rather than a market friction.

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, one more suitable for longer time frame. In the context of investor herding, we adopted a cost-based framework of trading concentration to see how return volatility decomposition should be evaluated. The dynamic trading intensity helps us capturing how 'friction' really arise 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. Most of the studies carried out to test for herding in capital markets have proved inconclusive. 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

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

expected.

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

Where r_i is the actual number of type i runs (up runs, down runs or zero runs), n is the total number of 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 percentages, not reported here, suggest that intraday trading concentration is heavier in the opening interval. Table II 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, and the ratios for FII's and Proprietary Dealers are higher than their counterpart in all periods. 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 as both rise 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 lower 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.

A model of trading concentration

VW proposed a model with two assets traded in two markets respectively. Measures of buyers and sellers of asset *i* are denoted by μ_b^i and μ_s^i respectively. For the buyers, there is a possibility of either enjoying the full value of the dividend flow or switching to a lower level with a Poisson rate of κ. Because buyers differ in their switching rates κ, they have different reservation values in the bargaining game. Investors are heterogeneous in their horizons, which are inversely related to the switching rates κ. More trading could be generated by shorter horizons as it reduces search times and trading costs. Switching rates could correspond to buyers' characteristics, such as long horizon is more relevant to insurance companies, while shorter ones belong to hedge funds. A clientele equilibrium where market 1 is the one with the most sellers has the following properties:

(a) More buyers and sellers in market 1: $\mu_b^1(\kappa) > \mu_b^2(\kappa)$ and $\mu_s^1(\kappa) > \mu_s^2(\kappa)$

(b) Higher buyer-seller ratio in market 1: $\mu_b^1(\kappa)/\mu_s^1(\kappa) > \mu_b^2(\kappa)/\mu_s^2(\kappa)$

(c) Higher prices in market 1: $p^1(\kappa) > p^2(\kappa)$ for all κ.

Market 1 has not only more sellers than market 2, but also more buyers, and a higher buyer-seller ratio[4]. Moreover, the price that any given buyer expects to pay is higher in market 1. Since there are more sellers in market 1, buyers' search times are shorter. Therefore, holding all else constant, buyers prefer entering into market 1. To restore equilibrium, prices in market 1 must be higher than in market 2. This is accomplished by higher buying pressure in market 1, i.e., higher buyer-seller ratio. In the resulting equilibrium, there is a clientele effect. Investors with high switching rates, who have a stronger preference for short search times, prefer market 1 despite the higher prices. On the other hand, low-switching-rate investors, who are more patient, value more the lower prices in market 2. The clientele effect is, in turn, what accounts for the larger measure of sellers in market 1 since the high-switching-rate buyers turn faster into sellers. So in essence, cost characteristics of investors determine concentration of trading and prices, rather than information about the assets.

Individual investors trading for own accounts with unleveraged funds are supposed to have

[4] Summary statistics from our data do indicated that average total buy orders, sell orders and their ratios of a stock in a given day are 498, 487 and 1.1035 respectively for days when herding measures are not significant. For days with significant herding measures, however, the corresponding figures are 3,281, and 1.4420 respectively.

lower switching rates and prefer market 2 in the model above. However, when market moves fast, lack of knowledge could elevate their switching rates so they turn to trade in market 1 instead. Naturally, there should be more herding from the individual and FII' s, according to prediction (a) and (b), especially at market open and close. If the ratio of number of buyer to that of seller contributes more to the buildup of trading noise, we would conclude that search cost, or the specific transaction cost, prevails in that occasion, and vice versa. In a quote-driven market setup, difference of composite buy and sell order price would be a good proxy for short term search cost too. Similarly, the time needed to fill a buy or sell order in a given period measures the cost of searching as well.

A measure of order dispersion

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 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) and Wei (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 measure by modifying the dispersion measure of Kang and Yeo (2008). The dispersion measure of stock i in a given day is defined as

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

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 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 Dsp_i to be comparable across stocks and various types of investors.

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, *et at.* (2008) which argued 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.

After applying the decomposition scheme in (1) and we report in Table III the noise proportion in return volatility, for the entire day and each intraday interval, for all and each type of investors and across different degrees of trading concentration, rise from open to close, as in Hu (2006). However, when there is significant trading concentration, trading noise proportion could fall from open to close. 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), this general transaction cost should apply to everyone in the market, regardless of market capitalization of stocks or which trading hour it is.

In order to explore the effects of trading concentration 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

$$N_{k,t} = \alpha + \beta AH_{k,t} + \varepsilon_{k,t} \tag{8}$$

where t=1,…,461 and k=1,…,525. A greater β in magnitude implies stronger noise is produced by more intensive herding activity. Table V gives the result of this model. Although the direction of β is consistent with its counterpart, with one lag, in Table IV, the distribution across intraday intervals and herding significance reveals a somewhat different implication. 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%. In another word, when trading is heavily concentrated, the degree of concentration contributes much less to trading noise. This is inconsistent with what we might want to conclude from Table IV. Trading concentration possibly prevents noise from going up. When trading is not heavy, it affects noise more, but not otherwise.

Lin, Tsai and Sun (2010) argued that trading concentration is closely related to the search cost model of VW. We intend to find out how, if any, search motive may affect noise in trading on an intraday level with the follow model,

$$N_{k,t} = \alpha + \gamma_1 Spread_{k,t} + \gamma_2 BFT_{k,t} + \gamma_3 SFT_{k,t} + \gamma_4 BSR_{k,t} + \varepsilon_{k,t} \tag{9}$$

where t=1,…,461 and k=1,…,525. We performed a panel regression with generalized least squares random effect. Implications of estimated parameters are as follows. The spread effect of search cost is proxied by *BSD*, the average price difference within the period of interest for buy and sell orders associated with transaction prices on a given stock. The search times of buy and sell orders are proxied by, *BFT* and *SFT* respectively. The former is the Ave. time to fill a buy order within the period of interest, while the latter is that to fill a sell order. A particular transaction price could correspond to more than one orders placed at different times. *BSR* is the ratio between total buy and sell orders for a given stock on a given day. A greater γ_1 implies stronger noise is accompanied by larger order price spreads, suggesting a weaker search cost effect. Greater γ_2 and γ_3 imply a stronger noise is induced by a longer search time for an equilibrium price, suggesting a stronger the search cost effect. A greater γ_4 in magnitude implies stronger noise is accompanied by higher buyer-seller ratios, indicating VW search model drives trading noise. The results of this model are given in Table V, rendering more insight in an intraday dimension. The bottom panel of Table IV shows that trading noise is much less likely to be driven by search cost when trading concentrates, and the weakest tie between noise and search cost happens at market close. This implies that trading noise is more compatible with a situation where not all market participants are bearing the transaction cost of noise. The estimation for time-to-fill and buy-sell ratio both supports the notion above.

Table VI reports the summary statistics of the order dispersion measure. Dsp_i 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. So the reported figures in Table V give for the whole market or each type of investor the relative extent of dispersion of the respective interval. It is apparent that order price dispersion goes down uniformly regardless or investor type. The dispersion of individual investor, however, exhibits the highest fluctuation. It is not only substantially higher than the other two types at market open, but is also much lower at market close. Order price of foreign institutional investors has the smallest dispersion swing, showing the lowest dispersion at market open and the highest dispersion at market close. The results in Table VI suggests that individual investors may have enjoyed the relatively lower search cost, and therefore producing more conservative order price pattern, at market open but the highest liquidity pressure at market close. If information is the cause of this distribution, we would expect to see a U-shaped pattern.

To determine factors that could have influenced order price dispersion, and hence the distribution pattern in Table VI, we chose turnover ratio, holdings and trading volume of foreign and domestic institutional investors to see how they affect trading noise. Specifically, we apply the following model on our data,

$$N_{k,t} = \alpha + \gamma_1 FII\_TO_{k,t} + \gamma_2 DI\_TO_{k,t} + \gamma_3 FII\_Share_{k,t} + \gamma_4 DI\_Share_{k,t} + \gamma_5 FII\_Vol_{k,t} + \gamma_6 DI\_Vol_{k,t} + \varepsilon_{k,t} \quad (10)$$

where t=1,…,461 and k=1,…,525. Results are estimated using a panel GLS with AR(1) adjustments on residuals. Results for the entire market are reported in Table VII, which shows that for low-cap stocks trading noise is influenced only, and positively, by institutional holdings. But for high-cap stocks, trading noise is affected by all six factors. But the effect of institutional holdings is negative, while that of FII trading volume is positive. This indicates that the rare case of high institutional holding of a certain small-cap stock causes difficulty in trading that specific stock and hence induce higher trading noise there. However, in large-cap stocks which institutionals favor, higher turnover caused by larger holding actually reduces trading noise for these investors.

Applying (10) for different types of investors, we could only report in Table VIII results for FII's and individuals, as the model for domestic institutional does not pass the validation test. For FII's, only results for the largest market capitalization are available, and reported at the bottom panel, as there are not enough orders submitted for the other four levels. They are similar to the results for large-cap in Table VII in that trading noise is reduced by turnover ratio. But FII holding and trading volume contributes positively to the build-up of trading noise. In the case of individuals, the results are quite apart from those for FII's, suggesting institutional turnover of a given stock somehow induces trading noise for individuals, especially in large-cap stocks. In small-cap stocks, institutional turnover is not influential, probably because institutional investors hold and trade less in this category.

The results of VII and VIII provide us a preliminary basis for the exploration of factors driving trading liquidity. Information may not be the main cause behind the observed facts, as large-cap should have the best information quality among all. So we take a further look at the effect of order price dispersion on trading noise. The following model is considered for this purpose,

$$N_{k,t} = \alpha + \gamma_1 Dsp_{k,t} + \varepsilon_{k,t} \quad (11)$$

where t=1,…,461 and k=1,…,525. Results are estimated using a panel GLS with AR(1) adjustments on residuals and reported in Table IX. 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 validates the distribution pattern of Table VI, supporting notion that low search cost for individuals at market open induces heavy trading and 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 V.

IV. Conclusion

This study examines intra-day order book data to study trading noise within stock volatility, particularly when trading is heavy, and its driving factors. We adopted 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. Although the analysis in the study is still preliminary, we have found strong evidences against the idea of trading being a general transaction cost, or a friction in market trading. Specifically, we found that trading noise on an intraday level, although tend to increase from market open to close, is less likely to take place when trading is concentrated at market close. If trading noise is not compatible with phenomena observed during heavy trading, then it may not be a general transaction cost. It somewhat explains why noise does not respond to heavy trading as much as to all trades when we examine the market as a whole. 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. We also found that noise relates positively to trading volume, but inversely to holdings and turnover ratio of institutional investors. Trading noise is also found to be sensitive to only certain investors, at certain trading hour and for stocks of certain market capitalization, in the market when they trade heavily. Responses from institutional and individuals are quite the opposite. The noise proportion generated by individual order rises with institutional turnover and search cost encountered, while that of institutional order behaves just oppositely. At market open, behaviors of noise from institutional and individual orders just switch mutually, and then switch back afterwards. Also, 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 search costs encountered in trading, 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 distribution among 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.

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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
MV1*	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
MV2	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
MV3	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
MV4	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
MV5	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
MV6	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
MV7	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
MV8	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
MV9	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
MV10	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

* MV1 denotes the decile containing stocks with the largest market capitalization.

Table II 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 III 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 IV 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

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

where t=1,…,495 and k=1,…,525. A greater β in magnitude implies stronger noise is produced by more intensive herding 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 V Effects of Search Cost on Noise in Panel Regression

Intraday Intervals

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

$$N_{k,t} = \alpha + \gamma_1 Spread_{k,t} + \gamma_2 BFT_{k,t} + \gamma_3 SFT_{k,t} + \gamma_4 BSR_{k,t} + \varepsilon_{k,t}$$

where t=1,…,495 and k=1,…,525. Implications of estimated parameters are similar to those detailed the illustration of Table IV.

Intraday interval	γ_1 (x100)	γ_2 (x1000)	γ_3 (x1000)	γ_4 (x100)	No. of obs.
			All days		
9:00-9:30	-3.810(0.028)***	0.070.003)***	0.010(0.000)***	-0.680(0.029)***	222,711
9:30-10:00	-2.090(0.035)***	-0.012(0.001)***	-0.026(0.000)***	1.420(0.032)***	217,529
10:00-10:30	-1.600(0.038)***	-0.016(0.001)***	-0.022(0.000)***	1.620(0.032)***	213,436
10:30-11:00	-1.260(0.040)***	-0.012(0.001)***	-0.015(0.000)***	1.690(0.031)***	209,637
11:00-11:30	-1.000(0.041)***	-0.010(0.000)***	-0.014(0.000)***	1.720(0.031)***	206,076
11:30-12:00	-0.740(0.041)***	-0.008(0.000)***	-0.012(0.000)***	1.850(0.029)***	202,803
12:00-12:30	-0.600(0.041)***	-0.009(0.000)***	-0.010(0.000)***	2.030(0.032)***	202,750
12:30-13:00	-0.710(0.040)***	-0.010(0.000)***	-0.009(0.000)***	2.210(0.034)***	208,049
13:00-13:30	-0.520(0.038)***	-0.011(0.000)***	-0.011(0.000)***	-1.890(0.049)***	223,711
			Days when herding is significant at 10%		
9:00-9:30	4.470(0.028)***	0.261(0.003)***	-0.218(0.003)***	0.540(0.173)**	22,298
9:30-10:00	10.340(0.035)***	-0.040(0.001)**	-0.094(0.008)***	0.030(0.144)	21,815
10:00-10:30	10.590(0.038)***	-0.004(0.010)	-0.051(0.006)***	-0.120(0.179)	21,402
10:30-11:00	11.450(0.040)***	0.000(0.008)	-0.033(0.005)***	-0.130(0.164)	20,944
11:00-11:30	12.270(0.041)***	-0.016(0.006)**	-0.027(0.004)***	-0.130(0.128)	20,650
11:30-12:00	12.190(0.041)***	-0.008(0.005)*	-0.026(0.004)***	-0.110(0.167)	20,416
12:00-12:30	13.440(0.041)***	-0.013(0.004)***	-0.024(0.003)***	-0.150(0.175)	20,464
12:30-13:00	13.290(0.040)***	-0.019(0.004)***	-0.024(0.002)***	-0.380(0.201)*	20,959
13:00-13:30	13.220(0.038)***	-0.020(0.003)***	-0.025(0.001)***	-0.610(0.208)***	22,497

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

Table VI Dispersion of Order Book up to the Fifth Best Orders

relative to daily average, across 525 firms and over 461 days

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

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

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. The 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 and shows the competitiveness between the limit order traders. The higher the dispersion is, the less tight the book is, and the lower amount of liquidity the limit order book provides.

Intraday Intervals	Whole Market	Domestic Institutionals	Foreign Institutionals	Individuals
09:00-09:30	6.55%	0.99%	0.12%	14.10%
09:30-10:00	1.87%	0.19%	0.05%	2.17%
10:00-10:30	-0.24%	0.11%	0.03%	-0.19%
10:30-11:00	-1.24%	0.06%	0.00%	-1.27%
11:00-11:30	-2.13%	0.01%	-0.01%	-2.23%
11:30-12:00	-2.76%	0.00%	-0.03%	-2.90%
12:00-12:30	-3.28%	0.00%	-0.06%	-3.47%
12:30-13:00	-3.61%	0.04%	-0.05%	-3.91%
13:00-13:30	-3.81%	-0.90%	-0.04%	-4.28%

Table VII Effects of Stock Characteristics on Noise in Panel Regression

Whole Market, 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

$$N_{k,t} = \alpha + \gamma_1 FII\_TO_{k,t} + \gamma_2 DI\_TO_{k,t} + \gamma_3 FII\_Share_{k,t} + \gamma_4 DI\_Share_{k,t} + \gamma_5 FII\_Vol_{k,t} + \gamma_6 DI\_Vol_{k,t} + \varepsilon_{k,t}$$

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

Intraday interval	γ_1 (x100)	γ_2 (x1000)	γ_3 (x10)	γ_4 (x10)	γ_5 (x10^5)	γ_6(x10^5)
			Smallest Market Caps			
9:00-9:30	-1.43(0.59)*	-0.21(0.68)	0.49(0.23)**	-7.38(1.67)***	-2.06(0.72)**	0.52 (1.03)
9:30-10:00	-0.43(0.29)	-0.86(0.68)	0.51(0.21)**	-11.32(1.65)***	-0.39(0.75)**	0.69 (1.09)
10:00-10:30	-0.38(0.32)*	-1.31(0.81)	0.18(0.22)	-12.41(1.67)***	2.20(0.78)**	1.98 (1.13)*
10:30-11:00	-0.42(0.36)*	-1.57(0.94)*	0.50(0.26)**	-10.87(1.86)***	0.42(1.31)	0.80 (1.18)
11:00-11:30	-0.65(0.32)**	-1.16(0.85)	0.61(0.24)**	-11.51(1.84)***	0.90(1.39)	-0.09 (1.20)
11:30-12:00	0.25(0.30)	0.06(0.84)	0.21(0.22)	-11.27(1.71)***	-1.06(0.87)**	0.73 (1.22)
12:00-12:30	-0.44(0.33)	0.07(0.90)	0.39(0.24)	12.50(1.85)***	1.88(1.47)	0.86 (1.23)
12:30-13:00	-0.12(0.39)	-0.86(0.87)	0.88(0.24)***	-10.13(1.65)***	1.54(1.49)	0.65 (1.21)
13:00-13:30	-0.02(0.28)	0.15(0.69)	0.84(0.21)**	-10.17(1.71)***	0.39(0.78)**	1.34 (1.04)
			Middle Market Caps			
9:00-9:30	-0.18(0.17)	-0.56(0.64)	-1.38(0.09)***	-8.37(0.23)***	-0.09(0.06)	-0.23 (0.08)**
9:30-10:00	-0.27(0.17)	0.05(0.69)	-1.30(0.09)***	-7.96(0.22)***	0.02(0.07)	0.16 (0.08)**
10:00-10:30	-0.31(0.31)	-0.12(0.65)	-1.36(0.16)***	-7.30(0.36)***	-0.46(0.31)	1.07 (0.22)**
10:30-11:00	0.03(0.22)	0.71(0.87)	-1.38(0.10)***	-7.45(0.23)***	0.10(0.09)	0.28 (0.10)**
11:00-11:30	-0.30(0.25)	-0.70(0.91)	-1.15(0.11)***	-7.23(0.22)***	0.02(0.09)	0.34 (0.11)***
11:30-12:00	-0.41(0.24)	0.10(0.90)	-1.15(0.010)***	-7.56(0.23)***	0.02(0.09)	0.40 (0.11)***
12:00-12:30	-0.34(0.23)	0.09(1.00)	-1.08(0.10)***	-6.62(0.22)***	0.02(0.10)	0.17 (0.11)**
12:30-13:00	-0.29(0.22)	1.35(0.81)*	-1.40(0.10)***	-7.36(0.23)***	-0.01(0.08)	0.18 (0.10)**
13:00-13:30	-0.51(0.18)**	1.21(0.75)	-1.55(0.09)***	-7.50(0.22)***	-0.12(0.08)	0.13 (0.09)**
			Largest Market Caps			
9:00-9:30	-12.51(1.59)***	-5.87(1.38)***	-3.15(0.06)***	-16.89(0.42)***	0.03(0.00)***	-0.14 (0.01)***
9:30-10:00	-12.00(1.79)***	-3.00(1.35)***	-3.06(0.06)***	-16.45(0.38)***	0.04(0.00)***	-0.07 (0.01)***
10:00-10:30	-11.59(1.82)***	-2.29(1.37)*	-3.14(0.06)***	-16.16(0.38)***	0.05(0.00)***	-0.05 (0.02)***
10:30-11:00	-13.59(1.98)***	-3.37(1.51)**	-3.22(0.06)***	-16.28(0.38)***	0.06(0.00)***	-0.01 (0.01)
11:00-11:30	-18.71(2.16)***	-3.14(1.71)***	-3.20(0.06)***	-15.80(0.37)***	0.06(0.00)***	-0.04 (0.02)**
11:30-12:00	-13.56(2.17)***	-5.16(1.68)**	-3.12(0.06)***	-16.00(0.35)***	0.06(0.00)***	-0.04 (0.02)***
12:00-12:30	-15.65(1.14)***	-3.32(1.57)**	-3.04(0.06)***	-16.05(0.36)***	0.06(0.00)***	-0.06 (0.02)***
12:30-13:00	-16.87(2.03)***	-3.52(1.51)**	-2.97(0.06)***	-16.77(0.37)***	0.05(0.00)***	-0.02 (0.01)**
13:00-13:30	-12.04(1.82)***	-6.11(1.48)***	-3.02 (0.06)***	-17.46(0.39)***	0.04(0.00)***	-0.05 (0.02)**

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

Table VIII Effects of Stock Characteristics on Noise in Panel Regression

Foreign Institutional and Individual Investors, by Market Caps

To explore the effects of search motive on intraday 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

$$N_{k,t} = \alpha + \gamma_1 FII\_TO_{k,t} + \gamma_2 DI\_TO_{k,t} + \gamma_3 FII\_Share_{k,t} + \gamma_4 DI\_Share_{k,t} + \gamma_5 FII\_Vol_{k,t} + \gamma_6 DI\_Vol_{k,t} + \varepsilon_{k,t}$$

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

Intraday interval	γ_1 (x100)	γ_2 (x1000)	γ_3 (x10)	γ_4 (x10)	γ_5 (x10^5)	γ_6(x10^5)
			Smallest Market Caps - Individuals			
9:00-9:30	-0.31(0.41)	2.73(1.67)	3.07(0.80)***	52.56(4.20)***	3. 40(1.42)**	13.19(2.25)***
9:30-10:00	0.70(0.41)	2.53(1.70)	3.04(0.73)***	34.44(3.76)***	6. 71(1.47)***	23.10(2.23)***
10:00-10:30	0.79(0.38)**	-1.68(1.72)	3.18(0.63)***	24.33(3.61)***	5. 77(1.60)***	30.63(2.37)***
10:30-11:00	0.68(0.38)*	-0.20(1.66)	2.89(0.55)***	22.73(3.39)***	8. 50(1.77)***	24.15(2.30)***
11:00-11:30	0.15(0.33)	-0.44(1.67)	2.12(0.50)***	18.66(3.29)***	6. 67(1.62)***	27.45(2.23)***
11:30-12:00	-1.12(1.18)	-3.25(1.58)**	2.76(0.53)***	16.60(3.22)***	23.40(2.88)***	26.13(2.23)***
12:00-12:30	0.19(0.46)	0.98(1.60)	1.40(0.46)***	17.35(3.12)***	20.24(2.85)***	19.13(2.18)***
12:30-13:00	1.92(0.43)***	-0.06(1.70)	1.57(0.52)***	15.82(3.04)***	6. 07(1.63)***	23.54(2.21)***
13:00-13:30	0.36(0.32)	3.02(1.44)**	1.30(0.61)***	38.19(3.69)***	7. 41(1.48)***	21.63(2.02)***
			Middle Market Caps - Individuals			
9:00-9:30	-16.59(3.91)***	-35.20(6.51)***	14.27(0.15)***	-6.67(0.50)***	0.93(0.02)***	0.27 (0.07)***
9:30-10:00	-16.77(3.58)***	-28.03(6.05)***	12.77(0.14)***	-4.62(0.45)***	0.94(0.02)***	0.27 (0.07)***
10:00-10:30	-21.46(4.27)***	-40.98(7.84)***	12.58(0.15)***	-4.88(0.49)***	0.91(0.02)***	0.36 (0.07)***
10:30-11:00	-20.68(4.53)***	-54.41(8.89)***	12.73(0.15)***	-5.45(0.53)***	0.91(0.02)***	0.47 (0.07)***
11:00-11:30	-18.50(4.50)***	-60.18(9.88)***	12.85(0.15)***	-6.52(0.55)***	0.86(0.02)***	0.53 (0.08)***
11:30-12:00	-13.18(4.29)***	-50.76(10.1)***	13.56(0.16)***	-6.75(0.55)***	0.85(0.02)***	0.43 (0.08)***
12:00-12:30	-19.24(4.98)***	-25.24(6.38)***	13.90(0.16)***	-6.74(0.59)***	0.88(0.02)***	0.51 (0.08)***
12:30-13:00	-16.03(4.70)***	-31.21(7.16)***	14.79(0.16)***	-6.66(0.57)***	0.84(0.02)***	0.55 (0.08)***
13:00-13:30	-13.56(3.30)***	-18.56(4.57)***	13.49(0.13)***	-5.30(0.40)***	0.85(0.02)***	0.27 (0.06)***
			Largest Market Caps – Foreign Intitutionals			
9:00-9:30	8.74 (3.77)**	7.10(3.60)**	0.07(0.06)	-1.94(0.20)***	0. 09(0.01)***	-0.06(0.03)*
9:30-10:00	21.56(4.12)***	16.95(3.97)***	0.66(0.08)***	0.55(0.24)**	0. 07(0.01)***	0.11(0.03)***
10:00-10:30	36.12(4.64)***	18.05(4.41)***	1.07(0.10)***	1.82(0.29)***	0. 09(0.01)***	0.25(0.04)***
10:30-11:00	51.96(5.20)***	19.61(4.81)***	1.61(0.11)***	3.70(0.33)***	0. 11(0.01)***	0.40(0.04)***
11:00-11:30	63.50(5.48)***	24.13(4.94)***	1.98(0.12)***	4.48(0.37)***	0. 14(0.01)***	0.55(0.04)***
11:30-12:00	77.99(5.90)***	35.91(5.06)***	2.32(0.12)***	5.06(0.38)***	0. 15(0.01)***	0.61(0.04)***
12:00-12:30	75.48(5.81)***	37.05(5.01)***	2.26(0.12)***	5.30(0.39)***	0. 16(0.01)***	0.65(0.05)***
12:30-13:00	61.27(5.41)***	29.05(4.65)***	1.76(0.11)***	2.73(0.35)***	0. 11(0.01)***	0.43(0.04)***
13:00-13:30	30.35 (4.68)***	8.31(4.21)**	0.87(0.08)***	0.35(0.26)	0. 09(0.01)***	0.19(0.04)***
			Largest Market Caps - Individuals			
9:00-9:30	8.74 (3.77)**	7.10(3.60)**	0.07(0.06)	-1.94(0.20)***	0. 09(0.01)***	-0.06(0.03)*
9:30-10:00	21.56(4.12)***	16.95(3.97)***	0.66(0.08)***	0.55(0.24)**	0. 07(0.01)***	0.11(0.03)***
10:00-10:30	36.12(4.64)***	18.05(4.41)***	1.07(0.10)***	1.82(0.29)***	0. 09(0.01)***	0.25(0.04)***
10:30-11:00	51.96(5.20)***	19.61(4.81)***	1.61(0.11)***	3.70(0.33)***	0. 11(0.01)***	0.40(0.04)***
11:00-11:30	63.50(5.48)***	24.13(4.94)***	1.98(0.12)***	4.48(0.37)***	0. 14(0.01)***	0.55(0.04)***
11:30-12:00	77.99(5.90)***	35.91(5.06)***	2.32(0.12)***	5.06(0.38)***	0. 15(0.01)***	0.61(0.04)***
12:00-12:30	75.48(5.81)***	37.05(5.01)***	2.26(0.12)***	5.30(0.39)***	0. 16(0.01)***	0.65(0.05)***
12:30-13:00	61.27(5.41)***	29.05(4.65)***	1.76(0.11)***	2.73(0.35)***	0. 11(0.01)***	0.43(0.04)***
13:00-13:30	30.35 (4.68)***	8.31(4.21)**	0.87(0.08)***	0.35(0.26)	0. 09(0.01)***	0.19(0.04)***

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

Table IX Effects of Stock Characteristics on Noise in Panel Regression

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

$$N_{k,t} = \alpha + \gamma_1 Dsp_{k,t} + \varepsilon_{k,t} \quad \text{with} \quad Dsp_{k,t} = \frac{1}{2}\left[\frac{\sum_{j=1}^{5} w_j^b Dst_j^b}{\sum_{j=1}^{5} w_j^b} + \frac{\sum_{j=1}^{5} w_j^s Dst_j^s}{\sum_{j=1}^{5} w_j^s}\right]$$

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 γ_1 (x1000)	FII's *No. of Obs.*	Individuals γ_1 (x100)	Individuals *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%.