

Trade Size and the Cross Section of Stock Returns: Informed versus Noise Traders in the Chinese Growth Enterprise Market

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ABSTRACT

We examine the impact of trade size on short-term stock returns in China's recently established Growth Enterprise Market (GEM) using a dataset uniquely suited for this purpose. We find that the size of trades relative to a stock's market capitalization (or trade volume) is significantly related to the stock's short-term contemporaneous returns. Small noise trades exhibit consistent loss trading behavior in contrast to large informed trades. More specifically, for each percentage increase of a stock's relative volume by noise trades, the stock price loses 0.07% daily, 0.37% weekly, and 0.66% biweekly. Trading behavior by small noise traders is a significant contrarian signal to short term contemporaneous return performance.

JEL Classifications: G02, G11, G12, G14, G15

Keywords: trade size; informed traders; stock returns; Chinese GEM

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I. INTRODUCTION

The trade characteristics of informed versus noise traders are of great research interest. DeLong, et al. (1990) theorize that noise traders could earn higher expected return than risk averse informed traders by creating more noise risks than arbitrageurs are willing to bet against. Odean (1999), Barber and Odean (2000), and Hvidkjaer (2008) find that stocks bought by individual noise traders tend to significantly underperform those stocks they sold.

Researchers have also presented opposing evidence of trade size impact on stock returns. On one hand, trade size is significant in addition to number of trades and trade imbalance so that trade size and information set are positively correlated (Kim and Verrecchia, 1991; Chan and Fong, 2000), adverse selection (when small traders piggyback on large informed trades) is therefore a problem. Large trades impose greater price impacts than smaller trades do (Dufour and Engle, 2000; Easley and O'Hara, 1987; Easley et al., 1997; Holthausen et al., 1987, 1990; Lin et al., 1995).

On the other hand, Jones et al. (1994) find that the number of trades is significant, but not the size of trade. In addition, informed investors may camouflage or cloak their trades in package by splitting orders to reduce the adverse selection, thus medium-sized (or even small) trades have bigger price impact than large trades. (Alexander and Peterson, 2007; Chakravarty, 2001; Chan and Lakonishok, 1995; Hasbrouck, 1995; Keim and Madhavan, 1995; Barclay and Warner, 1993; Kyle, 1985).¹ Chan and Lakonishok (1995) also find that the order-splitting behavior often takes four or more days.² Chordia and Subrahmanyam (2004) provide theoretical framework that motivates traders to split their orders.

Griffin et al. (2003) find that "stocks with the largest institutional sell imbalances experience an extremely low (contemporaneous) excess return of -4.29%, whereas stocks with the largest institutional buying activity experience a 3.69% excess return" (p. 2295). Campbell et al. (2009) also find that institutions tend to be daily momentum traders that demand liquidity with near-term negative returns but contrarian investors for relatively longer term that earn positive returns. Also, the demand for liquidity is higher for sales than for buys. The finding seems to suggest that large traders may not have trading advantage over small traders in the short term.

Asthana et al. (2004) show that small traders do trade correctly on and benefit (more than large traders) from annual report filings on EDGAR. However, the direct gains or losses of small versus large trades are not directly tested.

Foster et al. (2011) find that "neither the number of funds trading, nor the volume of shares purchased and sold by institutions is correlated with contemporaneous stock returns" (p. 3384) because the dynamics of growth and value managers tend to offset the impact on price changes. Their sample includes only the largest 50 stocks listed on the Australian Securities Exchange.

Kaniel et al. (2008) find that contrarian individuals gain positive subsequent excess monthly returns trading against institutions demanding for immediacy. Dorn et al. (2008) and Barber et al. (2009) both find that individual investors herd -- they tend to trade the same stocks in the same direction at the same time. The former find that individual investors' net limit buy orders are negatively (positively) correlated with contemporaneous (following) weekly returns. The latter, however, find that stocks

mostly purchased (sold) by small investors yield significantly positive (negative) returns in the current and following week; the subsequent weekly pattern is opposite for stocks dominated by large trades.

In this paper, we examine the impact of trade size on stock returns on China's recently established Growth Enterprise Market (GEM). The GEM started trading on Oct. 1, 2009 and is China's own NASDAQ-style market to foster the growth of young, entrepreneurial type of high-growth high-risk companies. The relatively new data from a relatively new market in this paper have both the absolute trade size and the relative trade size (out of total volume or market capitalization) for each stock on a daily, weekly, and bi-weekly basis, the tests of weekly and bi-weekly relationship between trade size and stock returns should mitigate the order-splitting behavior of informed traders presented in the literature. In addition, as elaborated below, the trade size categorization in China is different from the tradition of the literature, offering potentially a new perspective to interpretation of the findings in the literature. Moreover, there are no shorts and market order allowed in the market so that the transaction data are free of certain test issues raised in the literature (e.g., Barber et al., 2009).

We find that when a stock's net buys are dominated by small (large) traders, the stock price tends to go down (up) during the daily, weekly, and bi-weekly periods. There is a definite positive relation between the size of trades and short-term contemporaneous stock returns. Thus, our findings are inconsistent with those of some recent studies (e.g., Barber et al., 2009). Perhaps more interestingly, the trading behavior of small (noise) traders serves as a stronger contrarian signal than that of large traders to a stock's short-term contemporaneous returns.

The paper is organized as follows. Section II presents the hypotheses. Section III explains the data and methodology and Section IV provides the empirical results. Section IV offers concluding remarks.

II. HYPOTHESES

The main hypothesis is whether there is a positive relationship between trade size and short-term contemporaneous stock returns. More specifically, we test that for an average stock for a given day or (bi)week, the higher the proportion of the largest net buys (sales) out of the total volume or market capitalization, the higher (lower) the stock's return; the higher the proportion of the smallest net buys (sales) out of the total volume or market capitalization, the lower (higher) the stock's return. The premise is that large trades are associated with smart money and informed traders while small trades are associated with noise traders. When trades take place between informed traders and noise traders, the informed traders will win and the noise traders will lose. As such, the proportion of a stock's trading volume based on different trade sizes can be used to signal stock performance in the short horizon.

As discussed above, researchers (e.g., Barclay and Warner, 1993; Chan and Lakonishok, 1995) have attempted to address the issues with regard to the potential cloaking of informed trades that are split into or hid by uninformed form. The weekly and bi-weekly data of cumulated stock returns and trading volume categorized by trade size should minimize the potential confounding effect due to order splitting behavior by informed traders.

To control for any effects caused by sample size, the tests are conducted for the whole sample and two reduced samples that contain only the stocks yielding top and bottom returns during a specific period or frequency. Finally, despite all stocks are small in terms of market capitalization relative to stocks listed on the main boards (Shanghai Stock Exchange and Shenzhen Stock Exchange), the size factor is controlled in the sense that a scaled trading volume relative to market capitalization is also used in all the tests.

III. DATA AND METHODOLOGY

A. Data

The data for this study are from the Eastmoney Research Database and Tong Daxin Database. Eastmoney is the only publicly traded financial news and data company in China and Tong Daxin is a leading data source provider for major trading platforms in China. The sample consists of all stocks in China's Growth Enterprise Market (GEM) on the Shenzhen Stock Exchange for the second half of 2012. The GEM is modeled after NASDAQ with the objective of fostering the growth of small, innovative, and entrepreneurial type of firms in China. The Exchange operates as an electronic open limit order book market with no specialists or market makers. In addition, there is a daily price limit of $\pm 10\%$ for each stock from the previous close. Short selling on the GEM is prohibited. The Exchange opens 4 hours a day (from 9:30 a.m. to 11:30 a.m. in the morning and from 1:00 p.m. to 3:00 p.m. in the afternoon).

The GEM listed about 340 stocks as of the start of the sample period (July 2012). The total market capitalization was about RMB 854 billion (about US \$136 billion) at the same time. Our sample is a collection of the cross-sections of all stocks on a daily, weekly, and non-overlapping bi-weekly frequency.

For each cross-section, there are three separate datasets: single-day sample, weekly sample, and non-overlapping bi-weekly sample. Each sample contains individual stock returns for the sampling period, four types of trades, namely, largest trades, large trades, medium-sized trades, and small trades. For each trade type, a stock's total net transaction volume (or trade imbalance) in RMB and the percentage of the volume over the stock's total trade volume in that category are provided. The largest trade type includes the trade that is equal to or greater than half million shares or one million RMB; the large trade type includes those smaller than the largest trade, but equal to or greater than 100,000 shares or 200,000 RMB; the medium trade type includes those smaller than the large trade, but equal to or greater than 20,000 shares or 40,000 RMB; and the small trade type refers to the rest.³

The single-day sample provides stock returns on one day with all the above trade information, the (bi)weekly sample provides cumulative stock returns and cumulative trade information during one (two) week(s). For each sample period, tests are run separately for all stocks; for 100 stocks with top 50 and bottom 50 returns only; and for 50 stocks with top 25 and bottom 25 returns only. Stocks with tickers equal to or higher than 300304 are deleted so all stocks have at least 3 months of trading history. (All tickers are sequenced by the IPO time, e.g., ticker 300001 was assigned to the first firm chosen to be listed.). A stock is also deleted if not traded on that day or during a

sampling period (a few to several stocks). The tradable market value is determined by the current price and the tradable number of shares outstanding. The ratio of a stock's tradable number of shares outstanding over its total number of shares outstanding ranges from 10% to 70%, with an average of 38%. The non-tradable shares have a locking period of three years after IPO. None of the shares face locking period expiration during the sampling period. Tests conducted using total number of shares outstanding yield similar results and are not reported in the paper.

Table 1 shows the major industry distribution of the companies listed on the GEM. Software industry takes the top spot with 37 stocks listed, followed by electrical parts and equipment industries. Table 2 shows the market capitalization (size) distribution of the sample firms and the descriptive statistics of the size factor. There are 132 firms (44% of total) whose market capitalization is between one billion and two billion RMB. 76% of the firms had a market capitalization less than three billion RMB. The mean and median market capitalization is 2.5 billion and 1.8 billion RMB, respectively. Table 3 presents the distribution and descriptive statistics for book value, price to book ratio (PB), and net profit margin, respectively. The majority of the firms (209) had a book value less than 1 billion RMB, with the mean of 0.94 billion RMB. 69% of the firms (210) had a PB ratio less than 3, with the mean of 2.7. 87% of the firms (264) had a net profit margin between 0% and 30%, with the mean of 15%.

Table 1

Major industry distribution of the firms listed on the GEM (as of Dec. 31, 2012)

Industry	Count	Industry	Count
Software	27	Semiconductor	14
Electrical parts	24	Electrical Instrument	14
Electrical equipment	22	Medicare	11
Chemical materials	21	Pharmaceutical	10
Special Machinery	20	Environment Protect	8
Telecom Equipment	18	Internet	7
Total Count	206		

Note: The list shows an industry if at least seven companies are from the industry.

Table 2

Distribution of total market capitalization (RMB billion, as of Dec. 31, 2012)

	Boundary			Boundary			
	Lower	Higher	Count	Lower	Higher	Count	
0.70	<	1	33	6	<	7	9
1	<	2	132	7	<	8	3
2	<	3	63	8	<	9	4
3	<	4	35	9	<	10	3
4	<	5	12	10	<	22	3
5	<	6	3				
Total Count		300					
Mean		2.5					
Median		1.8					
Stdev		2.2					

Table 3
Descriptive statistics of book value, price to book ratio, and net profit margin as of Dec. 31, 2012

Book Value Boundary (RMB Billion)			Price to Book Ratio Boundary			Net Profit Margin Boundary (%)		
lower	Higher	Count	Lower	Higher	Count	Lower	Higher	Count
0.3 (min)	< 1	209	1.04 (min)	< 2	111	-49.9 (min)	< 0	11
1	< 2	77	2	< 3	99	0	< 10	90
2	< 3	14	3	< 4	44	10	< 20	125
3	< 3.5 (max)	3	4	< 5	29	20	< 30	49
			5	< 8.55 (max)	20	30	< 40	18
						40	< 57.6 (max)	10
Total		303	Total		303	Total		303
Mean	0.94		Mean	2.7		Mean	15.0	
Median	0.78		Median	2.4		Median	13.7	
Stdev	0.57		Stdev	1.4		Stdev	11.5	

B. Methodology

We use the step-wise regression method to identify from the relevant trade size information the final key variables most significantly affecting the stock returns. The relevant trade size information includes XL/FLMV, XL/TV, X/TV, L/TV, M/TV, and S/TV. For each day (week or bi-week), the XL/FLMV is a stock's sum of the volume of the largest trades and the volume of the large trades divided by the stock's tradable market value. XL/TV is a stock's sum of the volume of the largest trades and the volume of the large trades divided by the stock's total trade volume. By the same token, X/TV, L/TV, M/TV, and S/TV are a stock's largest trade volume (X), large trade volume (L), medium trade volume (M), small trade volume (S) divided by the stock's total trade volume, respectively. The correlation tests are also conducted between these variables and returns for different sampling periods and sample sizes.

The final regression model to explain a stock's return (R_i) is as follows:⁴

$$R_i = \beta_0 + \beta_1(XL/FLMV)_i + \beta_2(S/TV)_i + \varepsilon_i. \quad (1)$$

The hypothesis is that large trades tend to be informed trades versus small trades that tend to be noise trades. As such, for an average stock, we expect β_1 to be significantly positive and β_2 significantly negative.

IV. EMPIRICAL RESULTS

Table 4 and Table 5 show the correlation coefficient estimates between the major variables for the full sample (about 300 stocks) and the reduced sample (100 stocks) which are presented in Panel A for daily frequency, Panel B for weekly frequency, and Panel C for biweekly frequency. The highest and lowest correlations are consistent throughout the samples: the highest correlation is between XL/TV and L/TV, typically ranging between 84% and 90%; and the lowest correlation is between XL/TV and S/TV, typically ranging between -62% and -77%. Also, the correlation between L/TV and S/TV is very close to the correlation between XL/TV and S/TV. It seems that large traders, more often than not, tend to split their orders into large orders and forsake immediacy to certain extent.

Table 4
Correlations between key variables for the full sample (300 stocks)

		Return	XL /FLMV	XL/TV	X/TV	L/TV	M/TV	S/TV
Panel A	Return	1						
Daily	XL/FLMV	0.5921	1					
Results	XL/TV	0.5213	0.6158	1				
	X/TV	0.3535	0.4216	0.4098	1			
	L/TV	0.4012	0.4698	0.8996	-0.0168	1		
	M/TV	0.1140	-0.1799	-0.3135	-0.1895	-0.2521	1	
	S/TV	-0.5546	-0.3969	-0.6187	-0.2045	-0.5796	-0.5470	1
Panel B	Return	1						
Weekly	XL/FLMV	0.5067	1					
Results	XL/TV	0.5212	0.6579	1				
	X/TV	0.3339	0.3917	0.4532	1			
	L/TV	0.3951	0.5181	0.8632	-0.0368	1		
	M/TV	0.1469	-0.2106	-0.3106	-0.2365	-0.2130	1	
	S/TV	-0.5912	-0.4297	-0.6584	-0.2248	-0.6028	-0.4981	1
Panel C	Return	1						
Biweekly	XL/FLMV	0.4390	1					
Results	XL/TV	0.4779	0.6613	1				
	X/TV	0.3055	0.3360	0.4373	1			
	L/TV	0.3584	0.5412	0.8543	-0.0610	1		
	M/TV	0.1546	-0.2073	-0.2947	-0.2534	-0.1810	1	
	S/TV	-0.5504	-0.4397	-0.6819	-0.2004	-0.6276	-0.4894	1

Note: All correlation coefficients are significant at the 1% level. The XL/FLMV is a stock's sum of the volume of the largest trades and the volume of the large trades divided by the stock's tradable market value. XL/TV is a stock's sum of the volume of the largest trades and the volume of the large trades divided by the stock's total trade volume. By the same token, X/TV, L/TV, M/TV, and S/TV are a stock's largest trade volume (X), large trade volume (L), medium trade volume (M), small trade volume (S) divided by the stock's total trade volume, respectively.

Table 5
Correlations between key variables for the reduced sample
(Top 50 and bottom 50 stocks based on returns)

		Return	XL /FLMV	XL/TV	X/TV	L/TV	M/TV	S/TV
Panel A	Return	1						
Daily	XL/FLMV	0.6301	1					
Results	XL/TV	0.6654	0.6654	1				
	X/TV	0.4190	0.4372	0.5518	1			
	L/TV	0.5347	0.5389	0.8452	0.0596	1		
	M/TV	0.1246	-0.1924	-0.2619	-0.2624	-0.1601	1	
	S/TV	-0.7074	-0.4885	-0.7460	-0.9362	-0.6651	-0.4345	1
Panel B	Return	1						
Weekly	XL/FLMV	0.5499	1					
Results	XL/TV	0.6199	0.6862	1				
	X/TV	0.4103	0.4538	0.5034	1			
	L/TV	0.4632	0.5129	0.8375	-0.0165	1		
	M/TV	0.1740	-0.2106	-0.2387	-0.2392	-0.1197	1	
	S/TV	-0.6925	-0.4853	-0.7509	-0.3044	-0.6629	-0.4338	1
Panel C	Return	1						
Biweekly	XL/FLMV	0.4994	1					
Results	XL/TV	0.5837	0.6848	1				
	X/TV	0.4181	0.4137	0.5027	1			
	L/TV	0.4457	0.5617	0.8762	0.0354	1		
	M/TV	0.1716	-0.1557	-0.1853	-0.2558	-0.0696	1	
	S/TV	-0.6346	-0.5119	-0.7729	-0.2836	-0.7390	-0.4648	1

Note: All correlation coefficients are significant at the 1% level. The XL/FLMV is a stock's sum of the volume of the largest trades and the volume of the large trades divided by the stock's tradable market value. XL/TV is a stock's sum of the volume of the largest trades and the volume of the large trades divided by the stock's total trade volume. By the same token, X/TV, L/TV, M/TV, and S/TV are a stock's largest trade volume (X), large trade volume (L), medium trade volume (M), small trade volume (S) divided by the stock's total trade volume, respectively.

In terms of the correlation between stock return and trade size, the combination of the largest and the large trades yields the highest coefficient estimates, ranging between 44% and 59% for the full sample and between 50% and 66% for the reduced sample. Consistent with the expectation, the S/TV tends to have the lowest correlation with stock return, ranging between -55% and -59% for the full sample and between -63% and -70% for the reduced sample.

Table 6 shows the results from the regression model presented in the previous section. The F-values of all regressions are significant at the 1% level. Panel A reports the daily regression results for the full sample, the first reduced sample which includes the best 50 stock performers and the worst 50 stock performers, and the second reduced sample which includes the best 25 stock performers and the worst 25 stock performers. The results are all significant at the 1% level except for one case (XL/FLMV for the

second reduced sample) which is marginally insignificant at the 5.73% level. The marginal insignificance is due to the decrease of the test power when the sample size is reduced from about 300 stocks to 50 stocks. As expected, the higher the volume of the larger net buys (X & L) for a stock, the higher the stock's daily return; the higher the volume of the smallest net buys (S) for a stock, the lower the stock's daily return. For each percentage increase of a stock's relative volume by the smallest trades, the stock price loses 0.07% daily, 0.37% weekly, and 0.66% biweekly, respectively.

Table 6
Regression statistics

Panel A: Daily Results				
<i>Full Sample (300 stocks)</i>		R-square	F-value	P-value
	Coeff.	S.E.	T-value	P-value
Intercept	0.0129	0.0009	16.96	0.0001
XL/FLMV	1.8409	0.2054	9.72	0.0000
S/TV	-0.0721	0.0085	-8.42	0.0000
<i>Top 50 & Bottom 50 Stocks</i>		R-square	F-value	P-value
		0.6162	81.09	4.81E-18
	Coeff.	S.E.	T-value	P-value
Intercept	0.0160	0.002	9.00	0.0004
XL/FLMV	1.6007	0.3332	5.23	0.0101
S/TV	-0.1383	0.0188	-7.31	0.0000
<i>Top 25 & Bottom 25 Stocks</i>		R-square	F-value	P-value
		0.6869	54.25	2.04E-11
	Coeff.	S.E.	T-value	P-value
Intercept	0.0189	0.0033	6.3709	0.0047
XL/FLMV	1.3151	0.4433	3.1839	0.0573*
S/TV	-0.1973	0.0315	-6.1966	0.0000
Panel B: Weekly Results				
<i>Full Sample (300 stocks)</i>		R-square	F-value	P-value
		0.4412	123.92	8.39E-18
	Coeff.	S.E.	T-value	P-value
Intercept	0.0181	0.0023	8.81	0.0201
XL/FLMV	1.4538	0.2251	6.57	0.0007
S/TV	-0.3672	0.0392	-9.58	0.0000

Table 6 (continued)

<i>Top 50 & Bottom 50 Stocks</i>		R-square	F-value	P-value
		0.5585	77.19	1.74E-12
	Coeff.	S.E.	T-value	P-value
Intercept	0.0310	0.0047	5.98	0.0202
XL/FLMV	1.4343	0.3698	4.21	0.1037*
S/TV	-0.5550	0.0758	-7.68	0.0000
<i>Top 25 & Bottom 25 Stocks</i>		R-square	F-value	P-value
		0.6566	50.71	0.0000
	Coeff.	S.E.	T-value	P-value
Intercept	0.0447	0.0081	5.39	0.0115
XL/FLMV	1.5366	0.5258	2.90	0.0978*
S/TV	-0.7080	0.1254	-5.82	0.0000
Panel C: Bi-Weekly Results				
<i>Full Sample (300 stocks)</i>		R-square	F-value	P-value
		0.3666	88.93	1.16E-14
	Coeff.	S.E.	T-value	P-value
Intercept	0.0324	0.0035	9.66	0.0001
XL/FLMV	1.0255	0.2373	4.69	0.0254
S/TV	-0.6583	0.0776	-8.78	0.0000
<i>Top 50 & Bottom 50 Stocks</i>		R-square	F-value	P-value
		0.4713	53.31	0.0000
	Coeff.	S.E.	T-value	P-value
Intercept	0.0508	0.0075	6.90	0.0940
XL/FLMV	1.1245	0.428	3.02	0.0155
S/TV	-0.9445	0.1547	-6.40	0.0002
<i>Top 25 & Bottom 25 Stocks</i>		R-square	F-value	P-value
		0.5484	34.97	0.0001
	Coeff.	S.E.	T-value	P-value
Intercept	0.0738	0.0131	5.27	0.0203
XL/FLMV	1.3030	0.6218	2.21	0.0465
S/TV	-1.1744	0.2582	-4.87	0.0022

Note: “*” in all Panels denotes the only three cases where XL/FLMV is not significant at the 5% level. All other p-values are significant at either the 1% or the 5% level.

The test results for weekly regressions in Panel B and the results for non-overlapping bi-weekly regressions in Panel C reveal similar evidence as in Panel A. That is, the higher the largest (smallest) net buys for a stock, the higher (lower) the weekly and bi-weekly returns for the stock. For the reduced sample consisting of top 50 and bottom 50 stocks, for each percentage increase of a stock's relative volume by the smallest trades, the stock price loses 0.14% daily, 0.56% weekly, and 0.94% biweekly, respectively. The results are more notable for the sample that consists of only top 25 and bottom 25 stocks. Table 5 also shows that the p-values for the smallest trades are always significant at the 1% level whereas the p-values for the larger trades are significant at the 1% level in two cases, significant at the 5% level in four cases, and not significant at the 5% level in three cases. The evidence seems to suggest that the smallest trades tend to dominant the larger trades in signaling a stock's short-term contemporaneous return. It appears that while certain informed trades may not lead to outperformance, the overwhelming effect of noise trades is completely counterproductive—they follow a path of wealth destroying. The results presented here are inconsistent with the findings of some recent studies (e.g., Barber et al., 2009).

Figure 1 and Figure 2 show the relationship between a stock's average daily stock return and the proportion of the stock's larger and smallest net buys relative to its daily total trading volume for all stocks in the sample, respectively. Figure 1 shows that when a stock's daily return is negative (positive), its larger trades tend to be net sales (buys). The evidence in Figure 2 is opposite: for a stock, when the smallest trades tend to be net buys (sales), the stock's return tends to be negative (positive).

Figure 1
Daily return (Ret) vs. larger trade flows (XL_TV)

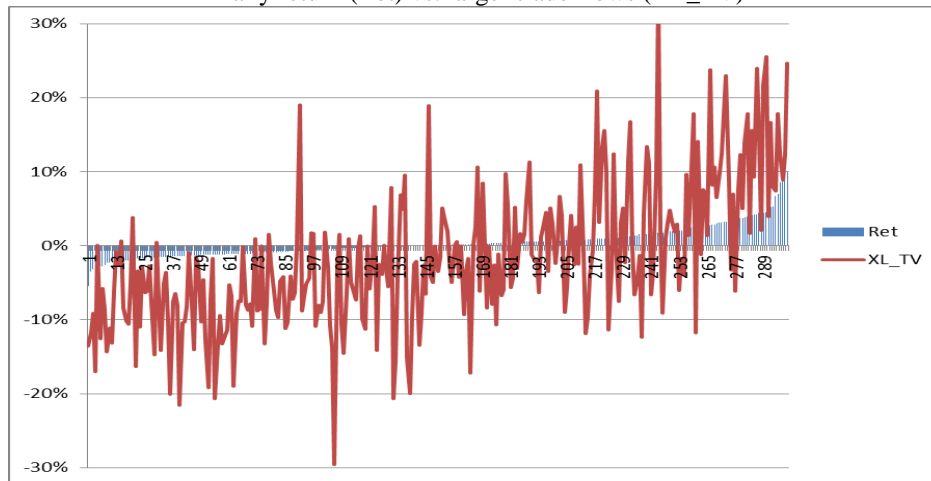


Figure 1 shows the relationship between a stock's average daily stock return and the proportion of the stock's larger net buys relative to its daily total trading volume for all stocks in the full sample. The vertical axis represents the average daily stock return (Ret) and the net trade balance of the stock's larger trades (XL_TV). The horizontal axis represents the individual stocks in the sample.

Figure 2
Daily return (Ret) vs. smallest trade flows (S_TV)

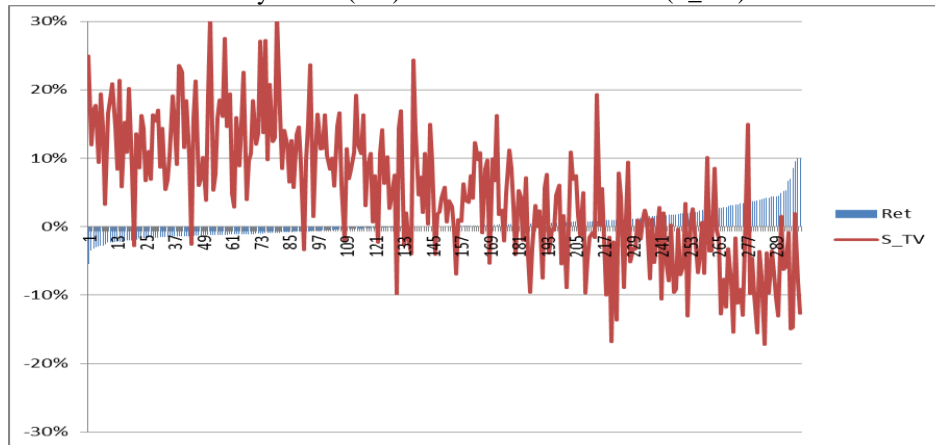


Figure 2 shows the relationship between a stock's average daily stock return and the proportion of the stock's smallest net buys relative to its daily total trading volume for all stocks in the full sample. The vertical axis represents the average daily stock return (Ret) and the net trade balance of the stock's smallest trades (S_TV). The horizontal axis represents the individual stocks in the sample.

V. CONCLUSIONS

This paper adds evidence to the literature that emphasizes the effect of trade size and adverse selection in short-term stock price discovery. Using the data from a relatively new market, we find that trade size is significantly and positively associated with information set and short-term contemporaneous stock returns, the larger the proportion of larger more informed (small more noisy) net buys relative to the total volume, the higher (lower) the stock returns. The results are not affected by the size of the firm. We also find that small noise traders' behavior tends to be a much stronger indicator than that of larger informed traders when signaling short-term contemporaneous stock returns.

ENDNOTES

1. Huang and Masulis (2003), Anand and Chakravarty (2007), Chou and Wang (2009), Asciglu et al. (2011) show similar findings in the London Stock Exchange, the S&P 500 options market, the Taiwanese futures market, the Japanese stock market, respectively.
2. Often in these studies, a medium-sized trade is between 500 and 9,900 shares. Alexander and Peterson (2007) also examine the trade size clustering.
3. This dollar-based cutoff point between the two larger and two smaller trade size types (RMB 200,000) is not much different from the \$20,000 cutoff rule proposed by Lee and Radhakrishna (2000) to identify individual trades for "small" stocks. In

our sample, the minimum and maximum price share (as of 12/31/2012) are RMB2.69 and RMB57.61, respectively.

4. We also included size (total market capitalization and float market capitalization) and price-to-book ratio in the model and find them not significant throughout the tests.

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