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A Re-examination of Informed Trading and Firm Size in the Thailand Capital Market

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The paper investigates the stylized fact, addressed in several prior studies, that large-cap firms may have a lower probability of informed trading. Using 30 million intraday trades, daily trades, and firm accounting data of sample firms listed on the Stock Exchange of Thailand (SET), the paper finds an opposing pattern for the sample firms in Thailand, showing that large firms have a higher probability of informed trading. The paper also suggests that a clientele effect could be one potential explanation for this finding. Consistent with this conjecture, the paper finds those large firms tend to have high stock prices, and that stocks with high prices have a high probability of informed trading. This is because the monotonic positive relation between firm size and share price may repel uninformed investors, who are usually individual traders, from investing in these large firms, which usually have higher stock prices. In contrast, informed investors, who are often institutional investors, may be inclined to invest in these large firms.

Field of Research: Market Microstructure, Investor Preference, Firm Size

1. Introduction

The daily stock trading process exhibits a persistent and substantial imbalanced order flow. The degree of the imbalance is positively related to the level of informed trading (Kyle, 1985). Such trading might stem from information asymmetry, where a subgroup of investors has private value-enhancing information. Vega (2005) states that the private value-relevant information may be derived from either the analysis of publicly available information, or from insider information.

The most well-informed investors are corporate insiders, as they should have access to all of the value-relevant, firm-specific information. The second class of investors has a better ability to analyse public information, and are typically institutional traders. Finally, typical public and individual investors are uninformed investors, also known as liquidity traders, who usually bear information risk initiated by the two classes of informed investor.
Employing a numerical maximization of the likelihood function as well as intraday buy and sell transaction data, Easley et al. (1996) have developed a percentage measure to evaluate the intensity of informed investors relative to uninformed investors (liquidity investors) in a certain stock. This is referred to as the PIN variable. A full year horizon (minimum 120 trading days) is often proposed to obtain a reliable value (Aslan et al., 2007; Duarte and Young, 2009).

Since the publishing of Easley et al. (1996) that outlined the PIN variable, a large number of papers have used PIN to study a broad range of topics in corporate finance, investment, and market microstructure. Some of them suggest that firm size is negatively related to the probability of informed trading (Aslan et al., 2007; Bardong et al., 2007; Vega, 2005; Brown et al., 2004; Lai et al., 2008).

In response to the empirical findings of some other studies that the level of informed trading actually increases in firm size, Easley et al. (2001) and Brown et al. (2004) explain that larger firms may attract even more uninformed investors, which leads to a decrease in the intensity of informed trading. This suggests that the extent of informed trading for a certain stock could be affected by preferences of different types of investors.

A large body of studies show that a class of informed investors, being mostly institutional investors, typically prefer large, high priced, liquid, and visible stocks, whereas individual investors, who are usually viewed as a whole as being uninformed investors, are usually inclined to invest in low priced stocks.

Furthermore, this negative relation is mainly detected when studying the US market, which is the most mature financial market in the world. Emerging markets, however, are very different from the US market in a variety of aspects. In our paper, we deliberately select the Thai market, because it is dominated by individual investors. These investors show a strong preference for low priced stocks and they initiate most of their trading on stocks with prices below THB5, while institutional investors in Thailand account for most of the trading among high priced stocks.

Coincidentally, in the Thai market stock price increases monotonically with market capitalisation, which leads to a concentration of institutional investors in large firm stocks and that of individual investors in small firm stocks, an investment pattern that differs from that of many other countries.

The special market pattern motivates us to explore the following question: Does the negative relation between firm size and informed trading suggested by Easley et al. (1996) always hold in the Thai markets? In particular, we expect to see that based on our Thai firm samples, large firms in the Thai market may have a higher probability of informed trading than small firms, and that firms with high stock prices have a lower level of uninformed trading than firms with low stock prices.

The remainder of the paper is organised as follows. Section 2 introduces some of the related literature, and a discussion of the relation between firm size and informed trading. Section 3 presents the methodology. Section 4 details the data, the data processing procedures and the selection of the control variables. Section 5 reports the empirical results and the analysis of these results. Section 6 provides a discussion on some possible explanations for these results and summarises the paper.

2. Literature Review

Falkenstein (1996) suggests that mutual funds, which are more likely to be informed investors, bias their investments to certain stocks with high prices. He explains that such shares may also represent lower transaction costs, since they have a lower bid-ask spread ratio over their average prices.

Moreover, larger firms may be more liquid and allow investors to take a large position for such stocks without a significant price impact. To avoid a price impact, such investors usually need to mask their trading purposes more carefully by breaking up their block trades into smaller sized trades, leading to an increase in commission and monitoring costs (Bernhardt et al, 1997; Chordia et al, 2004; Barclay et al, 1993; Chakravarty, 2001; Hasbrouck, 1991, 1991a, 2007).

On the other hand, Baker et al. (1980) reveal that a stock split is usually used to bring the stock price into an optimal price range, and attract more uninformed investors. As individual investors are more wealth-constrained, they will prefer to buy lower priced stocks, which are associated with smaller ticker sizes and, thus, lower transaction costs in absolute values (Baker et al, 1980). Copeland (1979) and Lakonishok et al. (1987) argue that low priced stocks are somewhat cheaper to diversify.

Although Easley et al. (2001) find a negative relation between the probability of informed trading and firm size, which is mainly based on US market data, the empirical result may not necessarily be valid for other financial markets, especially emerging markets. Lai et al. (2008) show that there is high cross-sectional fluctuation in informed trading across firm- and country-level characteristics.

The Thai stock market is a typical emerging market, dominated by individual investors, whose trades account for 70% of the daily market trading volume (Pavabutr et al., 2007).These individual investments are mainly concentrated in stocks with low prices, in particular those priced below THB5. Of these low-priced stock trades, 90% stem from public investors, while institutional investors account for 76% of the transactions involving stocks priced above THB200 (Pavabutr et al., 2007).

Interestingly, small firms in Thailand tend to have low stock prices, while large firms usually have high stock prices (Pavabutr et al., 2008). In comparison, US stock prices remained at an average of about USD35 per share due to frequent stock splits (Weld et al., 2009). Under the monotonic positive relation, institutional investors will like investing in large firms, while Thai public investors are repelled from investing in them.

Some researches (Pavabutr et al., 2007, Pavabutr et al., 2009) study stock spilt impacts on the liquidity of the Thai Market and indicate that there is a distinct effect of optimal trading range from THB 10 to THB 25. This clientele hypothesis implies that lower stock prices attract more individual investors. Pavabutr et al. (2009) provide evidence that the number of individual investors decreases monotonically as stock prices increase. In our sample, the stock prices ranges from THB 1 to more than THB 400, and nearly one third of the companies are above the upper bound of the optimal trading range of THB 25.

When choosing investment targets, informed investors may prefer large and liquid firms. Uninformed traders may desire small cap companies. Putting these two aspects together may arrive at a high intensity of informed trading measured by PIN and AdjPIN in large Thai firms.

Hence, we expect that the special trader composition that differs from other market samples may cause some deviation from the negative relation between firm size and the probability of informed trading shown in prior studies**.**

3. Methodology

3.1 Measures of intensity of informed trading

Since the 1990s, Easley and others have spent the decades in developing and extending the PIN measure in order to detect informed trading. The symbol α denotes the rate at which an information event occurs. When an information event occurs, it might be bad news regarding the decreased value of an underlying asset with a probability of δ, or good news with the probability of 1- δ. The arrival rate of informed traders is denoted as µ.Trades are assumed to arrive independently at the market in terms of the Poisson process. ϵ_b denotes the arrival rate of uninformed buyers. ϵ_s is the arrival rate of uninformed sellers. All of the above can be summarised as one of three Poisson processes, which is estimated using MLE to obtain a parameter vector θ= ($\alpha, \delta, [\![\epsilon]\!]_{\downarrow}(b)\ ,\ [\![\epsilon]\!]_{\downarrow}(s), \mu)$.

$$L\ (B, S\ |\theta) = (1- \alpha\ )\ e^{-\epsilon_b}\frac{\epsilon_b^B}{B!}e^{-\epsilon_s}\frac{\epsilon_b^S}{S!} + \alpha\delta e^{-\epsilon_b}\frac{\epsilon_b^B}{B!}e^{-(\mu+\epsilon_s)}\frac{(\mu+\epsilon_s)^S}{S!} + \alpha(1-\delta[\square])e]^{-[(\mu+\epsilon]_b)}\frac{(\mu+\epsilon_b)^B}{B!}e^{-\epsilon_s}\frac{\epsilon_s^S}{S!}$$

(1)

In Equation 1, B and S stand for the total daily number of buyer- and seller-initiated trades, respectively. The PIN represents the expected ratio of trades arising from informed trades, to the total order flow. The fraction can be simply written as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \epsilon_b + \epsilon_s}$$

(2)

Duarte and Young (2009) extend Easley et al.'s (1996) PIN measure to allow for the large differences in the buy and sell variance, and find a positive correlation between buy and sell orders. Duarte and Young (2009) relaxed the strict assumption in Easley et al.'s (1996) model by allowing the arrival rate of informed buyers μ_b to differ from that of informed sellers, μ_s . This relaxation can better fit the fact that buy trades are more volatile than sell trades. Moreover, their model takes into account the symmetric order flow shock. They use θ to represent the probability of the situation, conditional on there being no arrival of private information, and θ´ to denote the probability conditional on the arrival of private information. The additional arrival rate of buys and sells are Δ_b and Δ_s, respectively. They also design an adjusted probability of informed trading, being:

AdjPIN=

$$\frac{\alpha \times [(1-\delta) \times \mu_b + \delta \times \mu_s]}{\alpha \times [(1-\delta) \times \mu_b + \delta \times \mu_s] + (\Delta_b + \Delta_s) \times [[\alpha \times \theta' + (1-\alpha) \times \theta] + \epsilon]_b + \epsilon_s} \quad (3)$$

After conducting a series of comparisons and Monte Carlo simulations, Duarte and Young (2009) select a preferred extended model by imposing the restriction $\theta = \theta'$.

3.2 Cross-sectional regressions

Following Aslan et al.'s (2007) method, we include several market and firm accounting variables to extract the net effect of firm size on the extent of informed trading. The regression equation is:

$$\text{PIN (or } AdjPIN_i) = \alpha_1 + \alpha_2 size_i + \alpha_3 Amihud_i + \alpha_4 Roa_i + \alpha_5 Stdev_i + \alpha_6 Tobinq_i + \varepsilon_i \quad (6)$$

In Equation 6, size represents the natural log of the market value of equity in firm i. Amihud refers to the Amihud measure, an illiquidity measure that defines an average ratio of the daily absolute price percentage change over the trading volume in dollar value on that day in firm i. Since firm size is correlated with liquidity, we include the Amihud measure as a control variable of the price impact (liquidity). Duarte and Young (2009) also report a positive relation between the Amihud measure and PIN (or AdjPIN).

Roa represents the return on assets in firm i in the last year. The variable represents firm performance. Profitable firms may be associated with high PINs/ AdjPINs (Aslan et al., 2007). Investors would have greater incentives to seeking out those firms that offer potential returns.

Stdev is the annualised standard deviation of daily returns for firm i in the last year. The variable is a proxy of firm trading performance (Lai et al., 2008), and measures the uncertainty of a firm, reflecting the firm-level trading environment.

Tobinq is the Tobin'Q, which is obtained by the market value of equity plus the book value of liabilities in firm i, divided by the book value of the total asset of firm i. Tobin's Q is used to measure the firm's investment opportunity. Firms with high Tobin's Q may have greater growth options.

4. Data

4.1 Data collection

Since our study mainly examines the cross sectional relation between PIN (AdjPIN) and firm size, we randomly choose intraday transactions and the limit order book data for 2006 on the Stock Exchange of Thailand. The data are obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA) for the purpose of calculating yearly firm AdjPIN and PIN.

Following some extant studies (Bardong et al., 2007; Vega, 2005; Brown et al., 2004; Lai et al., 2008; Duarte et al., 2009), our research excludes financial institutions from the sample, and only selects stocks with at least 120 qualified trading days and available quote data. With these exclusions, a sample covering 58 firms remains for our research.

The Market Value (MV), daily trading volume in quantity of shares traded (VO), daily trading volume in value (VA), net income (wc01751), total assets (wc02999), liabilities (wc03351), the market to book ratio (MTBV), the daily price (P#S), and the number of shares outstanding (NOSH) are obtained from Data Stream.

4.2 Classification trades and PIN and AdjPIN estimation

Classification trades

To implement the Maximum Likelihood Estimation (MLE) required for computing the PIN and AdjPIN, the daily number of buy- and sell-initiated transactions needs to be estimated. As the SET (Stock Exchange of Thailand) has no designated market maker, we define the quote spread as the difference in the best selling and buying limit orders.

Following a technique developed by Lee and Ready (1991), we classify a transaction as buyer-initiated (seller-initiated) if the transaction is above (below) the mid-point of the quoted spread. If the trade occurs at the mid-point of the spread, we classify this sort of transaction as buyer- (seller-) initiated in terms of a previously quoted mid-point spread. The transaction can be classified as a buy if the executed price is higher than the previous quoted mid-point spread, and as a sell if it is lower than the previous quoted mid-point spread. If the transaction coincidentally occurs again at the same price as the quoted mid-point spread, the transaction price will be compared to the further lagged quoted mid-point spread until the value has been lagged three times.

4.3 Data cleaning

Trades

SIRCA provides all of the intra-day stock trades' data required for this examination, including ticker, date, time, type indicator of quote or trade, trade price, best bid price, best ask price, and qualifiers.

Using the qualifiers, we find it useful to remove the first and last 30 minutes of each trading session from the sample. The first trade each day is excluded from our sample using qualifiers. We consolidate all trades occurring within each five second period as a single trade, and record the executed time as the time of the first of these trades.

Quotes

The prevailing quote used to determine the direction of a transaction must be five seconds before the trade is executed. Otherwise, we use the previous quote for the classification scheme.

Trading days

If there are either buys or sells no more than 60 in a certain trading day, the trading day will not be added to the aggregate number of trading day of the firm. We then select the firms which have the summation more than 120 qualified trading days, since a nonlinear Maximum likelihood algorithm can obtain a reliable solution based on these criteria.

Matching with accounting data

We also exclude the stocks of which accounting data are not available. After cleaning the transaction data, we merge the qualified stocks with firm accounting information obtained from the DataStream database using the RIC (ticker) codes provided by SIRCA. As a result, year 2006 has the greatest number of qualified sample.

5. Results and Analysis

5.1 Descriptive statistics

The descriptive statistics on all of the variables we have discussed are listed in Table 1. The table provides the cross-sectional mean, median, maximum, minimum, standard deviation, skewness, and kurtosis of the set of 58 stock samples.

The logarithm of the market value of equity (LOGMV) ranges from 7.90 to 13.36, indicating the very diverse firm size in the sample. Not surprisingly, the log form of the stock price (LOGPRICE) ranges from -0.698 to 5.589, similarly presenting the wide range of stock prices in our sample.

Table1 Descriptive statistics

The PIN is the probability of information-based trading in stock i. The AdjPIN is the adjusted probability of informed trading in stock i. PSOS is the estimated probability of symmetric order flow shock. LOGMV is the logarithm of the market value of equity in firm i at the end of 2005. LOGPRICE is the log form of the yearly-averaged daily stock price. TURNOVER represents the logarithm of the averaged daily number of shares traded divided by the number of shares outstanding for firm i in 2006. Amihud is the Amihud measure. ROA is the return on assets. STDEV is the annualised standard deviation of the daily returns for firm i in 2005 and TOBINQ is the Tobin's Q. TURNOVER represents the logarithm of the averaged daily number of shares traded divided by the number of shares outstanding for firm i in 2006. EPSILON is the arrival rate of uninformed trading.

	Mean	Median	Maximum	Minimum	Stdev	Skewness	Kurtosis	Obs
PIN	0.242	0.242	0.371	0.073	0.057	-0.418	4.242	58
ADJPIN	0.216	0.212	0.357	0.015	0.050	-0.409	7.102	58
PSOS	0.281	0.283	0.470	0.137	0.084	0.416	2.490	58
LOGMV	10.086	9.826	13.357	7.895	1.176	0.712	3.352	58
LOGPRICE	2.741	2.779	5.589	-0.698	1.491	-0.252	2.766	58
TURNOVER	-6.500	-6.656	-3.708	-8.453	1.109	0.196	2.306	58
AMIHUD	3.563	1.001	93.426	0.033	12.319	6.879	50.568	58
ROA	0.070	0.073	0.308	-0.456	0.114	-1.778	9.861	58
STDEV	1.686	1.462	5.066	0.249	1.143	0.962	3.351	58
TOBINQ	1.541	1.267	4.377	0.559	0.843	1.952	6.490	58
EPSILON	36.363	26.591	119.322	3.338	24.796	1.070	3.774	58

5.2 Univariate test

Table 2 presents how the variables of PIN and AdjPIN are correlated with other control variables employed in our research. Of particular interest is the positive correlation between firm size (LOGMV) and PIN (and AdjPIN), with correlations of 0.31 and 0.71, respectively. Both of them are positive and significant. This result preliminarily confirms our main finding that large firms in Thailand tend to have a higher intensity of informed trading.

The correlation between PIN and AdjPIN is positive and significant at around 0.41. Both PIN and AdjPIN are negatively correlated with PSOS at around -0.18 and -0.466, respectively. Since PSOS represents illiquidity (Duarte et al., 2009), this result is also in line with our hypothesis that informed trading in the Thai market is negatively correlated with illiquidity. This finding is further proved by the negative, and nearly significant, correlation between the Amihud measure (AMIHUD) and AdjPIN.

AdjPIN and PIN are, as expected, positively correlated with firm price (LOGPRICE), indicating that a higher stock price can, on its own, incur a higher intensity of informed trading. PIN and the return on assets (ROA) are slightly positively correlated, but AdjPIN is insignificantly negatively correlated with ROA. Firms in Thailand with high investment opportunities, namely high Tobin'q (TOBINQ), are often large firms with high profitability, therefore subject to more informed trading. This implies that the Thai market may also have a pattern of earning concentration, as documented by Dangelo et al. (2004).

A positive correlation between LOGMV and LOGPRICE once again provides evidence that large firms in Thailand usually have high stock prices. We further rank our sample firms by firm capitalization to examine whether or not the relation is strictly monotonic. As expected, the size deciles presented in Table 3 clearly show an almost strict monotonic relation with stock prices

Firm size has an unsurprisingly negative correlation with the proxies of illiquidity, AMIHUD and PSOS. This is consistent with prior studies that large firms may have less price impacts than smaller firms, and price impact can also be seen as a type of liquidity. The empirical correlation matrix also shows that LOGMV has a positive relation to ROA and TOBIN Q, and is negatively related to the annualized standard deviation of the daily returns (STDEV). This indicates that larger firms in Thailand are profitable, with high growth and less volatility in stock prices.

The arrival rate of uninformed trading, EPSILON, is positively related to LOGMV. In line with Easley et al. (2001) and Brown et al. (2006) we find that large firms tend to attract more uninformed trading, which is likely to originate from individual investors.

Table 2: Correlation Matrix

The PIN is the probability of information-based trading in stock i. The ADJPIN is the adjusted Probability of informed trading in stock i. The estimated probability of the symmetric order flow shock is PSOS. LOGMV is the logarithm of the market value of equity in firm i at the end of 2005. LOGPRICE is the log form of the yearly-averaged daily stock price. AMIHUD is the Amihud measure. ROA is the return on assets. STDEV is the annualized standard deviation of the daily returns for firm i in 2005. TOBINQ is the Tobin's Q. TURNOVER represents the logarithm of the averaged daily number of shares traded divided by the number of shares outstanding for firm i in 2006. EPSILON is the arrival rate of uninformed trading.

	AdjPIN	PIN	PSOS	LOGMV	LOGPRICE	AMIHUD	ROA	STDEV	TOBINQ	TURNOVER	EPSILON
AdjPIN	1										
p-value											
PIN	0.408	1									
p-value	(0.002)										
PSOS	-0.466	-0.187	1								
p-value	(0.000)	(0.160)									
LOGMV	0.708	0.311	-0.618	1							
p-value	(0.000)	(0.017)	(0.000)								
LOGPRICE	0.545	0.503	-0.396	0.68	1						
p-value	(0.000)	(0.000)	(0.002)	(0.000)							
AMIHUD	-0.201	0.058	0.3	-0.254	-0.059	1					
p-value	(0.130)	(0.667)	(0.022)	(0.055)	(0.662)						
ROA	-0.018	0.342	-0.387	0.263	0.46	-0.004	1				
p-value	(0.896)	(0.009)	(0.003)	(0.046)	(0.000)	(0.977)					
STDEV	-0.064	0.023	0.159	-0.146	-0.108	0.094	0.114	1			
p-value	(0.633)	(0.865)	(0.234)	(0.273)	(0.421)	(0.485)	(0.394)				
TOBINQ	0.266	0.232	0.056	0.244	0.364	-0.058	0.041	-0.101	1		
p-value	(0.043)	(0.08)	(0.675)	(0.065)	(0.005)	(0.666)	(0.757)	(0.449)			
TURNOVER	-0.059	-0.289	0.077	-0.244	-0.451	-0.183	-0.436	-0.134	-0.155	1	
p-value	(0.660)	(0.028)	(0.567)	(0.065)	(0.000)	(0.169)	(0.001)	(0.320)	(0.247)		
EPSILON	0.299	-0.155	-0.362	0.328	-0.134	-0.238	-0.201	-0.236	-0.108	0.670	1
p-value	(0.022)	(0.245)	(0.005)	(0.012)	(0.317)	(0.072)	(0.130)	(0.074)	(0.419)	(0.000)	

Table 3: Relation between LOGMV and LOGPRICE

The table reports the monotonic positive relation between LOGMV and LOGPRICE sorted by size deciles.

DECILE	TICKER	LOGMV	LOGPRICE	average	DECILE	TICKER	LOGMV	LOGPRICE	AVERAGE
HIGH	PTT.BK	13.3569	5.4618	4.3759	6th	MINT.BK	9.7540	2.1392	2.9759
	ADVA.BK	12.6719	4.5161			MAKR.BK	9.7220	4.3205	
	PTTE.BK	12.6415	4.6925			PSL.BK	9.7117	2.8866	
	SCC.BK	12.5872	5.4543			TTA.BK	9.7059	3.0321	
	IRPC.BK	11.9700	1.9922			BECL.BK	9.7051	3.0983	
	TOP.BK	11.7718	4.1385			SATT.BK	9.6960	2.3785	
2th	SHIN.BK	11.7497	3.5644	3.9077	7th	SSI.BK	9.5848	0.1805	1.7221
	PTTC.BK	11.4254	4.4026			CCET.BK	9.5579	1.3625	
	SCCC.BK	11.3386	5.5887			TPC.BK	9.5405	2.7821	
	AOT.BK	11.2252	4.0429			ITV.BK	9.4933	1.7200	
	THAI.BK	11.2219	3.7882			CK.BK	9.4790	2.2904	
	LH.BK	11.1460	2.0595			STEC.BK	9.4415	1.9971	
3th	RATC.BK	10.9929	3.6443	3.3255	8th	GSTE.BK	9.4345	0.1468	1.7818
	CPF.BK	10.7336	1.6734			KSL.BK	9.4255	2.2853	
	EGCO.BK	10.6606	4.4082			VNT.BK	9.3651	2.2037	
	BANP.BK	10.4801	4.9935			STAN.BK	9.3087	5.0379	
	ITD.BK	10.4515	1.8795			TTNT.BK	9.1973	0.9185	
	GLOW.BK	10.4366	3.3542			INOX.BK	9.1860	0.0985	
4th	TRUE.BK	10.4327	2.2467	3.0956	9th	MAJO.BK	9.1369	2.7699	1.3491
	ATC.BK	10.2578	3.3788			ROBI.BK	9.0668	2.3514	
	BGH.BK	10.2246	3.3442			SAMA.BK	8.9619	2.1675	
	BEC.BK	10.2036	2.7766			AP.BK	8.9580	1.3463	
	TUF.BK	10.1854	3.2729			QH.BK	8.8921	0.1569	
	BH.BK	9.9743	3.5547			NSM.BK	8.6179	-0.6977	
5th	HANA.BK	9.9693	3.3078	3.2249	LOW	GOLD.BK	8.3846	2.0412	1.1079
	DELT.BK	9.9593	2.9029			LOXL.BK	8.3129	0.9446	
	UCOM.BK	9.9510	3.8015			PICN.BK	7.9188	-0.6003	
	MCOT.BK	9.8824	3.5403			SOLA.BK	7.8954	2.0460	
	TPIP.BK	9.8509	2.7361						
	RCL.BK	9.8018	3.0608						

5.3 Multivariate test

To further test the robustness of the firm size effect on AdjPIN, or PIN, we select AMIHUD for illiquidity (an inverse measure of liquidity), ROA and STDEV for firm performance, and TOBINQ for the investment opportunity set of a firm. Combined with these control variables, PIN, or AdjPIN, can be expressed as a function of firm size.

Tables 4 and 5 illustrate that the coefficient of LOGMV is strongly significant and is positively related to both PIN and AdjPIN in both of the univariate and multivariate regressions. In Model 8 of Table 4, we obtain a strong, significant t-test result (t-statistic=7.33, p- value <0.00001) on the LOGMV coefficient. In Model 8 of Table 5, a coefficient with the same sign is still obtained, indicating a positive relation between PIN and LOGMV, while the t-statistic is marginally significant at 1.7 (with a P-value < 0.094).

In order to investigate the behaviour of uninformed trading individually, we use the arrival rate of uninformed trading, EPSILON, as a dependent variable for the regression on the set of control variables outlined in Table 6 above. The EPSILON has a negative and significant relation with LOGPRICE, while maintaining a positive relation with LOGMV. This proves that the activities of uninformed trading decrease as stock prices increase, which is consistent with the clientele hypothesis. The negative relation is further verified in the multivariate regression, the results of which are shown in Model 7 of Table 6. As a result, we find proof of our second hypothesis that firm stocks with high prices have a lower level of uninformed trading based on a sample of Thai firms.

Table 4: Cross-sectional Regression

The dependent variable is the adjusted probability of informed trading, AdjPIN, in stock i. LOGMV is the logarithm of the market value of equity in firm i at the end of 2005. LOGPRICE is a log form of the daily close price averaged across 2006. TURNOVER represents the logarithm of averaged daily number of shares traded divided by the number of shares outstanding for firm i in 2006. AMIHUD is the Amihud measure multiplied by 10E+6. STDEV is the annualized standard deviation of the daily returns for firm i in 2005. ROA is the return on assets for firm i in 2005 and TOBINQ is the Tobin's Q for firm i in 2005.

MODEL	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	DEPENDENT VARIABLES														
	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN	AdjPIN
INDEPENDENT VARIABLES	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF
INTERCEPT	-0.086	-0.062	-0.063	-0.083	-0.092	-0.104	-0.085	-0.113	0.166	0.225	0.170	0.167	0.162	0.162	0.158
p-value	(0.039)	(0.201)	(0.158)	(0.056)	(0.038)	(0.012)	(0.042)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LOGMV	0.030	0.027	0.031	0.030	0.030	0.032	0.029	0.032							
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
LOGPRICE		0.004							0.018	0.022	0.018	0.018	0.023	0.017	0.023
p-value		(0.358)							(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TURNOVER			0.005							0.011					
p-value			(0.219)							(0.061)					
AMIHUD				-93.700				-53.500			-686.000				-0.001
p-value				(0.815)				(0.890)			(0.132)				(0.123)
STDEV					0.002			0.004				0.000			0.003
p-value					(0.677)			(0.381)				(0.962)			(0.533)
ROA						-0.096		-0.100					-0.149		-0.151
p-value						(0.024)		(0.021)					(0.006)		(0.007)
TOBINQ							0.006	0.006						0.005	0.002
p-value							(0.311)	(0.298)						(0.522)	(0.826)
OBSERVATIONS	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58
ADJUSTED R-SQUARED	0.492	0.490	0.497	0.483	0.484	0.529	0.492	0.518	0.285	0.318	0.302	0.272	0.367	0.277	0.364

Table 5 Cross-sectional Regression

The dependent variable is the probability of information-based trading, PIN, in stock i. LOGMV is the logarithm of the market value of equity in firm i at the end of 2005. LOGPRICE is a log form of the daily close price averaged across 2006. TURNOVER represents the logarithm of the averaged daily number of shares traded divided by the number of the shares outstanding for firm i in 2006. AMIHUD is the Amihud measure multiplied by 10E+6. STDEV is the annualized standard deviation of daily returns for firm i in 2005. ROA is the return on assets for firm i in 2005 and TOBINQ is the Tobin's Q for firm i in 2005.

MODEL	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	DEPENDENT VARIABLES														
	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN	PIN
INDEPENDENT VARIABLES	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF
INTERCEPT	0.091	0.214	0.043	0.071	0.080	0.117	0.094	0.096	0.190	0.168	0.188	0.183	0.192	0.186	0.180
p-value	(0.147)	(0.003)	(0.524)	(0.277)	(0.225)	(0.061)	(0.135)	(0.157)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LOGMV	0.015	-0.003	0.012	0.017	0.015	0.011	0.013	0.011							
p-value	(0.017)	(0.722)	(0.051)	(0.010)	(0.016)	(0.067)	(0.042)	(0.094)							
LOGPRICE		0.021							0.019	0.018	0.019	0.019	0.017	0.018	0.016
p-value		(0.001)							(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.006)
TURNOVER			-0.012							-0.004					
p-value			(0.083)							(0.550)					
AMIHUD				670.000				575.000			401.000				379.000
p-value				(0.270)				(0.331)			(0.455)				(0.487)
STDEV					0.003			0.002				0.004			0.003
p-value					(0.590)			(0.799)				(0.507)			(0.664)
ROA						0.138		0.133					0.069		0.069
p-value						(0.033)		(0.042)					(0.286)		(0.308)
TOBINQ							0.011	0.012						0.004	0.006
p-value							(0.209)	(0.177)						(0.655)	(0.515)
OBSERVATIONS	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58
ADJUSTED R-SQUARED	0.081	0.227	0.114	0.085	0.069	0.139	0.091	0.138	0.239	0.231	0.233	0.232	0.242	0.228	0.215

Table 6 Cross-sectional Regression

The dependent variable is the arrival rate of uninformed trading, EPSILON, in stock i. LOGMV is the logarithm of the market value of equity in firm i at the end of 2005. LOGPRICE is a log form of the daily close price averaged across 2006. AMIHUD is the Amihud measure multiplied by 10E+6. STDEV is the annualized standard deviation of the daily returns for firm i in 2005. ROA is the return on assets for firm i in 2005 and TOBINQ is the Tobin's Q for firm i in 2005.

MODEL	1	2	3	4	5	6	7	8	9	10	11	12	13
							DEPENDENT VARIABLES						
	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON	EPSILON
INDEPENDENT VARIABLES	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF	COEF
INTERCEPT	-33.460	-99.316	-23.332	-20.451	-46.085	-34.775	-76.658	42.460	44.892	52.970	41.437	44.428	56.156
p-value	(0.221)	(0.001)	(0.409)	(0.469)	(0.086)	(0.198)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LOGMV	6.923	16.455	6.036	6.330	8.641	7.952	15.044						
p-value	(0.012)	(0.000)	(0.032)	(0.021)	(0.002)	(0.005)	(0.000)						
LOGPRICE		-11.049					-9.279	-2.224	-2.465	-2.678	-0.867	-1.809	-1.038
p-value		(0.000)					(0.002)	(0.317)	(0.258)	(0.221)	(0.727)	(0.451)	(0.694)
AMIHUD			-334.000				-159.000		-497.000				-461.000
p-value			(0.207)				(0.489)		(0.062)				(0.080)
STDEV				-4.168			-3.947			-5.496			-4.697
p-value				(0.133)			(1.109)			(0.056)			(0.104)
ROA					-67.133		-23.440				-38.508		-31.282
p-value					(0.017)		(0.394)				(0.238)		(0.333)
TOBINQ						-5.884	-2.866					-2.015	-3.371
p-value						(0.125)	(0.412)					(0.634)	(0.412)
OBSERVATIONS	58	58	58	58	58	58	58	58	58	58	58	58	58
ADJUSTED R-SQUARED	0.092	0.321	0.102	0.113	0.168	0.114	0.333	0.000	0.045	0.048	0.008	-0.014	0.074

6. Conclusions and Implications

Our result suggests that the stock price effect should be a proxy of the preference of uninformed investors, and that stock price may be of significance for informed trading in a firm. This should draw attention to the appropriateness of adding Price variables into the robustness test for future informed trading studies.

The paper also has implications from the market microstructure perspective that, in terms of the preferred trading range hypothesis, large Thai firms with relatively high stock prices should implement a stock split policy to attract more public investors and widen the clientele of their firms. This will be of benefit in liquidity provision.

Several papers (Bardong et al., 2007; Aslan et al., 2007; Duarte and Young, 2009) suggest that using a full year of intraday trade data will better achieve reliable values of PIN and AdjPIN. This estimation horizon, however, may tend to capture only the long-term effects of informed trading, which are likely to arise from the strategic cost-minimising behaviour of informed traders (Kyle 1985). In the meantime, it may also rule out short-term informed trading, which is more significant, especially for small firms, and leads to a model bias. All of these findings may imply that other measures of informed trading that can be applied to a short horizon should be appropriate when implemented together.

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