The Effect of Trading by Different Trader Types on Realized Volatility and Jumps: Evidence from the Thai Stock Market

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Abstract

We examine the effect that different trade measures for each investor type have on realized volatility and the components of volatility. By following Barndorff-Nielsen and Shephard (2004)'s techniques, the realized volatility is decomposed into the continuous and jump components. Using a detailed high-frequency data set during 1999-2009, we find that retail investors dominate trading on the Stock Exchange of Thailand and retail trades has the greatest effect on realized volatility, and the components of realized volatility. While the increase in trading by retail investors is associated with an increase in realized volatility, their withdrawal from the market is associated with jumps in volatility. Moreover, we find the number of trades by retail investors among others have the greatest association with the continuous component of volatility suggesting their trading is associated with the release of expected news on the market. This result may suggest that some of retail traders are likely to be informed.

Keywords: Realized Volatility, Trader Types, Thailand

JEL Classification: G15, G41

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บทคัดย่อ

เราตรวจสอบผลกระทบการซื้อขายของนักลงทุนแต่ละประเภทโดยใช้ตัวชี้วัดที่หลากหลายที่มีต่อความผันผวนที่แท้จริง (Realized Volatility) และส่วนประกอบของความผันผวน โดยใช้เทคนิคของ Barndorff-Nielsen และ Shephard (2004) เพื่อทำการแยกความผันผวนที่แท้จริงออกเป็น 2 ส่วน คือ ส่วนประกอบที่เป็นความต่อเนื่อง (Continuous Component) กับ ส่วนประกอบที่เป็นการกระโดด (Jump Component) โดยใช้ชุดข้อมูลที่มีรายละเอียดการซื้อขายความถี่สูง เราพบว่าการซื้อขายของนักลงทุนรายย่อยมีอิทธิพลในตลาดหลักทรัพย์แห่งประเทศไทย และการซื้อขายของนักลงทุนรายย่อยมีผลกระทบมากที่สุดต่อความผันผวนที่แท้จริง และส่วนประกอบของความผันผวนที่แท้จริง ขณะที่การเพิ่มขึ้นของการซื้อขายโดยนักลงทุนรายย่อยจะมีผลต่อการเพิ่มขึ้นของความผันผวนที่แท้จริง แต่การลดลงของการซื้อขายจากนักลงทุนรายย่อยมีผลต่อการกระโดดของความผันผวน นอกจากนี้เราพบว่าจำนวนครั้งของการซื้อขายโดยนักลงทุนรายย่อยเมื่อเทียบกับนักลงทุนกลุ่มอื่นจะมีความสัมพันธ์มากที่สุดต่อส่วนประกอบที่เป็นความต่อเนื่องของความผันผวนที่แท้จริง ซึ่งหมายความว่าการซื้อขายของนักลงทุนรายย่อยมีความสัมพันธ์ต่อการปล่อยข้อมูลข่าวสารที่เป็นไปตามที่ตลาดคาดคิด ผลดังกล่าวอาจเกิดจากการที่นักลงทุนรายย่อยบางส่วนเป็นนักลงทุนที่ได้รับข้อมูลข่าวสาร

คำสำคัญ: ความผันผวนที่แท้จริง ประเภทนักลงทุน ประเทศไทย

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1. Introduction

We investigate the relations between trading by different trader types and information dissemination on the Stock Exchange of Thailand (hereafter, SET) using a detailed data set that spans the period 1999 to 2009. We do so by focusing on how trading by four trader types (i.e., individual, institutional and foreign investors and proprietary traders) affect stock return volatility and the components of volatility. Volatility is decomposed into the continuous and jump components. The continuous component is associated with normal news innovations whereas the jump component is associated with infrequent large movements in returns brought about by unexpected news innovations.[1] The study of the relations provides us with insight into how trading by different trader types are associated with the flow of information into prices.

Prior studies such as Tauchen and Pitts (1983), Ross (1989), Fleming, Kirby, and Ostdiek (2006) and Treepongkaruna and Gray (2009) show return volatility is directly related to the flow of information to the market. Given the difficulty in measuring information flow, studies have relied on proxies in modelling the relation between information and return volatility. One commonly used proxy to indicate the arrival of news is trading volume (Chang 2012). Studies in the volume-volatility literature (e.g., Gallant, Rossi, and Tauchen 1992; Karpoff 1987; Schwert 1989; Wee and Yang 2012) show trading volume to play a role in explaining return volatility and price changes.

In further work on the volatility-volume relation, Bessembinder and Seguin (1992) suggest that different trader types can have differing effects on the relation. The evidence of the effect of trading by different trader types on volatility has, however, been inconclusive. Daigler and Wiley (1999), using data on the futures markets, find the positive volatility-volume relation is driven by “the general public”, which includes individual speculators, managed funds and small hedgers. On the other hand, Sias (1996) finds a positive contemporaneous relation between the level of

[1] The latent news process can be thought of as having two components: (1) normal and (2) unexpected (Maheu and McCurdy 2004). The normal news innovations are associated with smoothly evolving changes in the volatility in returns (i.e., continuous component of stock return volatility) whereas the unexpected news innovations are associated with infrequent large movements in returns (i.e., jump component).

institutional ownership and security return volatility after accounting for capitalisation. Sias (1996) hypothesises and shows that the positive relation is due to trading by institutional investors increasing with volatility. It is not clear whether findings from prior studies on investor type based on developed markets such as the United States are necessarily generalizable to emerging markets such as Thailand[2]. Besides being an emerging market, the composition of market participants on the Thai market is vastly different in that it is heavily dominated by individual investors. Prior studies have shown more than two-thirds of trading (based on volume and trading value) on the SET are by retail investors, with the proportion even higher during the "quiet" times between 1999 and 2003 (see Pavabutr and Sirodom 2010; Phansatan, Powell, Tanthanongsakkun, and Treepongkaruna 2012).

We extend the literature by not only examining a different retail dominated market but, more importantly, also examining the effects of trading by different traders on the components of return volatility. We construct our measures of volatility by summing the squared intraday interval returns over each trade day for each stock as described in Andersen, Bollerslev, Diebold, and Ebens (2001). These measures are model free and as the sampling frequency of the returns approaches infinity. They are also theoretically free from measurement error (Andersen, Bollerslev, Diebold, and Labys 2001). In our analysis, we decompose realized volatility into the continuous and jump components using the techniques developed by Barndorff-Nielsen and Shephard (2004). These components correspond to the expected and unexpected new events. Giot, Laurent, and Petitjean (2010) associate the continuous component with "good" volatility and the jump component with "bad" volatility. The continuous component is deemed to be directional and comparatively easier to anticipate while the jump component is difficult to foresee and associated with low volume. Our study also extends the literature on the volume-volatility relation by measuring the trading activity of the different trader types by trading volume, frequency of trades, and order imbalance. Unlike prior studies such as Giot, Laurent, and Petitjean (2010), our focus

[2] Focusing on Thai market also allows us to contribute to finance academe and practice in Asia-Pacific in the key topic areas of financial institutions and markets and international finance as classified in Benson et al. (2014).

is on the effect that different trade measures for each trader type have on realized volatility and the components of volatility. Our findings allow us to provide empirical evidence for the various theories and models developed to explain the volume-volatility relation. Understanding the relationship between volume and volatility would be benefits for related regulators to set the appropriate trading rules for various investor types.

Our analysis is based on 100 most actively traded stocks listed on the Stock Exchange of Thailand (SET). We find the Thai market is heavily dominated by retail investors and that trading by these investors, often thought of as uninformed in prior studies (see Barber and Odean 1999; Keloharju and Torstila 2002), is associated with stock return volatility. We also find that the number of trades by retail investors (among all traders) have the greatest association with the continuous component of volatility suggesting their trading is associated with the release of expected news on the market. Other trader types have, generally, a much weaker relation with return volatility. This is likely due to the dominant presence of retail investors in the Thai stock market where trading by retail investors accounts for 80% of the trading volume and that some of these traders are likely to be informed.

When examining the jump component, we find a negative relation between trading volume and the jump component of volatility. The relation is evident across all trader types suggesting there is generally lower liquidity in the market when there is unexpected news in the market. When trading activity is measured by number of trades, the negative relation between trading activity and jump is weaken for the proprietary traders, institutional and foreign investors. However, the relation remains stronger for the retail investors.

Our analysis of the trade frequency, trade size and order imbalance suggest that some retail traders engage in strategic behaviour. While retail traders are often thought of as uninformed in developed markets, we find evidence that their trading (i.e., trade frequency) is associated with volatility. Our findings echo those in Phansatan, Powell, Tanthanongsakkun, and Treepongkaruna (2012) where they find retail investors in the Thai stock market have (micro) informational advantages over foreign investors.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes the market architecture and data. Section 4 explains the methodology used in this study. Section 5 discusses the results and section 6 concludes.

2. Literature review

While there is much evidence that trading volume and stock returns volatility are positively related, there is no consensus on what are the key factors behind the relation (Chan and Fong 2006). The theoretical models to explain the positive relation between volume and volatility can be grouped into the following two classes: (1) market microstructure models and (2) mixture of distributions models.

Under the market microstructure models, the trading motives of different types of investors in an environment with asymmetric information are used to explain the volume-volatility relation. In the competitive microstructure models (also known as non-strategic models), informed traders prefer to trade in larger quantities to quickly exploit their informational advantage and hence, trade size has information content. In these models, volume measured by average trade size has a positive relation with volume (see Easley, Kiefer, and O'Hara 1997; Grundy and McNichols 1989; Kim and Verrecchia 1991; Pleiderer 1984). The strategic microstructure model, on the other hand, posits that the number of trades or order imbalance are more likely to be associated with movement in prices (see Admati and Pfleiderer 1988; Barclay and Warner 1993; Chakravarty 2001; Kyle 1985). The strategic model suggests that informed traders strategically break their large order into several smaller trades to avoid information leakage to uninformed traders. Hence, the number of trades, rather than trade size, is associated with information and subsequently related to price movement. In addition to the number of trades, order imbalance also contains important information in the event that market makers or liquidity providers are unable to determine the origin of a trade (i.e., whether a trade is from an informed or uninformed trader). In the strategic model, market makers or liquidity providers infer information of a trade from the order imbalance and adjust their quotes accordingly.

In the mixture of distribution models, information arrival is the latent factor that jointly drives volume and price changes (see Harris 1987; Tauchen and Pitts 1983). The argument is that a fixed number of traders will trade a fixed number of times in response to the release of information, thus the number of trades made during a day will be proportional to the number of information arrivals during that day. In these models, it is predicted that the number of trades rather than total volume that should move price and has a positive effect on return volatility (much like in the strategic microstructure models).

Empirical works have provided evidence on the effect of number of trades, trade size, and order imbalance on stock returns volatility. For example, Jones, Kaul, and Lipson (1994) decompose trading volume into number of trades and average trade size and find that stock return volatility is driven by number of trades per equally time-spaced intervals, and not trade size. Further, Huang and Masulis (2003) find that for large trades, the number of trades is the only factor that affects return volatility. Using realized volatility, rather than absolute return residuals, Chan and Fong (2006) find that only the number of trades, rather than trade size or order imbalance, plays a major role in explaining realized volatility. Further, Fleming, Kirby, and Ostdiek (2006) use state-space methods to investigate the relation between volume, volatility, and ARCH effects within a mixture of distributions hypothesis framework. They find evidence of a large non-persistent component of volatility that is closely related to the contemporaneous non-persistent component of volume.

In work closely related to this paper, Giot, Laurent, and Petitjean (2010) decompose volatility into the jump and continuous components and conclude that the number of trades has a significant impact on the volatility components. However, both average trade size and absolute order imbalance do not have significant explanatory power. While there has been much work on the volume-volatility relation, the empirical studies discussed above are based on the U.S. markets and none have examined the trading by different investor types. So, this paper tries to investigate the volume-volatility relation in developing market that has the retail investors as the largest trader group in the market.

Recent studies that have used the investor type data from the SET include Kamesaka and Wang (2004), Charoenwong, Ding, and Jenwittayaroje (2010) and Phansatan, Powell, Tanthanongsakkun, and Treepongkaruna (2012). Kamesaka and Wang (2004) investigate the behavior of individual, institutional and foreign investors on the Thai equity market from January 3, 1996 to December 30, 1999. Their results indicate that foreign investors tend to increase their net buying after stock prices have increased over a period of a few days. On the other hand, individual investors increase their net buying after stock prices have declined over a period of a few days. Kamesaka and Wang (2004) also show that foreign investors are generally more superior in market timing and have better trade performance.

Charoenwong, Ding, and Jenwittayaroje (2010) investigate which trade sizes move stock prices on the SET over two distinct bull and bear market conditions. They show that, unlike the stealth trading shown for the US, informed traders use larger-size trades than those employed by informed traders in the US. More recently, Phansatan, Powell, Tanthanongsakkun, and Treepongkaruna (2012) examine trading patterns and trade performance of different investor types using weekly aggregated investment flow data from January 1999 to December 2004 on the Stock Exchange of Thailand (SET). They find that the same trading patterns employed by different investor types result in different sources of performance and trading performance. More specifically, they find that foreign and institutional investors are excellent market timers. They also show that individual investors and proprietary traders appear to have poor market timing ability but they seem to make gains arising from the price spread.

3. Market architecture and data

The SET operates a pure limit order driven market with no designated market makers and where liquidity is provided by traders who places limit orders. Trading on the SET is conducted on a fully computerised trading system.[3] Like many other

[3] Charoenwong, Ding, and Jenwittayaroje (2010) and Phansatan, Powell, Tanthanongsakkun and Treepongkaruna (2012) provide a good overview of the SET market structure.

limit order driven markets, SET uses a call market to determine the opening price in the morning and after the lunch time break for each stock. During the trading sessions, buy and sell orders are matched according to price and then arrival-time priority. SET utilises a multiple tick size regime that is likely to benefit individual retail investors who dominate the market (Phansatan, Powell, Tanthanongsakkun, and Treepongkaruna 2012).

Real-time trade data in this study are sourced from the SET for the sample period of January 1, 1999 to 30 December 30, 2009. The database contains the date, time, price, volume, security symbol of each trade. Most importantly, the database contains the information on the trader type and the submission times of each buy and sell orders. The sample used comprises the 100 most actively traded stocks on the SET mainboard.[4] Using the tick by tick database, we construct the returns and volatility measures based on 5-minute intervals. To compute order imbalance, we identify whether a trade is buyer or seller initiated by cross checking the time of the trade with the time of the corresponding buy and sell order to the trade.[5] This allows an accurate identification of the trade initiator without having to rely on the Lee and Ready (1991) algorithm.

4. Methodology

We estimate the relation between (1) realized volatility, (2) the continuous and (3) the jump components of realized volatility with the trading activity of the four trader types, respectively. In examining trading activities, as suggested by Chan and Fong (2006), the daily trading volume is employed as one of the trading proxies. To provide further evidence of trading effect on realized volatility, we decompose

[4] In order to overcome the size bias of stocks in the sample, the stocks are selected based on the median number of shares traded per day over the sample period. The number of shares traded per day or volume is one of the two liquidity measures reported by SET. The stocks are not required to have traded over the period continuously but are required to have at least 200 days of trading to be included in the sample.

[5] The order with the latest submission time and time that is identical to the trade time is deemed as the initiating order.

trading volume into the number of trades and the average trade size. We also examine whether the order imbalance for each trader type has any effects on volatility. Based on the strategic microstructure model, order imbalance is argued to be a factor in explain volatility. A high absolute order imbalance can affect returns as liquidity providers such as investor who place limit orders struggle to re-adjust their position.

4.1 Realized volatility

Similar to Jones, Kaul and Lipson (1994) and Chan and Fong (2006), we use realized volatility as a measure of volatility. The use of realized volatility is advocated by Andersen and Bollerslev (1998) and is defined as the sum of the corresponding 1/Δ high-frequency intra-daily squared returns for day t:

$$RV_t(\Delta) = \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2 \qquad (1)$$

where, $r_{t,\Delta} = p(t) - p(t-\Delta)$ is the discretely sampled Δ-period return and 1/Δ is the number of intradaily periods.

4.2 The continuous and jump components of realized volatility

It is emphasized in Andersen and Bollerslev (1998) that by the theory of quadratic variation, realized variation converges uniformly in probability to the increment of the quadratic variation process as the sampling frequency of the underlying returns increases, suggesting that:

$$RV_t(\Delta) \rightarrow \int_{t-1}^{t} \sigma^2(s)\,ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2 \qquad (2)$$

$$RV_t(\Delta) \rightarrow \text{Integrated Variance + Jumps} \qquad (3)$$

for (Δ→) 0, where N_t is the number of jumps on day t and $\kappa_{(t,j)}$ is the j-th jump size on that day.

In this model, realized volatility estimates integrated volatility only in the absence of jumps. However, in general, realized volatility captures the dynamics of both the continuous sample path and the jump process. That is, in the presence of jumps, realized volatility does not consistently estimate integrated volatility as the measure captures both the continuous and discontinuous components of volatility. Thus, the bi-power variation proposed by Barndorff-Nielsen and Shephard (2004) is used to separate the two components of the quadratic variation process. Using this technique, we are able to consistently estimate the integrated variance in the presence of jumps. Bi-power variation, BV, is defined as the sum of the product of adjacent absolute intraday returns standardised by a constant and is shown as follows:

$$BV_t(\Delta) = \mu_1^{-2} \sum_{j=2}^{1/\Delta} | r^2_{t+j\ 1)\Delta,\Delta} || r^2_{t+(j-\Delta,\Delta} \tag{4}$$

where $\mu_1 = \sqrt{\frac{2}{\pi}} \cong 0.79788$

In the presence of discontinuous jumps, Barndorff-Nielsen and Shephard (2004) show that:

$$BV_t(\Delta) \to \int_{t-1}^{t} \sigma^2(s)\, ds \tag{5}$$

Therefore, the difference between the realized variation and the bi-power variation consistently estimates the jump contribution of the quadratic variation process, that is:

$$RV_t(\Delta) - BV_t(\Delta) \to \sum_{j=1}^{N_t} \kappa^2_{t,j}, \text{ when } \Delta \to 0 \tag{6}$$

Following prior research, we treat small jumps as measurement errors or part of the continuous sample path process and treat the large values of the jumps as the ‘significant’ jump component (Andersen, Bollerslev and Diebold 2007; Huang and Tauchen 2005). To determine if a movement is a jump, we compute the Z statistic as follows:

$$Z_t(\Delta) = \Delta^{-1/2} \frac{\left[RV_t(\Delta) - BV_t(\Delta) \right] RV_t(\Delta)^{-1}}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5 \right) \max\left\{ 1, TQ_t(\Delta) BV_t(\Delta)^{-2} \right\} \right]^{1/2}} \tag{7}$$

where,

$$TQ_t(\Delta) = \Delta^{-1}\mu_{4/3}^{-3}\sum_{j=3}^{1/\Delta} | r_{t+j\Delta,\Delta}^2 |^{4/3} | r_{t+(j-1)\Delta,\Delta}^2 |^{4/3} | r_{t+(j-2)\Delta,\Delta}^2 |^{4/3} \tag{8}$$

and $\mu_{4/3} = 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$

$TQ_t(\Delta)$ is the integrated quarticity and can be consistently estimated using equation (8). We obtain the significant jumps by comparing the test statistics to a standard normal distribution. Under the null hypothesis of no jumps, $Z_t(\Delta)$ has an approximately standard normal distribution and this test has been shown to have reasonable power against several plausible stochastic volatility jump diffusion models. In order to compare the test statistics with the standard normal distribution, we choose a significance level α and create an indicator variable, $I_{t,\alpha}\Delta = I\left[Z_t(\Delta) > \Phi_\alpha\right]$[6]. We can then compute the jump component, $J_{t,\alpha}(\Delta) = I_{t,\alpha}(\Delta)\left[RV_t(\Delta) - BV_t(\Delta)\right]$.

Andersen, Bollerslev and Diebold (2007) suggest the use of 'staggered' versions of the bi-power variation and integrated quarticity measures to tackle microstructure noise that results in autocorrelated high-frequency returns. We define integrated variance, $C_{t,\alpha}(\Delta)$, such that the summation of the jump and continuous component is equal to realized volatility:

$$C_{t,\alpha}(\Delta) = \left[1 - I_{t,\alpha}(\Delta)\right]RV_t(\Delta) + I_{t,\alpha}(\Delta)BV_t(\Delta) \tag{9}$$

Prior studies have shown that it is impossible to compute realized volatility that is free from measurement errors due to microstructure biases such as bid-ask bounce, price discreteness and nonsynchronous trading. Bid-ask bounce causes considerable noise in realized volatility and in order to minimise the noise we use 5-minutes sampling intervals to compute realized volatility. Andersen, Bollerslev, and Das (2001) and others show, in their simulations, sampling at the 5-minutes intervals is optimal and result in the lowest mean square error.

[6] When setting a smaller (i.e., more significant level) α, we have less and larger (in magnitude) jumps.

4.3 Test of trading effect on volatility

To investigate the effect of trading activities on realized volatility, we adapt the approach used by Chan and Fong (2006) where the relationship between trading activities and volatility is estimated using ordinary least squares (OLS). We regress realized volatility for each stock on the lagged realized volatility terms and the trading of the four investor types. We also include a dummy variable to account for the day-of-the-week effects. The regression is as follows:

$$RV_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} RV_{i,t-J} + \sum_{k=1}^{4} \beta_{ik} TR_{i,k,t} + v_{it} \tag{10}$$

where M_t is the Monday dummy taking the value of 1 when the trading day is Monday, $RV_{i,t}$ is the realized volatility for firm i at day t, and $TR_{i,k,t}$ is the four trading proxies for investor type k of firm i at day t measured by four variables i.e. the daily trading volume ($V_{i,k,t}$) , the number of trades ($NT_{i,k,t}$), the average trade size ($ATS_{i,k,t}$) , and the absolute order imbalance ($|OB_{i,k,t}|$).

Similar to Giot, Laurent, and Petitjean (2010), we replace RV in equation (10) with the continuous and jump components respectively in (11) and (12).

$$C_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} C_{i,t-J} + \sum_{k=1}^{4} \beta_{ik} TR_{i,k,t} + v_{it} \tag{11}$$

where C_t is the continuous component of realized volatility.

$$J_{i,t}^{*} = \alpha_i + \alpha_{im} M_t + \sum_{k=1}^{4} \beta_{ik} TR_{i,k,t} + v_{it}$$

where $J^{*} = \max(0, J)$ (12)

Because the jump component, J^{*}, (i.e., dependent variable) is non-negative and truncated at zero, we use a Tobit model to estimate the relation between trading activity and the jump component of realized volatility.

To test whether the number of trades ($NT_{i,k,t}$) or average trade size ($ATS_{i,k,t}$) has a stronger relation with the volatility and the components, we include both measures of trading in the models as follows;

$$RV_{it} = \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij} RV_{i,t-J} + \sum_{k=1}^{4} \beta_{ik} NT_{i,k,t} + \sum_{k=1}^{4} \lambda_{ik} ATS_{i,k,t} + \upsilon_{it} \quad (13)$$

$$C_{it} = \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij} C_{i,t-J} + \sum_{k=1}^{4} \beta_{ik} NT_{i,k,t} + \sum_{k=1}^{4} \lambda_{ik} ATS_{i,k,t} + \upsilon_{it} \quad (14)$$

$$J_{i,t}^{*} = \alpha_i + \alpha_{im}M_t + \sum_{k=1}^{4} \beta_{ik} NT_{i,k,t} + \sum_{k=1}^{4} \lambda_{ik} ATS_{i,k,t} + \upsilon_{it} \quad (15)$$

where $J^* = \max(0, J)$

The strategic microstructure model suggests that the liquidity providers, i.e., investors who use limit orders in the case of the limit order market, cannot distinguish whether an order comes from an informed or uninformed trader. Therefore, they will infer the information content of a trade from the order imbalance and revise prices accordingly. Furthermore, monopolist informed traders are likely to stealth trade by breaking large trades into multiple smaller trades (Barclay and Warner 1993; Chakravarty 2001). This suggests that absolute order imbalance and number of trades together should jointly explain volatility. To investigate this issue, we include both order imbalance and number of trades in the estimation models as follows:

$$RV_{it} = \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij} RV_{i,t-J} + \sum_{k=1}^{4} \beta_{ik} NT_{i,k,t} + \sum_{k=1}^{4} \theta_{ik} \left|OB_{i,k,t}\right| + \upsilon_{it} \quad (16)$$

$$C_{it} = \alpha_i + \alpha_{im}M_t + \sum_{j=1}^{12} \rho_{ij} C_{i,t-J} + \sum_{k=1}^{4} \beta_{ik} NT_{i,k,t} + \sum_{k=1}^{4} \theta_{ik} \left|OB_{i,k,t}\right| + \upsilon_{it} \quad (17)$$

$$J_{i,t}^{*} = \alpha_i + \alpha_{im}M_t + \sum_{k=1}^{4} \beta_{ik} NT_{i,k,t} + \sum_{k=1}^{4} \theta_{ik} \left|OB_{i,k,t}\right| + \upsilon_{it}$$

where $J^* = \max(0, J)$ (18)

5. Results

5.1 Summary statistics

Table 1 reports the summary statistics for the volatility measures and trading activities. Panel A shows the volatility measures are positively skewed with a fat tail distribution. The average daily realized volatility, RV, based on 5-minute intervals is approximately 2% while the continuous and jump components are both just under 1%. Panel B reports the summary statistics of average trade size, ATS. The average trade size transacted by foreigner investors is the largest at 21,452 shares, followed by proprietary traders with the average trade size of 19,817 shares[7]. The average trade size transacted by retail investors is 16,482 shares and by institutional investors is 15,640 shares. The average trade size in our sample for foreigners and proprietary traders is consistent with the results shown in Charoenwong, Ding, and Jenwittayaroje (2010) where the authors suggest large global investors are likely to use relatively larger trades. Because of the comparatively small mean trade size used on the SET, Charoenwong, Ding, and Jenwittayaroje (2010) propose that large global investors are likely to find the use of small orders unacceptable due to the time delay involved in fulfilling their desired and usually large positions.

[7] It should be noted that we find ATS for institutional trades is smaller than that of retail investor because our ATS is measured by trading volume, which included heavily traded penny stocks, popularly traded by retail investors. Further, institutional investors (e.g. mutual funds) are open-end funds and often trade in and out to serve the net flow of fund as such their ATS is not necessarily large.

Table 1 Summary statistics for volatility measures and trading activities variables
This table reports the summary statistics for the volatility measures and trading activities variables for the 100 most actively traded firms on the SET from January 1, 1999 to December 31, 2009. Data are obtained directly from the SET to construct the volatility measures and trading activity variables. Panel A reports the statistics for volatility measures used as dependent variables in Models 10 to 18. RV is the daily realized volatility computed using the sum of 5-minute squared returns. Realized volatility is decomposed into its continuous, and jump components denoted by C and J. This is done by using the realized bipower variation of Barndoroff-Nielsen and Shephard (2004) with a significance level of 0.01% to identify jumps. Panels B, C and D report the statistics for the average trade size (ATS), number of trades (NT) and trading volume, respectively, on a stock day level. Panel E reports order imbalance, |OB|, which is calculated as the absolute value of buyer minus seller initiated trades on a stock day level.

Variable	Mean	Median	Std Dev	Min	Max	N
Panel A: Volatility						
RV	0.0178	0.0010	0.5744	0.00	72.87	172,722
C	0.0094	0.0005	0.4593	0.00	72.87	172,722
J	0.0084	0.0004	0.3427	0.00	45.69	172,353
Panel B: Average Trade Size (ATS)						
Retail	16,481	6,792	46,335	1	2,748,993	172,596
Proprietary	19,817	7,933	52,158	1	3,333,333	86,067
Institutional	15,640	6,648	56,555	1	9,098,100	99,851
Foreign	21,452	8,779	67,412	1	5,907,900	160,669
Panel C: Number of Trades (NT)						
Retail	494	241	798	0	29,029	172,722
Proprietary	23	0	91	0	3,089	172,722
Institutional	32	4	67	0	3,309	172,722
Foreign	104	40	187	0	8,658	172,722
Panel D: Trading Volume (V) (‘000s)						
Retail	10,094	1,749	39,760	0	2,823,234	172,722
Proprietary	346	0	2,375	0	384,180	172,722
Institutional	449	16	1,879	0	304,673	172,722
Foreign	1,752	360	5,948	0	859,511	172,722
Panel E: Order Balance (|OB|) (‘000s)						
Retail	2,283	408	11,613	0	1,852,093	172,722
Proprietary	123	0	817	0	155,064	172,722
Institutional	332	10	1,625	0	304,673	172,722
Foreign	979	165	4,234	0	858,711	172,722

Panel C of Table 1 reports the daily average number of trades for the four types of traders. Retail investors trade most often among the four types of traders (*NT* = 494), followed by foreign investors (*NT* = 104) and institutional investors (*NT* = 32), with proprietary traders trading the least frequent (*NT* = 23). Panel D of Table 1 reports the daily average trading volume for the four types of traders. Retail investors are found to dominate the Thai market, with retail investors involved in approximately 80% of the total market volume.[8] Foreign, proprietary and institutional traders, together, only account for 20% of the trading volume. While foreigner and institutional investors trade less frequently and their trading volume accounts for a smaller proportion of the total trading volume, it is not clear if their trading is inconsequential to price fluctuations. Together with the findings from Phansatan, Powell, Tanthanong-sakkun, and Treepongkaruna (2012) where foreign and institutional investors are shown to be excellent market timers, our summary statistics suggest foreign and institutional traders enter the market less often but perhaps more strategically and only when they have information to trade on.

Panel E reports the daily average order imbalance for the four types of traders and shows retail investors who dominate the market have the greatest order imbalance, followed by foreign investors, institutional investors and proprietary traders.

5.2 Effect of trading on volatility

Table 2 reports the effect of trading activities measured by four proxies on volatility (models 10 to 12). In panel A, we find a positive, albeit weak, relation between volume and realized volatility for the retail investors (positive and significant for 21 of the 100 stocks examined). We find the relation between volume and the continuous component to be positive for the retail investors (19 of the 100 stocks examined). This implies that trading by retail investors is associated with the expected release of news to the market. The relations between realized volatility and trading volume and also

[8] The trading volume is categorised based on the initiator of the trade and does not consider the counterparty on the trade.

between continuous volatility and trading volume are generally weaker for other types of traders, suggesting the trading by the other investor types are not associated with news releases to the market. For the jump component of the volatility, we find similar results to Giot, Laurent, and Petitjean (2010) in that periods of low trading are associated with jumps. The findings indicate the withdrawal of trading by all investor types with the release of unexpected news with the relation strongest for the retail investors.[9]

In panel B, when using number of trades rather than trading volume as a proxy for trading, we find a stronger (albeit still weak) positive relation between the number of trades and volatility than those reported in panel A for the retail investors. For other investor types, the results are generally weak and non-directional. For the jump component of the volatility, we find periods with lower number of trades are associated with jumps. In particular, we find trading by retail investors is negatively associated with jumps with significant results for 47% of the firms.

Panel C[10] reports results when using the average trade size, rather than trading volume. The relations between trading and realized volatility and between trading and the continuous component of volatility are generally weaker than those reported in panel A. Also, the relation between trade size and jump are less clear.

Generally, our findings do not provide support for the competitive microstructure model where the average trade size contains information that move prices and has a positive association with return volatility. These results are consistent with Giot, Laurent, and Petitjean (2010), who do not find evidence to support the competitive model. Together with the results in panel B, our findings provide some support for the strategic model in that the number of trades moves prices. This is based on the assumption that informed investors engage in stealth trading by breaking up large trades into smaller transaction. Surprisingly, it is the number of trades made by retail investors that are associated with volatility. By contrast,

[9] Our tests do not allow the inference of causality and we are unable to infer if the release of unexpected news causes the decline in trading or the decline in trading causes the jumps.

[10] We run robustness check by using ATS measured based on market value, rather than trading volume and find slightly weaker but similar results. Results are available upon request.

these investors are often thought of as uninformed in prior studies conducted on more developed markets (see Keloharju and Torstila, 2002).

Panel D reports results when using the absolute order imbalance, rather than trading volume as a proxy for volume. We find a weaker positive relation between number of trades and volatility than those reported in panle A. Again, results are strongest for the retail investors. Our findings provide weak support for the strategic microstructure model where order imbalance contains important information. The variable *|OB|_R* is positively related to RV for 16% of the stocks examined and the results are even weaker for other types of traders. These results are consistent with Giot, Laurent, and Petitjean (2010) and Chan and Fong (2006), who do not find evidence to support the strategic model.

For the jump components of realized volatility, we find absolute order imbalances by all types of traders are generally negatively associated with jumps. This evidence is consistent with Giot, Laurent, and Petitjean (2010) and suggests that jumps are less likely when there is less heterogeneity in beliefs in the market (i.e., when there is excess demand or supply). This relation is evident across all investor types.

Table 2: Effect of trading on volatility

This table summarises the results of the regressions (Models 10, 11 and 12) conducted for the 100 most heavily traded firms on the SET over the period January 1, 1999 to December 31, 2009. Vol_R, Vol_P, Vol_M, Vol_F, NT_R, NT_P, NT_M, NT_F, ATS_R, ATS_P, ATS_M, ATS_F, |OB|_R, |OB|_P, |OB|_M, and |OB|_F are the trading volumes, number of trades, average trade size, and absolute order imbalance for retail investors, proprietary traders, institutional investors and foreigners, respectively. Models 10 and 11 are estimated by OLS while Model 12 is estimated by maximum likelihood using the Tobit model. The coefficient (Coeff) reported is the equally-weighted cross-sectional mean coefficient for the number of shares traded, with the corresponding Newey-West standard errors (se) and two-sided p-values. We also report the percentage of positive and negative coefficients which are statistically different from zero at the 5% level.

Panel A: Trading Volume

		RV (Model 10)	C (Model 11)	J (Model 12)
Vol_R	Coeff	0.0004	0.0001	-0.0001
	se	0.0004	0.0002	0.0000
	% p-value	0.4458	0.4218	0.0000
	% + significant	21	19	23
	% - significant	0	1	77
Vol_P	Coeff	-0.0013	-0.0011	0.0005
	se	0.0077	0.0049	0.0000
	% p-value	0.5410	0.5524	0.0000
	% + significant	3	1	31
	% - significant	8	5	69
Vol_M	Coeff	-0.0006	0.0001	-0.0030
	se	0.0089	0.0057	0.0000
	% p-value	0.6049	0.6051	0.0000
	% + significant	4	4	30
	% - significant	4	0	70
Vol_F	Coeff	0.0015	0.0016	-0.0002
	se	0.0024	0.0016	0.0000
	% p-value	0.5370	0.5521	0.0000
	% + significant	7	8	38
	% - significant	3	1	62

Panel B: Number of Trades				
		RV (Model 10)	C (Model 11)	J (Model 12)
NT_R	Coeff	-0.0008	-0.0027	-0.0227
	se	0.0113	0.0071	0.0094
	% p-value	0.4123	0.3815	0.1443
	% + significant	24	26	13
	% - significant	0	0	47
NT_P	Coeff	-0.0161	-0.0228	-0.0412
	se	0.5240	0.3565	0.4195
	% p-value	0.5373	0.5341	0.4458
	% + significant	3	1	2
	% - significant	9	6	12
NT_M	Coeff	-0.0439	-0.0300	-0.0940
	se	0.4114	0.2593	0.3500
	% p-value	0.5682	0.5816	0.4615
	% + significant	2	4	3
	% - significant	5	0	5
NT_F	Coeff	0.0231	0.0295	-0.0344
	se	0.1309	0.0842	0.1029
	% p-value	0.5168	0.5096	0.3607
	% + significant	7	7	6
	% - significant	6	1	14

Panel C: Average Trade Size				
		RV (Model 10)	C (Model 11)	J (Model 12)
ATS_R	Coeff	0.1189	0.0385	-0.2307
	se	0.6757	0.3113	0.2941
	% p-value	0.4489	0.4838	0.3661
	% + significant	8	8	19
	% - significant	4	3	36
ATS_P	Coeff	-0.0403	-0.0139	-0.0802
	se	0.1852	0.0903	0.0081
	% p-value	0.5620	0.5990	0.5159
	% + significant	1	4	42
	% - significant	0	0	54
ATS_M	Coeff	0.0012	0.0260	0.0691
	se	0.1520	0.0844	0.0175
	% p-value	0.5668	0.5360	0.4084
	% + significant	6	3	53
	% - significant	2	1	36
ATS_F	Coeff	0.1365	0.0636	0.2421
	se	0.3169	0.1590	0.0867
	% p-value	0.4789	0.5122	0.6029
	% + significant	3	3	44
	% - significant	4	4	34

Panel D: Order Imbalance				
		RV (Model 10)	C (Model 11)	J (Model 12)
|OB|_R	Coeff	0.0002	0.0000	-0.0012
	Se	0.0013	0.0007	0.0000
	% p-value	0.5263	0.4915	0.0000
	% + significant	16	14	23
	% - significant	0	0	77
|OB|_P	Coeff	0.0012	0.0000	-0.0006
	se	0.0170	0.0099	0.0000
	% p-value	0.5971	0.6278	0.0000
	% + significant	4	5	21
	% - significant	1	0	79
|OB|_M	Coeff	-0.0011	-0.0003	-0.0057
	se	0.0095	0.0059	0.0000
	% p-value	0.5975	0.6253	0.0000
	% + significant	4	3	22
	% - significant	1	0	78
|OB|_F	Coeff	0.0012	0.0010	-0.0007
	se	0.0031	0.0019	0.0000
	% p-value	0.5666	0.5789	0.0000
	% + significant	9	11	31
	% - significant	1	0	69

5.3 Volatility with number of trades vs. average trade size

Table 3[11] reports results for models 13 to 15. When volume is decomposed into number of trades and average trade size, we find a stronger positive relation between number of trades and volatility (i.e., RV and C) than between average trade size and volatility. The results are consistent with the mixture of distribution where information is related to the frequency of trading and not the quantity traded (i.e., average trade size and trading volume).

Again, results for retail investors are strongest whereas NT-volatility and ATS-volatility associations are weaker for other type of traders. The findings in Table 4 reinforce that shown in Table 3.

Table 3: Effect of ATS and NT on volatility

This table summarises the results of the regressions (Models 13, 14 and 15) conducted for the 100 most heavily traded firms on the SET over the period January 1, 1999 to December 31, 2009. Models 13 and 14 are estimated by OLS and Model 15 is estimated by maximum likelihood using the TOBIT models. The coefficient (Coeff) reported is the equally-weighted cross-sectional mean coefficient for the number of trades and average trade size, with the corresponding Newey-West standard errors (se) and two-sided p-values. We also report the percentage of positive and negative coefficients which are statistically different from zero at the 5% level.

		RV (Model 13)	C (Model 14)	J (Model 15)
NT_R	Coeff	0.0022	0.0011	-0.0076
	se	0.0088	0.0021	0.0123
	% *p*-value	0.3327	0.3619	0.2643
	% + significant	30	29	12
	% - significant	2	1	20

[11] We run robustness check by using ATS measured based on market value, rather than trading volume and find slightly weaker but similar results. Results are available upon request.

		RV (Model 13)	C (Model 14)	J (Model 15)
NT_P	Coeff	-0.1235	-0.0320	0.0723
	se	0.4918	0.0970	0.5230
	% *p*-value	0.4456	0.5086	0.4301
	% + significant	4	1	5
	% - significant	10	5	16
NT_M	Coeff	0.0738	0.0542	0.0172
	se	0.1488	0.0405	0.2355
	% *p*-value	0.5354	0.5669	0.4562
	% + significant	3	4	5
	% - significant	1	1	4
NT_F	Coeff	-0.0095	-0.0123	-0.0187
	se	0.0803	0.0250	0.1615
	% *p*-value	0.4870	0.5395	0.3775
	% + significant	6	8	12
	% - significant	3	1	8
ATS_R	Coeff	-0.0644	0.0497	-0.1957
	se	0.7081	0.3258	0.3184
	% *p*-value	0.4465	0.4795	0.4333
	% + significant	6	5	25
	% - significant	7	5	28
ATS_P	Coeff	-0.0385	-0.0193	-0.0936
	se	0.1859	0.0898	0.0082
	% *p*-value	0.5600	0.5942	0.5602
	% + significant	1	3	40
	% - significant	0	1	56

		RV (Model 13)	C (Model 14)	J (Model 15)
ATS_M	Coeff	0.0061	0.0290	0.0836
	se	0.1526	0.0847	0.0179
	% *p*-value	0.5631	0.5527	0.5137
	% + significant	5	4	50
	% - significant	3	0	38
ATS_F	Coeff	0.1465	0.0454	0.2089
	se	0.3165	0.1574	0.0872
	% *p*-value	0.5100	0.5137	0.5711
	% + significant	4	5	39
	% - significant	1	2	38

We also run the robustness check by using data during financial crisis period between February 1, 2007 to December 31, 2009. When trading volume is decomposed into number of trades and order imbalance, we find similar results to those reported in Tables 2 and 3. That is, the number of trades by retail investors is positively associated with realized volatility and the continuous component of volatility.

5.4 Incremental effect of order imbalance on number of trade and volatility relation

Table 4 reports the results when trading volume is decomposed into number of trades and order imbalance. We find similar results to that reported in Tables 2. That is, the number of trades by retail investors is positively associated with realized volatility and the continuous component of volatility. Also, the trading by retail investors is negatively associated with jumps. By contrast, the negative relation between order imbalance and jump is no longer evident. Overall, our findings provide some support for the strategic model where the number of trades is associated with price movements.

Table 4: Incremental effect of OB and NT-Volatility relation

The table summarises the results of the regressions (Models 16, 17 and 18) conducted for the 100 most heavily traded firms on the SET over the period January 1, 1999 to December 31, 2009. Models 16 and 17 are estimated by OLS and Model 18 is estimated by maximum likelihood using the Tobit model. The coefficient (Coeff) reported is the equally-weighted cross-sectional mean coefficient for the number of trades and average trade size, with the corresponding Newey-West standard errors (se) and two-sided p-values. We also report the percentage of positive and negative coefficients which are statistically different from zero at the 5% level.

		RV (Model 16)	C (Model 17)	J (Model 18)
NT_R	Coeff	0.0001	-0.0010	-0.0249
	se	0.0134	0.0083	0.0098
	% *p*-value	0.4179	0.3818	0.1525
	% + significant	25	26	6
	% - significant	1	2	48
NT_P	Coeff	-0.0656	-0.0429	-0.1568
	se	0.6362	0.4304	0.5272
	% *p*-value	0.5788	0.6102	0.4941
	% + significant	2	0	2
	% - significant	6	1	12
NT_M	Coeff	-0.0291	0.0023	-0.1933
	se	0.6112	0.4098	0.5391
	% *p*-value	0.6118	0.6309	0.4292
	% + significant	5	5	2
	% - significant	2	0	8
NT_F	Coeff	-0.0081	0.0005	-0.0718
	se	0.1808	0.1152	0.1454
	% *p*-value	0.5387	0.4998	0.3411
	% + significant	8	9	3
	% - significant	5	4	14

		RV (Model 16)	C (Model 17)	J (Model 18)
|OB|_R	Coeff	-0.0003	-0.0002	0.0001
	se	0.0016	0.0008	0.0000
	% *p*-value	0.5214	0.5417	0.0000
	% + significant	4	3	51
	% - significant	5	1	49
|OB|_P	Coeff	0.0014	-0.0021	0.0129
	se	0.0216	0.0125	0.0000
	% *p*-value	0.6441	0.6626	0.0000
	% + significant	4	1	46
	% - significant	1	0	54
|OB|_M	Coeff	0.0000	0.0003	0.0012
	se	0.0139	0.0091	0.0000
	% *p*-value	0.6487	0.6550	0.0000
	% + significant	3	3	55
	% - significant	3	3	45
|OB|_F	Coeff	-0.0001	-0.0005	0.0015
	se	0.0046	0.0029	0.0000
	% *p*-value	0.5056	0.5311	0.0000
	% + significant	7	8	59
	% - significant	4	3	41

6. Conclusion

This paper investigates the relation between realized volatility and the trading volume of four investor types on the Stock Exchange of Thailand using high-frequency data from January 1999 to December 2010. Given the detailed high-frequency SET data, we are able to examine the trading by different type of investors and help provide insight into the trading activities of these investors in an emerging market. To some extent, our study allows us to examine which type of investors plays a more significant role in affecting return volatility. In general, we find retail investors dominate the trading on the Thai market accounting for more than 80% of the trading volume. Collectively, foreign, institutional and proprietary investors are found to trade less frequently but with larger average trade sizes.

There is generally a positive (albeit weak) relation between volume and volatility for retail investors. Our findings provide some support for the strategic models, in that the number of trades is positively related to volatility. In these models, traders strategically break their big lot trade into several smaller trades to avoid the leaking of information to other traders. Hence, the number of trades, rather than trade size, contains important information that can move prices. Further analysis on the trading by retail investors provide support for the mixture of distribution model where only the number of trades is associated with return volatility and not the average trade size.

Our results are surprising as retail investors have, in prior studies, been assumed or shown to be naïve and uninformed. While our findings do not allow us to make inference on whether retail traders on the whole are informed, we find retail traders move prices in an emerging market such as Thailand where trading is dominated by these traders.

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