Information Asymmetry and Investors' Behavior around Earnings Announcements

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Abstract

In our study, we investigate the information asymmetry and investors' behavior around earnings announcements listed on the Taiwan Security Exchange (TSE) from June 1999 to January 2005. Second, we separate the announcements into those deemed positive and those deemed negative. The third part of our design focuses on investor's behavior, to see whether they exhibit any form of increasing reactions to similar types of surprise information.

Our empirical results show that earnings announcements reduce information asymmetry once they become public. This implies that the relationship between public and private information could be substituted. Further, firms announcing negative news have higher information asymmetry than those announcing positive news. These results support our former hypotheses and the finding of prior research.

In terms of investors' behavior, small traders exhibit attention buying behavior around announced dates, whether the news is good or bad. Upon comparing the reaction of small and large traders, small traders show stronger reactions than do large traders. These interesting results support our hypotheses and interest us in the possible linkages of these topics. Although the degree of reaction for consecutive earnings surprises isn't significant, we still observe learning behavior in a same-type series, especially for large traders. Large traders begin to exhibit significant reversal reactions on a third surprise announcement. Our results imply that small traders tend to be uninformed traders, provide liquidity to the market, and do not have sufficient means to hold precise information as do large traders.

1. Introduction

In recent years, there has been growing interest in issues related to the microstructure of securities markets. An important component of the transaction risk faced by investors in financial securities is the information asymmetry set by the security issuers. The original paper on this topic, Ball and Brown (1968), shows that accounting income numbers have information content. Numerous empirical studies have been conducted to examine market behavior around earnings announcements. Since earnings announcements are routine and public information, market participants will project their expectations to forthcoming announcements in terms of the security price. Subrahmanyam (2005) argues that managers may be very adept at concealing true value, and that there may be large information asymmetries between outside investors and firms. Several earlier studies demonstrate that the anticipation of earnings news increases information asymmetry in the market, as investors increase their search for private information that will allow them to profit once earnings are announced (Kim and Verrecchia (1994) and Verrecchia (1982)). With this in mind, the objective of our article is to explore the effects of earnings announcements on the variation of information asymmetry. Furthermore, we also examine investors' behavior in terms of earnings announcement surprises, which may be caused by information asymmetry.

Bamber (1987) found the absolute value of unexpected earnings is positively related to the magnitude and duration of the trading volume reaction. He examined the relations between market reaction and the degree of unexpected earnings. The unexpected earnings could be divided into positive and negative ones. Generally, these are defined as the good earnings news and bad earnings news. Prior research usually focused on market reactions to these two types. Woodruff and Senchack(1988) found that stocks with extremely good earnings news exhibited a more rapid adjustment than those with extremely bad earnings news. Wael (2004) found that prices converged to equilibrium more quickly for good news than for bad news. Accordingly, the different surprises cause asymmetric responses in the market. Different degrees of information asymmetry may exist around the earnings announcements. However, prior research has usually been limited to that focusing on price reaction, while we are curious to study this phenomenon in more detail. This is the first important issue this article discusses.

As the information environment in emerging markets is not as complete and efficient as that in mature markets, we expect the phenomenon of information asymmetry to be more significant than that exhibited in mature markets. In this paper, we use more exact measurements to examine the information asymmetry around earnings announcements dates, even in regards to different earnings surprises.

Since Varian (1986) developed the difference in opinion model, Kim and Verrecchia (1991a, b) argued that the heterogeneous beliefs around earnings announcements induce market participants to trade. Further, numerous research have discussed different types of investors' behaviors. Intuitively, investors usually form their expectations based on their information endowments. The precision of their information plays an important role in their decision making. Kim and Verrecchia (1991) argued that different trader reactions are caused by differing amounts of precisions of their private information, since investors' trading behavior is based on their held information and when it was gathered. This means investors in the market also exhibit information asymmetry among themselves. Many studies discuss investors' behavior around earnings announcements. Daniel, Hirshleifer and Subrahmanyam (1998) propose a model, based on investor "overconfidence" and "biased self-attribution," in which investors underreact to news that disagrees with their views, and overreact to news that agrees. Barberis and Thaler (2003) show that individuals make basic trading mistakes which institutions do not make. Theoretical and empirical findings in the US use different measurements to distinguish investors by cutting trades, and also analyze their behaviors. In this article, we further analyze the behavior of small and large investors around the earnings announcements.

Madhavan (1992) shows that relative to continuous mechanisms (defined as the quote-driven system and the continuous auction), the periodic auction (call) pooling orders for simultaneous execution aggregates information efficiently and overcomes the problems of information asymmetry better. However, a periodic system cannot provide immediate order execution, and imposes higher costs for traders who must collect market information instead of observing price quotations. Thus, Chow, Lee and Liu (2004) inferred that traders in the Taiwan stock market who do not observe trading as frequently under a call mechanism as under a continuous market could tend to be more conservative in placing the orders than the traders observe under a continuous market. Further, they found traders to be more conservative at the market opening than at other intraday points. This characteristic raised many questions for us regarding investors' behavior in this market. We divided our sample into small and large traders based on trading volume and analysis of their reactions to news.

There are several important findings in our article. First, we find that quarterly earnings announcements can reduce information asymmetry between firms and investors. This is consistent with Verrecchia (1982), who suggests that when public information is available, private information becomes less valuable. Consequently, information asymmetry increases before earnings announcements and decreases after the announcements because private information becomes public at the time of the announcement. Furthermore, we divide the earnings announcements into good or bad news, and the results suggest that the reactions to bad news are stronger than those to good news. This is consistent with Engle and Ng (1993), who investigated several asymmetric volatility models and suggested that impacts of negative return shocks are larger than positive return shocks. Second, the results of our paper show that small traders would be net buying after earnings announcements and small traders react more strongly to good news than to bad news. Third, small traders react more strongly to a series of similar earnings surprises, but they react weaker significant than large traders in a series of similar earnings surprises. This may be attributed to accounting conservatism, as investors will react to the news only upon observing some signal consistent to their private information. Further, small traders are more likely to make mistakes in the market, and they tend to be conservative. Consequently, we could not find strong evidence to support our hypothesis.

The remainder of the paper is organized as follows. The literature review and hypothesis development are introduced in section 2. Section 3 discusses the data and descripts the Taiwan security market. Section 4 presents the research methodology. Section 5 exhibits the empirical results and the findings. Finally, section 6 offers discussion and conclusions.

2. Theory and hypothesis development

2.1 Information asymmetry around earnings announcements

Market reactions to earnings announcements have long been a topic of interest to the accounting community. One issue is whether public information, such as earnings announcements, is a substitute for or a complement to private information.

A substitute relationship implies that more public information leads to less private information gathering and hence, less information asymmetry in capital markets. Mc Nichols and Trueman (1994), and Demski and Feltman (1994) argue that information asymmetry should increase before earnings announcements, as there is a risk that trades are initiated by informed investors. Morse and Ushman (1983) use such an argument to predict that an earnings announcement should be accompanied by a decrease in bid-ask spreads. In contrast, if private information is generated by processing and interpreting a public announcement, or the anticipation of more public information encourages more private information acquisition, more public information leads to more private information and hence more information asymmetry. Kim and Verrecchia (1994) argued that the disclosure of the earnings actually increases information asymmetry. Because the ability of information processors to produce superior assessments of a firm's performance on the basis of an earnings announcement provides them with a comparative information advantage over other participants.

We assume that private and public information are substitutes, and yet we show that information asymmetry will be reduced once the earnings go public. These arguments lead to the following hypotheses:

Hypothesis 1: *If earnings announcements reduce information asymmetry, the proxy of* *information asymmetry will be lower in post-announced period than in pre-announced period.*

Proxy of Information Asymmetry

Bid-Ask Spread

In general, the degree of information asymmetry presented in the market can be measured by the bid-ask spreads. In market microstructure theory, the bid-ask spread is explained by two principle theories: the inventory control model and the asymmetric information model. Glosten and Milgrom (1985) argued that a higher proportion of informed traders on the market will lead the market maker to widen his bid-ask spread to compensate for the additional adverse selection risk. Easley and O'Hara (1987) further argued that if market conditions are such that market makers become concerned about a higher proportion of informed traders in the market, or that the informed traders have better information, they will widen their bid-ask spread to compensate themselves for the additional adverse selection risk. Cohen et al. (1981) demonstrated that a natural bid-ask spread exists in an order driven market because of the "gravitational pull" that an already posted order has on a new, incoming order. Handa, Schwartz and Tiwari (2003) suggested that the bid-ask spread is a function of both the adverse selection cost and differences in valuation. Thus, the spread is also a proxy of information asymmetry in an order-driven market.

The greater the informational asymmetry in the market is, the greater the benefit to informed traders who possess superior information. This tends to result in wider bid-ask spreads.

Adverse Selection Cost

Krinsky and Lee (1996) suggest that the total spread used in previous studies may not be an accurate measure of information asymmetry. Due to lower inventory holding and order processing components, the change in quoted bid-ask spreads will be less pronounced, although earnings releases still result in increased information asymmetry among market participants. They also believe that adverse selection costs increase significantly before and following the announcements. This result can be interpreted as evidence of increased information asymmetry.

Price Volatility

In addition, if information about the firm's value is less transparent, then dispersion of beliefs in the capital market tends to be greater as a result.

Shalen (1993) has shown that price volatility is related to the dispersion of expectations about future market prices, and can act as a good proxy of informational asymmetry. Uninformed traders with more divergence may exacerbate even higher volatility. If earnings announcements can reduce informational asymmetry, there should be a corresponding reduction in price volatility.

Realized Volatility

The measure of volatility is a model proposed by Andersen et al. (2001) (henceforth ABDL). ABDL (2001) introduced realized volatility to measure volatility over the interval of interest. They used five-minute intraday data to determine the realized volatilities. Thus, if earnings announcements reduce informational asymmetry, realized volatility also should reduce.

2.2 Information asymmetry to good- and bad-news

Hayn (1995) suggested that losing firms require investors to gather more information for their valuation analysis than profitable firms. This stems from the higher probability of bankruptcy and liquidation for loss-making firms. Therefore, when assessing the value of a firm, investors must also collect and interpret information regarding the probability of default and the firms' default and liquidation value. Lang and Lundholm (1993) showed that successful firms provide more information than unsuccessful firms. Their analysis also indicated that the information environment of successful firms would be more stable(less information asymmetry and less uncertainty) than that of bad-news firms. Ertimur (2003) provided additional evidence about the information environment of loss firms, loss-making firms have higher bid-ask spreads than profitable firms. Earnings announcements are a routine informational event to display performance of firms. When they have been divided into good and bad news, it implies that we can discuss the information environment of these two groups. Underperforming firms are more likely to either abandon a project or sell some of their assets. Moreover, poor-performance firms are more likely to change or replace their management, governance structure, and business strategy and to engage in restructuring, than are successful firms. These actions would generate more uncertainty and therefore increase the likelihood of information asymmetry trading among the bad-news firms.

The accounting conservatism principle also relates to bad-news firms' information environment. Accounting rules imply that declines in profitability, losses, and write-offs would be more transitory and larger, on average, than gains. Basu (1997) found that good earnings news[1] is more likely to be persistent than bad earnings news as a result of conservatism. It means bad earnings news is more likely to be temporary. They examined the conservatism principle on accounting. For instance, unrealized losses are typically recognized earlier than unrealized gains. This asymmetry in recognition leads to a systematically different persistence of earnings. Gains are more stationary since they are a result of economic expansion of previous and current periods. Thus, it should be easier to predict earnings for good news firms. In fact, for good-news firms, unlike for bad-news firms, simple time series models are good predictors of earnings. The analysis above suggests that the information environment of bad-news firms, including profitable ones, would be associated with high information costs and high information uncertainty environments.

[1] They define positive earnings changes as good earnings news, the same to bad earnings news.

From the above arguments we conclude that good-news firms are more likely to have less information uncertainty, on average, than bad-news firms.

Hypothesis 2: *If bad-news portfolios have higher information asymmetry, the proxy to information asymmetry of bad-news portfolios will be higher than good-news portfolios.*

2.3 Order flow around earnings announcements

In the market microstructure theory, there are two kinds of traders defined by information asymmetry models existing in the market – informed traders and liquidity traders. We can view informed traders as traders who have private information which represents the "true" value of the asset. They can either be insiders or traders who are particularly skillful in processing public information. Kim and Verrecchia (1991) showed that informed traders prefer to trade large amounts at any given price. Hasbrouck (1999) examined the relation between trades and quote revisions for the stocks in the NYSE and found strong evidence that large trades convey more information than small trades. Brown et al. (1997) suggested that smaller trades do not react immediately to "news" in return, but tend to follow.

Large trades perhaps appear to indicate that they are more informed than smaller trades. But Kyle (1985), Admati and Pfleiderer (1988) indicated that a monopolist informed trader may camouflage his trading activity by splitting one large trade into several small trades. Thus, large share positions are likely to be broken up into several trades. However, transaction costs and delay costs would prevent informed traders from engaging in a sequence of small size trades. Therefore, Barclay and Warner (1993) argued that if informed traders prefer to break up trades so that they can camouflage their trades with liquidity traders, it might be optimal for them to submit medium-sized orders.

The strongest motivation is a growing empirical behavioral finance literature that repeatedly shows that individuals make basic trading mistakes which institutions do not make. Barberis and Thaler (2003) provided a summary of this literature. In particular, large traders will be more correlated with professional investors and professional investment advisors, who are likely to have greater financial education, more experience and more time to make investing decisions. Barber and Odean (2001) argued that the individual investors tend to be net purchasers of stocks on high attention days. Their buying behavior is more heavily influenced by attention than their selling behavior. Lee (1992) found that after an announcement there is a significantly greater number of buys than sells for small orders. Griffiths et al. (2000) found that aggressive buys are more likely to be motivated by information than aggressive sells. Earnings announcements represent the performance of a company going public. When earnings have been announced, it will gain the attention of participants in the market. Prior research has shown that small and large traders trade differently around earnings announcements. We would like to observe the behavior of small and large traders in the TSE and expect that they will have different reactions to the routine earnings announcements.

Examining order flow data can potentially reveal valuable information that is not available from transaction data. The data allows us to examine investors' trading behavior directly. The greater the order imbalance is, the smaller the opinion difference. In addition to testing the degree of divergence in opinions, it can also be used to test investor's reaction. In Lee (1990), the imbalance in buy-sell orders is used to measure the market response to an information event. The earnings announcement is an information event and makes us infer investors' behavior directly. As we mentioned above, different investors have different reactions to the news. Lee (1992) examined the imbalance of trade direction[2]to test the behavior of small traders and found that after an announcement, there is a significantly greater number of buys than sells for small orders. Shanthikumar (2002) also used trade imbalance to test investor's behavior. This paper presents consistent evidence of an eventual overreaction in small trader behavior, both relative to large traders and to a benchmark of zero.

Hypothesis 3.1: *If earnings announcements are high attention days, the order imbalance of small traders will be net buying in the post-announced period.*

Hypothesis 3.2: *Small traders react more strongly than large traders.*

Proxy of different traders

Trade Size

Prior research has used two alternative proxies to distinguish between small and large traders: (1) the number of shares traded (trade-size-based proxy[3]), and (2) the dollar value of the transaction (dollar-value-based proxy[4]). Easley et al. (1997a.b) classified the trades into large (at least 1,000 shares) and small trades (fewer than 1,000 shares). Barclay and Warner (1993) classified the trades into small (fewer than 500 shares), medium (500-9,900shares), and large (above 10,000). Bessembinder and Kaufman (1997) classified the trade into three categories based on dollar volume: small trade (less than $10,000), medium trade ($10,000-$199,999), and large trade (above $200,000). Shanthikumar (2003) used two primary cutoffs, with a buffer between small and large trades to reduce noise. The lower cutoff of $5,000 splits small and medium trades, and the higher cutoff of $50,000 splits medium and large trades.

The limitation of the trade-size based proxy is that it does not reflect differences in stock prices. Lee and Radhakrishna (2000) found that dollar-value-based proxies are generally less noisy than trade-size-based proxy in separating small and large investor transactions. Dollar-value-based

[2] the net number of sell orders, not the net number of shares sold

[3] See Cready (1988), Cready and Mynatt(1991)

[4] See Lee (1992), Lee and Radhakrishna(2000)

proxies are, however, sensitive to stock price changes, and mean to the wealth that traders have. Thus, our research adopts two measurements to distinguish between small and large traders.

Lee, Lin and Liu (1999) examined the order flow data of the Taiwan stock market and classified orders of 10 or more lots, which are placed by large individual investors, and orders of less than 10 lots as orders placed by small individual investors. And their results implied that large individual investors are the most well informed players. Besides, they found similar empirical results of the TSE when they changed the cutoff points from 10 round lots to 20 round lots. Our research also examines the phenomenon of the Taiwan Stock Exchange; hence, we adopted 10 lots (10,000 shares) as our cutoff.

2.4 Investors' behavior to good- and bad-news

Earnings announcements release good and bad news. Intuitionally, we consider that investors will react positively to good news and negatively to bad news. However, different groups of investors have different reactions to news. Barber and Odean (2001) argued that individual investors tend to be net purchasers of stocks on high attention days, whether the news is good or bad. Their buying behavior is more heavily influenced by attention than their selling behavior. Hirshleifer et al. (2002) looked only at individual investors' behavior and found that individuals are net buyers after both extremely positive and extremely negative earnings surprise. Lee (1992) displayed an intra-day focus and also found that individual and small traders buy after earnings surprises, whether the surprise is good or bad.

Shanthikumar (2003) empirically tested the NYSE and found that small traders exert buying pressure after an earnings announcement, whether that announcement is good or bad news. They also found that small traders react more strongly to successive surprises, but large traders do not.

Hypothesis 4.1: *If small traders represent the behavior of attention buying, small traders react more strongly than large traders both in good-news and bad-news portfolios.*

Hypothesis 4.2: *If small traders represent the behavior of attention buying, small traders react more strongly to good news than to bad news.*

2.5 Investors' behavior around consecutive earnings surprises

Barberis, Shleifer and Vishny (1998) developed a model based on experimental evidence of what is known as a "conservatism bias," which essentially means that individuals tend to underweight new information when updating their prior beliefs. If an investor sees a particular earnings surprise for the first time, he believes that earnings are mean-reverting and so he under-reacts to the news. On the other hand, if he sees two similar earnings surprises in a row, he believes that earnings are following a trend process, so he overreacts to the later announcements.

Daniel, Hirshleifer and Subrahmanyam (1998) proposed a model, based on investor "overconfidence" and "biased self-attribution," in which investors underreact to news that disagrees with their views and overreact to news that agrees. News that agrees with an investor's opinions strengthens that opinion more than contradictory information weakens it. As a sequence of same-sign earnings surprises continues, individuals' personal views will shift towards the direction of the surprises. Because of this, the later surprises in the sequence will cause a stronger reaction than the surprises at the beginning.

The key difference between two behavioral models regards the initial reaction. Daniel, Hirshleifer and Subrahmanyam (1998) predicted initial overreaction, but Barberis, Shleifer and Vishny (1998) predicted initial underreaction. While the specific models vary in their details, there is consensus among these papers that investors react more strongly as similar information continues to arrive. Barberis and Thaler (2003) summarized two investors' behavior when they face a series of information, in terms of "conservatism" and "representativeness". Moreover, the two behaviors would delay or over reflect the information incorporate into the security price. An investor who displays conservatism will tend to underweight new information if the directions of the information are not consistent with each other. An investor who exhibits representativeness will tend to overweight new information if they take place by the same direction. Shanthikumar (2004) looked at investor behavior conditioning on past surprises. They found that small traders display increasing reactions in their trading behavior. Intuitionally, small traders have less information than large traders to evaluate the quality of new information. Thus we develop the hypothesis as followings:

Hypothesis 5: *Small traders will react more strongly in a series of similar earnings surprises.*

3 Sample Data

Quarterly earnings announcements dates and earnings per share are taken from the Taiwan Economics Journal (TEJ) Company from January 1, 1995 to December 31, 2004. First of all, we need to use the former historical data to calculate standard unexpected earnings. For measuring the investors' reaction, we collected daily stock prices from June 1, 1999 to January 31, 2005 from the TEJ, which included closing bid and ask price, closing price, open price, high price, and low price. We also collected intra-day database which contained the details of transactions on the TEJ from 2003 to 2004. The sample is restricted to securities listing on the TSE, and we excluded some targets with conditions as follows: (1) Stocks belonging to the financial industry. (2) Stocks with low liquidity, if the number of transactions to each trading day is less than 10. (3) Stock price was lower than three New-Taiwan dollars in long terms. (4) Stocks had been fully completed or unlisted. The final samples included 217 firms and 4,774 times quarterly earnings announcements between June 1, 1999 and January 31, 2005.

The measure of information, quarterly earnings announcements dates is another important sample for us. The fourth quarterly announced dates are usually closed to annually announced dates in April. Moreover, companies sometimes revised their reports of earnings in one month and announced twice. To avoid duplicating, we adopted the first ones if there are two announcement dates in the same month. And the criterion of our event dates depended on the earnings going public by mass media.

4 Methodology

4.1 Measurements to the information asymmetry

Relative Effective Bid-Ask Spread

The bid-ask spread is the difference between the lowest available price to sell (the ask price) and the highest available price to buy (the bid price).

As in Hebb and MacKinnon (2000), the effective spread, $S_{i,d}$, and the relative effective spread, $RS_{i,d}$, are calculated as follows:

$$S_{i,d} = 2*|P_{i,d} - MP_{i,d}|$$
$$RS_{i,d} = \frac{2*|P_{i,d} - MP_{i,d}|}{MP_{i,d}} \quad \text{...(1)}$$

Where $P_{i,d}$ is the closing price of firm *i* on day *d*, $MP_{i,d}$ is the midpoint of bid-ask spread, which is calculated as $(ask_{i,d} + bid_{i,d})/2$. Meanwhile, $ask_{i,d}$ and $bid_{i,d}$ represent the closing ask price and closing bid price of firm *i* on day *d*, respectively.

Adverse Selection Cost

The informational asymmetry component of the bid-ask spread is the compensation to market makers for trading with informed traders who possess superior information. As a result, when market makers perceive an increase in the degree of informational asymmetry, they widen the bid-ask spread. We adopt the method of George, Kaul and Nimalendran (1991) to estimate the informational asymmetry part of the bid-ask spread. The informational asymmetry cost, $\phi_{i,d} = 1 - \pi_{i,d}$, is the proportion of the bid-ask spread due to informational asymmetry of firm i on day d, and $\pi_{i,d}$ is the proportion of the bid-ask spread other than informational asymmetry, which can be expressed as follows:

$$\pi_{i,d} = \frac{2\sqrt{-Cov(RD_{i,t}, RD_{i,t-1})}}{S_{i,d}} \quad \text{..(2)}$$

where $RD_{i,t} = R_{iTt} - R_{iBt}$, R_{iTt} is the 10-minute intraday return of firm i based on transaction prices at time intervals between t-1 and t, R_{iBt} is the 10-minute intraday return calculated from bid prices, B, $S_{i,d}$ is the mean average of bid-ask spread of twenty-seven 10-mimute intervals of firm i at each day, and $Cov(RD_{i,t}, RD_{i,t-1})$ represents the serial covariance of $RD_{i,t}$.

Price Volatility

The traditional approach to calculate variance of security price returns is to use daily closing prices. Improved estimator of security price volatility, however, is formulated by Garman and Klass (1980) (hereafter, GK). They proposed a volatility measure taking account of today's high (H), low (L), opening (O) and closing (C) prices under the assumption that a logarithm of stock prices follows the Brownian motion without drift. Therefore, the GK volatility measure contains more information of price volatility than many volatility estimators considering the closing prices only. We adopt the volatility measure of the GK model to estimate daily volatilities of each firm. It can be expressed as follows:

$$\sigma_{i,d}^2 = 0.511(a-b)^2 - 0.019[x(a+b) - 2ab] - 0.383x^2 \quad \text{........................(3)}$$

where a = ln(H/O), b=ln(L/O), and x=ln(C/O), and $\sigma_{i,d}^2$ represent the volatility of firm i on day d.

Realized Volatility

The measure of volatility is a model proposed by Andersen et al. (2001) (henceforth ABDL) ABDL (2001) introduced realized volatility to measure volatility over the interval of interest. They used five-minute intraday data to determine the realized volatilities. ABDL claimed that sampling at five-minute intervals is sufficient to ensure that there is minimal measurement error in the daily realized volatilities, while also preventing microstructure bias from becoming a concern. Because the daily trading time is from 9:00AM to 1:30PM, 54 five-minute observations were conducted each day. The realized volatility proposed by ABDL (2001) used in this study to measure the volatility of stock i at time t is:

$$RV_{i,t} = \sum_{j=1,2...[1/\Delta]} r_{i,t,j}^2 \quad \text{..(4)}$$

Where $r_{i,t,j}$ denotes the 5-minute stock return, Δ =1/54. Because the problems of non-synchronous trading and bid-ask bounce could lead to biased conclusions, our research uses the average of bid prices and ask prices as the price series.

4.2 Dividing the good- and bad-news based on Earnings Surprises[5]

We assume that earnings expectations are based on seasonal random walk with drift：

$$E(e_t^i) = e_{t-4}^i + \delta^i \text{, where } \delta^i = \text{the earnings drift for firm I} \quad (5)$$

$$\widehat{\delta}^i = \frac{1}{n}\sum_{j=1}^{n}(e_{t-j}^i - e_{t-j-4}^i) \text{, where n } \le 16 \quad (6)$$

Then, standardize the unexpected earnings measurement by dividing each firm surprise by the standard deviation of that firm's earnings, as measured by the available subset of the preceding 20 announcements.

$$\text{SUE}_t^i = \frac{e_t^i - e_{t-4}^i - \widehat{\delta}^i}{\sqrt{Var(e_t^i)}}\ ^{6} \quad (7)$$

Where Var(e_t) is estimated using the previous 20 announcements

Earnings announcements are then ranked by the SUE within each year, and placed into deciles 0-9, where the most negative surprises are in decile 0 and the most positive in decile 9. Earnings announcements in deciles 4 and 5 are not strong surprises. The difference between expectation and actual ones is defined as unexpected earnings which are not revealed until the time of the disclosure. Earnings surprises have been divided into two groups, positive and negative earnings surprises. Prior research defined the positive earnings surprises as good news and the negative ones as bad news. In this paper, we use a more exact measurement to divide earnings surprises to good and bad news. The participants in markets represent different reactions to the two portfolios. Specifically, we expect that bad-news firms (decile0, 1, 2) are subject to more information asymmetry than good-news firms (decile7, 8, and 9).

4.3 Trade Size

Share volumes

It is commonly believed that big players on the TSE tend to split their transactions into several trades in order to prevent small players and officers of the regulatory authorities from seeing

[5] See Ball and Brown(1968), Jones and Litzenberger(1970), Jones and Latane(1982), Foster, Olsen and Shevlin (1984), Bernard and Thomas(1989,1990), Bhushan(1994)

[6] See Bernard and Thomas(1989)

through their trading strategies. For these reasons, we classify orders of 10 or more lots which are placed by large traders, and orders of less than 10 lots as orders placed by small traders. Lee, Lin and Liu (1999) used 10,000 shares as the dividing point for the following reasons :(1) The budget constraints of small investors imply that their trades are likely to be small in size. (2)Trades of 10,000 shares or more are commonly defined as block trades in US markets. (3) On the TSE, 10,000 shares is equivalent to 10 round lots, which should be regarded as a medium trade size.

Dollar volumes

The limitation of the trade-size based proxy is that it does not reflect differences in stock prices. Lee and Radhakrishna (2000) found that dollar-value-based proxy are generally less noisy than trade-size-based proxy in separating small and large investor transactions. Dollar-value-based proxies are, however, sensitive to stock price changes, and mean to the wealth that traders have. Thus, our research adopts two measurements to distinguish between small and large traders. The whole trading volume was sorted and adopted the top 20% and bottom 20% to represent large and small traders.

4.4 Abnormal Order Imbalance

In order to aggregate across firms, and to be able to make clearer conclusions regarding the comparison of event-time trading and non-event time trading, we calculated abnormal order imbalance. Shanthikumar (2004) used trade imbalance as follows:

The measure of trade imbalance:

$$IMB_{i,x,t} = \frac{buys_{i,x,t} - sells_{i,x,t}}{buys_{i,x,t} + sells_{i,x,t}} \quad \text{.........}(8)$$

The raw trade imbalance measure is calculated as follows, for firm i, investor type x, and date t. In order to determine which side initiated the trade, they used the modified Lee and Ready (1991) algorithm recommended in Odders-White (2000). The algorithm involves matching a trade to the most recent quote, which precedes the trade by at least 5 seconds. If a price is nearer the bid price it is classified as seller initiated and if it is closer to the ask price it is classified as buyer initiated. If a trade is at the midpoint of bid-ask spread, they classified based on the previous price.

We then normalized this trade imbalance measure by subtracting off the non-event-time firm year mean, and dividing by the non-event-time firm-year standard deviation.

$$IMB_{i,x,t}^{abnormal} = \frac{IMB_{i,x,t} - E\left(IMB_{i,x,year(t)}\right)}{\sqrt{Var\left(IMB_{i,x,year(t)}\right)}} \quad \text{.........}(9)$$

We calculate the sample mean and variance of trade imbalance in each year, for the given firm and investor type, excluding days that are close to an earnings announcement. The event period that is excluded in calculating $E(IMB_{i,x,year(t)})$ and $Var(IMB_{i,x,year(t)})$ consists of days -15 through 15 in event time; the thirty one trading days centered on any earnings announcement date. This allows us to aggregate across firms without concern for differences in the non-event-time trading behavior associated with them. Normalizing the measure by the standard deviation allows us to make qualitative comparisons of our final values that would be impossible to make if the values were not normalized. Dividing by the standard deviation controls for systematic differences in the volatility of large trades and small trades or in the volatility of the stocks large and small traders invest in.

4.5 Regression Model

Different Investors' Behavior to Good and Bad Earnings News

To get a better estimate of the difference in slope between the two reactions, the difference in how trading depends on surprise deciles, we used the following regression. We estimate the following regression, for t∈ [-15,+15]

$$IMB_{t,x} = \alpha_t^s I(x=S) + \alpha_t^L I(x=L) + \beta_t^s I(x=S)Surp + \beta_t^L I(x=L)Surp + \varepsilon_{t,x} \quad \text{............(10)}$$

where t is the trading day in event-time.

x is trade type, S for small trade and L for large trade

Surp is the surprise of good- and bad-news groups

Different Investors' Behavior to Consecutive News:

In this part of our article, we assign an earnings surprise a value of N=0 if it is a mild surprise, in deciles 3, 4, 5 or 6. We assign it a value of N=1 if it is a very negative surprise (deciles 0,1 or 2) and the preceding surprise for that firm was not strongly negative. Similarly a surprise receives a value of N=1 if it is very positive (deciles 7, 8 or 9) and the preceding surprise was not positive. The surprise has a value of N=2 if it is the second surprise of the same type, strongly negative or strongly positive, N=3 if it is the third and so on.

$$IMB_t^{abnormal} = \begin{array}{l} \alpha_1^t I(N_s = 1) + \alpha_2^t I(N_s = 2) + ... + \alpha_M^t I(N_s \geq M) + \beta_1^t I(N_s = 1)Surp + \\ \beta_2^t I(N_s = 2)Surp + ... + \beta_M^t I(N_s \geq M)Surp + \varepsilon_t \end{array} \quad \text{.....(11)}$$

where t is the trading day in event-time

s is the specific earnings surprise

Surp is the surprise of good- and bad-news groups

$I(N_s = X)$ is the indicator that the N value for surprise s has value X

In these regressions, α measures the intercept for the reaction to the earnings announcement, which is roughly the reaction to an extremely negative surprise (decile 0). The coefficient, β, reflects the way in which the given volume measure depends on surprise deciles. Essentially, β measures the strength of the reaction caused by the degree of earnings surprise.

5 Empirical Results

5.1 Information asymmetry around earnings announcements

In this section, we adopt four proxies to examine the information asymmetry around earnings announcements. The relative effective spread was widely accepted to examine information asymmetry in market micro-structure field. In addition, we use adverse selection cost, price volatility and realized volatility to test this phenomenon. In Table 1, Panel A shows the results of our models in the pre-announced period, as well as Panel B in the post-announced period. Then we compare these results between the pre-announced and the post-announced periods. Panel C presents their difference by interval design. We can observe that the relative effective spread, adverse selection cost, and realized volatility are all positive in Panel C, which means information asymmetry in the pre-announced period is larger than the post-announcement. This should be attributed to the earnings announcements. The difference of relative effective spread and adverse selection cost is larger than the other two variables and significantly from interval 1 to interval 5. These results support our hypotheses as mentioned above, the relative effective spread and adverse selection cost in the post-announced period is lower than that in the pre-announced period. Earnings announcements indeed reduce information asymmetry, and imply that the relationship between public information and private information is substitute. They also support the theoretical models of Mc Nichols and Trueman (1994), Demski and Feltman (1994).

Unfortunately, the result of volatility doesn't present strong evidence to support our hypotheses. The realized volatility is positive in Panel C, but only significant in interval 5. Price volatility is positive in interval 1, but turns to be negative if we broaden the interval design. Besides, their difference is not as obvious as the former variables.

5.2 Information asymmetry between good- and bad-news groups

The investors under good- and bad-news may exhibit different behavior. [7] We analyze the variation of information asymmetry to the good-news and bad-news firms in terms of relative effective spread, adverse selection cost, price volatility and return volatility by employing the t-test.

First of all, we used the same design of earnings surprises to divide the earnings announcements into two groups: good-news and bad-news firms. We placed deciles 0, 1, 2 as bad-news groups and deciles 7, 8, 9 as good-news groups.

Table 2 shows the relative effective spread and differences between good-news and bad-news

[7] See Engle and Ng (1993), Koutmos (1998), French et al. (1987) and Schwert (1989)

firms. Relative effective spread is the general measurement in market microstructure to estimate information asymmetry. The investors will widen the spread when they face the bad earnings news since there may exist other bad news behind. The evidence in Table 2 indicates that there is a significant difference in the relative effective spread between these two sets. Generally, the relative effective spread of bad-news firms is higher than that of good-news firms, especially around earnings announcements. However, the results are mixed. The difference of information asymmetry between good- and bad-news firms is significant, which is weakly support hypothesis 1. From day 3 to day6, the degree of information asymmetry goes up and goes to be stable after day 10. The spread in day 0(event day) isn't significant, and the degree of difference is smaller than that in the pre-announced period. Since the earnings announcements may smooth away some information asymmetry on the event day and investors reflect this information into the trade price.

In order to require more robust results, we borrow the method of George, Kaul and Nimalendran (1991) to estimate the adverse selection cost, which is part of the bid-ask spread. The results in Table 3 present the difference of adverse selection cost between good-news and bad-news firms. We obtained certain results around event day. From day -3 to day 4, the difference is larger and significant. From these results, we could prove that bad-news firms have higher information asymmetry than good-news firms regardless of the pre- or post-announced period. Moreover, the degree of difference in the post-announced period is smaller than that in the pre-announced period. These results are consistent with our former test, the information asymmetry in the post-announced period will be lower than that in the pre-announced period.

The GK volatility measure contains more information of price volatility than many volatility estimators considering the closing prices only. Table 4 displays the price volatility difference between the two sets. It starts to fluctuate on day -7, and then continues to day 8, the time period of reaction is longer than the former two proxies. But the difference does not become smaller once earnings go public, it only reduces around announcements from day -1 to day 1. These results present an interesting phenomenon about information asymmetry. We suggest that the fluctuation of price volatility was not only caused by information asymmetry.

Table 5 exhibits the realized volatility difference between good- and bad-news firms. We used the intraday measurement to examine daily change. From day -5, the difference suddenly becomes larger than former days, and lasts to day 9. But day 0 and day 1 aren't significant and become smaller than other days around announcements. Although the result of volatility seems a little different from former measurements, the difference between the two sets is positive and significant around the announced day. It also proves that the bad-news firms have higher information asymmetry than good-news firms. Hence, the results are all consistent with our hypothesis: Bad-news firms have higher information asymmetry than good-news firms. Generally, the evidence show the disclosure of quarterly earnings announcement reduces information asymmetry to the firms, especially for bad-news firms. This may be attributed to that the bad-news firms do not prefer to release information before earnings announcements comparing with the good-news firms.

5.3 Investors' behavior around earnings announcements

It is interesting to investigate the investors' behavior to earnings announcements. We view at the whole picture of trading around the event day from for day -15 to day 15. First, the investors should be divided into two groups: small and large traders. Since the two group investors, on average, do not own the same resources to discriminate the truth of security price. They may have different behaviors to the earnings announcements. Accordingly, we employ the trade imbalance of two types of investors to analysis their behavior around the earnings announcements. Table 6 presents the trade imbalance of small and large traders. We examine trade imbalance in the pre-announced and post-announced periods first. The results in table 6 show that small traders react to the earnings announcements strongly in the post-announced period than in the pre-announced period. In other words, small traders exhibit net-buying behavior in post-announced period. Barber and Odean (2002) found that individuals buy an abnormally high amount of a company's stocks after news about the company- whether the news is good or bad. Their buying behavior is more heavily influenced by attention than their selling behavior. This result is consistent with the finding of Lee (1992), Hirshleifer et al. (2002), and Shanthikumar (2004). On the other hand, large traders do not have obvious fluctuation from day-15 to day 15 as much as small traders. It implies that large traders do not react to earnings surprises as strongly as small traders, since large traders more likely to be institutional investors who have more information and skill to evaluate this news.

5.4 Investors' behavior to good- and bad-News

Furthermore, we test various investors' behavior under good- and bad-news. The purpose is to compare the degree of different investors' reactions. We compare the reaction of small and large traders to the good- and bad-news firms. To get a better estimate of the difference in slope between the two reactions, we use the regressions (10) to examine the effect. In this model, α measures the intercept of the reaction to the earnings announcements and β reflects the relation between investors' behaviors depends on earnings surprise. In fact, β unearth the strength of the reaction. Table 7 displays the results to this regressions, with t-statistics for our tests of $\alpha^S = \alpha^L$ and $\beta^s = \beta^L$.

In order to see reaction to good-news and bad-news, we use two tables to observe them. Table 7-A presents the trade imbalances of large and small traders to the earnings surprise deciles 0, 1 and 2. The evidence in Table 7-A shows that α^S is significantly higher than α^L from day -6 to day 4, around event day. The relationship between β^s and β^L is non-significant around the announced date. The strength of small traders' reactions to earnings announcements, β^s is significantly higher than β^L, but unclear from day -1 to event day. It seems large traders and small traders have the same reaction strength around the announced date. This may be caused by information asymmetry which is higher on day -1. As we mentioned above, small traders react more strongly to the type of earnings surprises than large traders do. Besides, α^S is positive from day -15 to day 15, and this result seems to confirm that small traders exhibit attention buying, which is consistent with our former test.

Table 7-B presents the abnormal trade imbalance to earnings surprises deciles 7, 8, and 9. In other words, those are investors' behavior to good-news firms. In additional, α^S is also significantly higher than α^L from day -6 to day 5, also, β^s is also significantly higher than β^L from day -4 to day 1. The evidence in this table indicates that small traders also (compared with bad-news group) react more strongly to earnings surprises than large traders do. The results of the two tables are consistent to support our hypothesis. Small traders will react more strongly than large traders, regardless with the news is good or bad. And the results are consistent with the findings to Lee (1992), Hirshleifer et al. (2002). Table 7-C compares the reactions of small traders to good and bad news. The difference is positive from day 0 to day 6 and significantly from day -3 to day -1. Unfortunately, the evidence in this table is unclear and weak to support our hypothesis. The phenomenon of this result may be attributed by two reasons. First, no matter good- or bad-news, small traders react to earnings announcements as attention net-buying. Thus, we could not observe that small traders strongly react to good news than to bad news. Second, small investors do not own mature skills to analysis the news. They may need the representative news to encourage their behavior. Alternatively, the small traders may be conservative to the earnings news. In general, this finding less supports our hypothesis and inconsistent to the findings of Shanthikumar (2004).

5.5 Investors' behavior to consecutive news

In this part, we investigate the investors' behavior to a series the same news based on shares and dollars. The earnings surprises are conditioned by consecutive past news. We expect that small traders display increasing reactions in their trading behavior when they face a series the same information. N1 means that the surprise is the first one in a similar series. N2 is the second one, and so on. We examine the dollar-based and shares-based volumes in this section. The intercept, α represents the initial reaction of small and large traders and shows their transactional behavior. In table 8-A, α of small traders are all positive and significant to show their buying behavior. However, the coefficient, β in table 8-A presents the degree of investors' buying or selling behavior caused by the earnings surprises. On the other side, large traders reverse their behavior when the surprise is the third similar surprise (i.e. N=3) in a series. Most of them tend to sell stocks in the later surprises. This may be attributed to that large traders usually have more financial knowledge to setup the loss-stop point and the profitable point. In addition, the evidence in table 8-A and table 8-B do not have a clear pattern to support our expectation. Although our design in this section does not distinguish good and bad news, it implies that large traders will revise their behavior when similar earnings surprises continue. If the consecutive earnings news is good, large traders will complete their transaction to get profit. Even to bad news, large traders also have flexibility to transfer their capital to invest in other stocks. Table 8-B shows that small traders also learn from the former consecutive surprises and begin to revise their behavior (while the four ones) check this.

6. Conclusion

In this paper information asymmetry and investors' behavior are the two major topics that we discuss around earnings announcements. First, we investigate information asymmetry and investors' behavior around earnings announcements. While many researches have discussed developed markets, we concentrate on emerging market in our research. Our results present interesting information to discuss. In the first part, we would like to know the information asymmetry around earnings announcements which are not defined as good or bad news. The relative effective spread and adverse selection cost between the pre-announced and post-announced periods are significant, and they are lower in the post-announced period than in the pre-announced period. These results are strong evidence to support our former hypotheses. Once earnings go public, this event reduces information asymmetry and implies that public and private information is substituted on the TSE. They also support the theoretical models of Mc Nichols and Trueman (1994), Demski and Feltman (1994). Although price volatility and realized volatility are not significant and even present reversed results. We think these results are due to the characteristics of these variables and models.

In this part, we use trade imbalance to see investors' behavior simultaneously. Barber and Odean (2001) argued that individual investors tend to be net purchasers of stocks on high attention days, whether the news is good or bad. An important finding for us is to prove that small traders indeed have attention buying behavior around announced dates. The trade imbalance of small traders is positive and significant around event date, and consistent with the finding of Barber and Odean (2001) and Lee (1992).

The second part is to investigate information asymmetry and investors' behavior to good- and bad-news. The four proxies of information asymmetry are all positive and significant around event date. We confirm that bad-news firms have higher information asymmetry than good-news firms. Poor-performance firms are more likely to change or replace their management, governance structure, and business strategy and to engage in restructuring, than are successful firms. These actions would generate more uncertainty and therefore increase the likelihood of information asymmetry trading among the bad-news firms. Moreover, the managers may tend to cover up poor-performance leakage under the self-benefit principle. It could also be the reason for the higher information asymmetry among bad-news firms.

Small traders also exhibit stronger reaction than large traders, whether the news is good or bad. The coefficient of difference is positive and significant around announced dates. On the contrary, large traders do not react strongly in their behavior. This finding is also consistent with that of several prior research papers on developed markets. It implies that small traders do not hold as precise information as large traders and cannot revise their behavior flexibly, but still exhibit attention buying behavior.

In the third part, we can see that investors have learning behavior in a same-type series of surprises, especially for large traders. They exhibit significantly reversed reaction in the third and fourth surprises and tend to sell stocks.

The empirical results also caused us to wonder about the linkage of these topics. The TSE is an emerging market and not as efficient as developed markets. Traditional micro-market structure divides investors into liquidity traders and informed traders. The difference between them should be larger in an emerging market if information asymmetry exists. In our research, we could observe their obvious differences. When we observe the behavior of two sets, we find that small traders are the major resource of liquidity on the TSE. While they exhibit attention buying, the high frequency transactions provide liquidity to the market and large traders around event dates. It implies that small traders tend to be uninformed traders while large traders have more ability to judge the public information, even to arbitrage on the TSE.

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Table 1: Information asymmetry difference between pre-announced and post-announced period

This table presents the relative effective spread, adverse selection cost, price volatility, and realized volatility for pre-announced and post-announced period. Panel A reports the mean of four proxies from day –15 to day-1. Day 0 reports the mean of announcement date. Panel B reports the mean of four proxies from day 1 to day 15. Panel C presents the mean of each proxy in each time interval. Panel C compares the difference between pre-announced and post-announced period in intervals.

Day t	Relative Effective Spread	Adverse Selection Cost	Price Volatility ($*10^{-3}$)	Realized Volatility ($*10^{-3}$)
Panel A Pre-announced period				
-15	0.0441	0.4601	0.4349	0.2476
-14	0.0487	0.4017	0.2136	0.2563
-13	0.0485	0.4705	0.2890	0.2678
-12	0.0501	0.5071	0.3578	0.4389
-11	0.0498	0.4904	0.3520	0.3784
-10	0.0520	0.5031	0.3789	0.3098
-9	0.0526	0.5429	0.4577	0.4621
-8	0.0577	0.5375	0.5297	0.4591
-7	0.0576	0.5289	0.5432	0.4432
-6	0.0591	0.5309	0.5583	0.3992
-5	0.0602	0.5037	0.5767	0.4821
-4	0.0634	0.5189	0.5918	0.5052
-3	0.0684	0.5626	0.6032	0.4903
-2	0.0732	0.5732	0.6602	0.5109
-1	0.0765	0.6079	0.7845	0.5339
0	0.0725	0.5868	0.7404	0.5045
Panel B Post-announced period				
1	0.0702	0.5420	0.7421	0.5041
2	0.0683	0.5216	0.7034	0.5092
3	0.0625	0.4917	0.6452	0.4732
4	0.0594	0.4852	0.5534	0.4023
5	0.0569	0.4715	0.5409	0.3687
6	0.0561	0.4809	0.5423	0.4001
7	0.0542	0.4604	0.5022	0.3902
8	0.0543	0.4599	0.4891	0.3734
9	0.0521	0.4323	0.4729	0.3891
10	0.0493	0.4529	0.4563	0.3584
11	0.0474	0.4278	0.4401	0.3301
12	0.0465	0.4064	0.4382	0.3201
13	0.0479	0.4325	0.4267	0.2801
14	0.0454	0.4191	0.3729	0.2248
15	0.0447	0.3998	0.3806	0.1509
Panel C Difference in Pre- and Post-announced period				
(-1,0) v.s (0,1)	0.0032	0.0554**	0.0212	0.0149
(-2,0) v.s (0,2)	0.0038*	0.0414*	-0.0003	0.0105
(-3,0) v.s (0,3)	0.0043*	0.0495**	-0.0107	0.0126
(-4,0) v.s (0,4)	0.0043*	0.0414*	-0.0009	0.0303
(-5,0) v.s (0,5)	0.0041*	0.0372*	0.0052	0.0442*

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 2: Relative effective spread differences between good-news and bad-news group

This table presents the relative spread differences between good-news and bad-news groups. Panel A reports the mean of relative effective spread from day-15 to day-1. Day 0 reports the mean of announced date. Panel B reports the mean of relative effective spread from day 1 to day 15.

Day t	Good-news	Bad-news	Difference
Panel A	Pre-announced period		
-15	0.0400	0.0441	0.0040
-14	0.0490	0.0487	-0.0003
-13	0.0478	0.0491	0.0012
-12	0.0462	0.0521	0.0059
-11	0.0463	0.0525	0.0062
-10	0.0484	0.0541	0.0057
-9	0.0499	0.0557	0.0058
-8	0.0545	0.0600	0.0055
-7	0.0541	0.0595	0.0054
-6	0.0532	0.0633	0.0101**
-5	0.0556	0.0668	0.0112**
-4	0.0564	0.0689	0.0125***
-3	0.0622	0.0731	0.0109**
-2	0.0668	0.0768	0.0100***
-1	0.0699	0.0823	0.0124***
0	0.0694	0.0756	0.0062
Panel B	Post-announced period		
1	0.0666	0.0734	0.0069**
2	0.0653	0.0709	0.0056
3	0.0600	0.0657	0.0057
4	0.0561	0.0647	0.0086**
5	0.0521	0.0611	0.0090**
6	0.0510	0.06093	0.0100**
7	0.05110	0.0579	0.0068**
8	0.04903	0.0583	0.0093*
9	0.0511	0.0545	0.0034
10	0.0469	0.0539	0.0070**
11	0.0447	0.0510	0.0064
12	0.0478	0.0469	-0.0008
13	0.0465	0.0473	0.0008
14	0.0456	0.0451	-0.0005
15	0.0452	0.0448	-0.0004

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 3: Adverse selection cost difference between good-news and bad-news groups

This table presents the adverse selection cost differences between good-news and bad-news groups. Panel A reports the mean of relative effective spread from day-15 to day-1. Day 0 reports the mean of announced date. Panel B reports the mean of relative effective spread from day 1 to day 15.

Day t	Good-news	Bad-news	Difference
Panel A	Pre-announced period		
-15	0.4564	0.4623	0.0059
-14	0.4110	0.4001	-0.0109
-13	0.4732	0.4798	0.0066
-12	0.5098	0.5043	-0.0055
-11	0.4879	0.5023	0.0144
-10	0.4903	0.5087	0.0184
-9	0.5276	0.5675	0.0399
-8	0.5237	0.5399	0.0162
-7	0.5190	0.5405	0.0215
-6	0.5198	0.5623	0.0425
-5	0.5012	0.5112	0.0100
-4	0.5034	0.5348	0.0314
-3	0.5134	0.5987	0.0853**
-2	0.5264	0.6219	0.0955***
-1	0.5347	0.6509	0.1162***
0	0.5562	0.6329	0.0767**
Panel B	Post-announced period		
1	0.5046	0.5710	0.0664**
2	0.5024	0.5576	0.0552**
3	0.4698	0.5490	0.0792**
4	0.4621	0.5201	0.0580**
5	0.4512	0.4981	0.0469
6	0.4492	0.5091	0.0599**
7	0.4349	0.4995	0.0646**
8	0.4092	0.4981	0.0889***
9	0.41095	0.4672	0.0563**
10	0.4376	0.4671	0.0295
11	0.4132	0.4298	0.0166
12	0.3988	0.4171	0.0183
13	0.4112	0.4496	0.0384
14	0.3920	0.4356	0.0436
15	0.3982	0.4023	0.0041

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 4: Price volatility difference between good-news and bad-news groups

This table presents the price volatility differences between good-news and bad-news groups. Panel A reports the mean of relative effective spread from day-15 to day-1. Day 0 reports the mean of announced date. Panel B reports the mean of relative effective spread from day 1 to day 15.

Day t	Good-news ($*10^{-3}$)	Bad-news ($*10^{-3}$)	Difference ($*10^{-3}$)
Panel A Pre-announced period			
-15	0.4321	0.4409	0.0088
-14	0.2209	0.2096	-0.0113
-13	0.2845	0.2987	0.0142
-12	0.3398	0.3786	0.0388
-11	0.3498	0.3676	0.0178
-10	0.3761	0.3865	0.0104
-9	0.4398	0.4761	0.0363
-8	0.4987	0.5461	0.0474
-7	0.5098	0.5891	0.0793**
-6	0.5201	0.5671	0.0470
-5	0.5325	0.6091	0.0766**
-4	0.5109	0.6253	0.1144***
-3	0.5573	0.6521	0.0948**
-2	0.5781	0.7327	0.1546***
-1	0.7372	0.8267	0.0895**
0	0.6945	0.7893	0.0948**
Panel B Post-announced period			
1	0.6890	0.7694	0.0804**
2	0.6654	0.7458	0.0804**
3	0.6231	0.6785	0.0554
4	0.5092	0.6952	0.186***
5	0.4376	0.5980	0.1604***
6	0.4876	0.5732	0.0856**
7	0.4980	0.5451	0.0471
8	0.4530	0.5251	0.0721**
9	0.4671	0.4832	0.0161
10	0.4451	0.4532	0.0081
11	0.4387	0.4483	0.0096
12	0.4265	0.4489	0.0224
13	0.4210	0.4306	0.0096
14	0.3690	0.3786	0.0096
15	0.3789	0.3865	0.0076

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 5: Realized volatility difference between good-news and bad-news groups

This table presents the realized volatility differences between good-news and bad-news groups. Panel A reports the mean of relative effective spread from day-15 to day-1. Day 0 reports the mean of announced date. Panel B reports the mean of relative effective spread from day 1 to day 15.

Day t	Good-news (*10^{-3})	Bad-news (*10^{-3})	Difference (*10^{-3})
Panel A	Pre-announced period		
-15	0.2452	0.2499	0.0047
-14	0.2537	0.2591	0.0054
-13	0.2653	0.2690	0.0037
-12	0.4098	0.4567	0.0469
-11	0.3561	0.3862	0.0301
-10	0.2987	0.3108	0.0121
-9	0.4381	0.4782	0.0401
-8	0.4347	0.4672	0.0325
-7	0.4256	0.4562	0.0306
-6	0.3876	0.4012	0.0136
-5	0.4290	0.5231	0.0941**
-4	0.4479	0.5671	0.1192***
-3	0.4271	0.5781	0.1510***
-2	0.4521	0.5779	0.1258***
-1	0.4781	0.5961	0.1180***
0	0.4981	0.5532	0.0551
Panel B	Post-announced period		
1	0.4871	0.5349	0.0478
2	0.4765	0.5471	0.0706**
3	0.4432	0.5491	0.1059***
4	0.3562	0.4563	0.1001***
5	0.3347	0.4192	0.0845**
6	0.3251	0.4832	0.1581***
7	0.3562	0.4351	0.0789**
8	0.3364	0.4237	0.0873**
9	0.3289	0.4287	0.0998***
10	0.3467	0.3719	0.0252
11	0.3298	0.3532	0.0234
12	0.3109	0.3459	0.0350
13	0.2786	0.2997	0.0211
14	0.2188	0.2451	0.0263
15	0.1479	0.1587	0.0108

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 6: Investor's behavior between pre-announced and post-announced period Trade imbalance surrounding earnings announcements

This table presents the results of raw trade imbalance measure as follows:

$$IMB_{i,x,t} = \frac{buys_{i,x,t} - sells_{i,x,t}}{buys_{i,x,t} + sells_{i,x,t}}$$

, for firm i, investor type x, and date t. Panel A reports the trade imbalance of two types of traders from day –15 to day-1. Day 0 presents the trade imbalance of announced date. Panel B reports the trade imbalance of two types of traders from day 1 to day 15.

Day *t*	Small Trades	Large Traders
Panel A Pre-announced period		
-15	0.0254	0.0242
-14	0.0261	0.0109
-13	-0.0212	0.0192
-12	-0.0198	-0.0238
-11	0.0352	0.0239
-10	0.0281	0.0211
-9	0.0531	0.0312
-8	-0.2190	-0.0119
-7	-0.5310	0.0231
-6	0.0423	0.0126
-5	-0.0433	-0.0092
-4	-0.0101	0.0432
-3	0.0254	0.0321
-2	0.0321	0.0234
-1	-0.0362	-0.0109
0	0.0103	0.0231
Panel B Post-announced period		
1	0.0531	0.0421
2	0.0461	0.0341
3	0.0532	-0.0650
4	0.0492	0.0321
5	0.0521	0.0264
6	0.0492	0.0521
7	0.0457	0.0356
8	0.0412	0.0331
9	0.0309	0.0251
10	0.0398	0.0312
11	0.0412	0.0409
12	0.0387	0.0212
13	0.0352	0.0110
14	0.0362	0.0231
15	0.0391	0.0321

Table 7-A Trade imbalance surrounding earnings announcements with N∈ {0,1}

This table presents the results for a regression of abnormal trade imbalance to earnings surprise deciles 0, 1, and 2 (bad-news group):

$$IMB_{t,e,x} = \alpha_t^s I(x=S) + \alpha_t^L I(x=L) + \beta_t^s I(x=S) SurpDec_e + \beta_t^L I(x=L) SurpDec_e + \varepsilon_{t,e,x}$$

where α is the intercept, and β is the slope, represents the dependence of trade imbalance on surprise. The earnings surprise sample contains all extreme (bottom 30%) earnings surprise for TSE sample firms from 2003-2005. T-statistics for equality to zero are in parentheses. “t-stat for equality” tests whether the coefficients for small and large traders are equal. If it is less than zero, the small trader coefficient is smaller. If the comparative t-stat is greater than zero, the small trader coefficient is larger.

Day t	**Large trader** α^L	**Small trader** α^S	**t-stat for equality**	**Large trader** β^L	**Small trader** β^S	**t-stat for equality**
-15	-0.0093	0.0064	0.9045	0.0034	0.0029	-0.4810
-14	-0.0078	0.0083**	0.9265	0.0065	0.0059	-0.5622
-13	-0.0071	0.0045	1.1053	0.0026	0.0054	0.9472
-12	-0.0092	0.0063**	1.0835	0.0018	0.0041	0.8739
-11	-0.0038	0.0029	0.9881	0.0028	0.0051	0.9099
-10	-0.0101	0.0052	1.3891	-0.0008	0.0088	0.9821
-9	-0.0065	0.0072	1.6192	0.0031	0.0071	0.8702
-8	-0.0059	0.0059	0.9932	-0.0051	0.0093	0.8301
-7	-0.0029	0.0062	1.0968	0.0031	0.0097	1.0932
-6	0.0007	0.0068**	1.7943*	0.0081	0.0109	1.0092
-5	-0.0081	0.0071**	1.9843**	0.0098	0.0873	1.8721*
-4	-0.0033	0.0092**	2.3813***	0.0051	0.0998	1.9904**
-3	-0.0019	0.0126***	2.0983**	0.0088	0.0131	2.3283***
-2	-0.0093	0.0135***	2.6589***	0.0101	0.0148	2.0912**
-1	-0.099	0.0209***	2.8711***	0.0138	0.0102	-1.0141
0	-0.0093	0.0164***	2.9838***	0.0091	0.0159	1.0932
1	-0.0106	0.0103**	2.0912**	0.0083	0.0138	2.8901***
2	-0.0098	0.0110**	1.0743	0.0056	0.0101	1.9984**
3	-0.0088	0.0165***	1.9432*	-0.0076	0.0128	1.9823**
4	-0.0073	0.0102**	1.9838**	0.0081	0.0090	0.9893
5	-0.0067	0.0098*	1.5652	0.0071	0.0109	0.8976
6	-0.0042	0.0082	1.2391	0.0084	0.0080	-0.0653
7	-0.0051	0.0072	1.1872	-0.0031	0.0081	1.6542*
8	-0.0033	0.0089*	1.0912	0.0043	0.0070	0.8794
9	0.0029	0.0078	0.9872	0.0037	0.0063	0.7632
10	0.0046	0.0084	0.8976	0.0023	0.0083	0.8554
11	-0.0021	0.0061	1.0031	0.0031	0.0066	0.7845
12	-0.0019	0.0055	0.7621	0.0018	0.0054	0.7642
13	-0.0031	0.0043	0.6521	0.0042	0.0031	-0.4592
14	-0.0063	0.0013	0.5412	0.0031	0.0062	0.8941
15	-0.0041	0.0035	0.7831	0.0021	0.0041	0.7765

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 7-B: Trade imbalance surrounding earnings announcements with N∈ {0,1}

This table presents the results for a regression of abnormal trade imbalance to earnings surprise deciles 7, 8, and 9 (good-news group):

$$IMB_{t,e,x} = \alpha_t^s I(x=S) + \alpha_t^L I(x=L) + \beta_t^s I(x=S) SurpDec_e + \beta_t^L I(x=L) SurpDec_e + \varepsilon_{t,e,x}$$

where α is the intercept, and β is the slope, represents the dependence of trade imbalance on surprise. The earnings surprise sample contains all extreme (top 30%) earnings surprise for TSE sample firms from 2003-2005. T-statistics for equality to zero are in parentheses. "t-stat for equality" tests whether the coefficients for small and large traders are equal. If it is less than zero, the small trader coefficient is smaller. If the comparative t-stat is greater than zero, the small trader coefficient is larger.

Day t	**Large trader** α^L	**Small trader** α^S	**t-stat for equality**	**Large trader** β^L	**Small trader** β^S	**t-stat for equality**
-15	-0.0099	0.0076	0.9218	0.0029	0.0043	0.8905
-14	-0.0083	0.0087*	0.9256	0.0045	0.0058	0.6743
-13	-0.0065	0.0072	0.9859	0.0054	0.0072	0.8799
-12	-0.0081	0.0069	0.9987	0.0032	0.0087	0.9239
-11	-0.0045	0.0051	0.9234	0.0056	0.0065	0.8895
-10	-0.0095	0.0047	1.0931	0.0076	0.0089	0.8823
-9	-0.0078	0.0065	1.1522	0.0067	0.0066	0.0000
-8	-0.0045	0.0068	1.0973	0.0083	0.0098	0.8982
-7	-0.0021	0.0071	1.4562	-0.0074	0.0094	1.2396
-6	0.0018	0.0079	1.8743*	0.0072	0.0119	1.4367
-5	-0.0101	0.0087	2.4021***	0.0104	0.0187	1.5563
-4	-0.0088	0.0094*	2.5341***	0.0097	0.0265	1.9879**
-3	-0.0071	0.0154**	2.7869**	0.0101	0.0321	2.5286***
-2	-0.0069	0.0289**	3.0851***	0.0092	0.0309	2.7142***
-1	-0.0165	0.0305**	3.3215***	0.0125	0.0298	1.9641**
0	-0.0078	0.0311**	3.0943***	0.0145	0.0243	1.9723**
1	-0.0123	0.0154**	2.8751***	0.0134	0.0209	2.0312**
2	-0.0101	0.0132**	2.6549***	0.0190	0.0189	0.0000
3	-0.0098	0.0110**	2.5427***	0.0097	0.0176	1.7633**
4	-0.0087	0.0198**	2.2231**	0.0099	0.0165	1.0943
5	-0.0071	0.0127**	1.7892*	0.0084	0.0143	0.9876
6	-0.0067	0.0093*	1.5415	0.0078	0.0098	0.8693
7	-0.0054	0.0085	1.3218	-0.0045	0.0076	0.9584
8	-0.0069	0.0078	1.0564	0.0065	0.0067	0.9984
9	-0.0048	0.0083	0.8769	0.0076	0.0070	-0.0062
10	0.0037	0.0088*	0.8231	0.0068	0.0087	0.8514
11	-0.0042	0.0076	0.9083	0.0053	0.0059	0.0045
12	-0.0065	0.0065	0.7843	0.0032	0.0051	0.6642
13	-0.0039	0.0056	0.7034	0.0037	0.0045	0.4852
14	-0.0058	0.0043	0.6028	0.0021	0.0054	0.7812
15	-0.0033	0.0039	0.6001	0.0045	0.0051	0.0154

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 7-C: Trade imbalance surrounding earnings announcements with $N \in \{0,1\}$

This table presents the comparison of small traders' reaction to good- and bad-news. β is the slope, represents the dependence of trade imbalance on surprise. T-statistics for equality to zero are in parentheses. "t-stat for equality" tests whether the coefficients for small traders' reaction to good-news and bad-news are equal. If the comparative t-stat is greater than zero, the small traders' reaction to good-news firms is larger.

Day t	Small trader's behavior under bad news (β^{S}_{Bad})	Small trader's behavior under good news (β^{S}_{Good})	Difference
-15	0.0029	0.0043	0.0014
-14	0.0059	0.0058	-0.0001
-13	0.0054	0.0072	0.0018
-12	0.0041	0.0087	0.0046
-11	0.0051	0.0065	0.0014
-10	0.0088	0.0089	0.0001
-9	0.0071	0.0066	-0.0005
-8	0.0093	0.0098	0.0005
-7	0.0097	0.0094	-0.0003
-6	0.0109	0.0119	0.0010
-5	0.0873	0.0187	-0.0686
-4	0.0998	0.0265	-0.0733
-3	0.0131	0.0321	0.0190**
-2	0.0148	0.0309	0.0161**
-1	0.0102	0.0298	0.0196**
0	0.0159	0.0243	0.0084
1	0.0138	0.0209	0.0071
2	0.0101	0.0189	0.0088
3	0.0128	0.0176	0.0048
4	0.0090	0.0165	0.0075
5	0.0109	0.0143	0.0034
6	0.0080	0.0098	0.0018
7	0.0081	0.0076	-0.0005
8	0.0070	0.0067	-0.0003
9	0.0063	0.0070	0.0007
10	0.0083	0.0087	0.0004
11	0.0066	0.0059	-0.0007
12	0.0054	0.0051	-0.0003
13	0.0031	0.0045	0.0014
14	0.0062	0.0054	-0.0008
15	0.0041	0.0051	0.0010

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 8-A Abnormal trade Imbalance, Reaction Levels (shares-based)

This table presents coefficient for a regression of abnormal trade imbalance on earnings surprise, where α is the intercept and β is the slope, and the earnings surprises contains all extreme (top and bottom30%) earnings surprises for TEJ samples firms. If a surprise is the first in a series of same-type extreme surprises, it receive a value of N=1. If it is the second in a series, N=2 and so on. The event time columns present the trading day, of the dependable variable trade imbalance. Traders are separated by share-based volumes.

Even Time	α				β			
	N=1	N=2	N=3	N>=4	N=1	N=2	N=3	N>=4
Small Trades: bottom 20% small trades								
-2	0.0123	0.0337*	0.0476***	0.0321*	0.0071	-0.00731	-0.0066	0.0079
-1	0.0218	0.0374**	0.0481***	0.0276	0.0080	0.00793	0.0074	0.0084
0	0.0087	0.0421**	0.0351**	0.0271	0.0084	0.00889	0.0084	0.0093
1	0.0361**	0.0354	-0.0213	0.0221	0.0082	0.00914	0.0089	0.0097
2	0.0431***	0.0388**	0.0183	0.0231	0.0073	0.00845	0.0077	0.0084
Middle Trades								
-2	0.0398**	0.0371**	0.0211	0.0163	0.0062	-0.0065	0.0060	0.0070
-1	0.0281	0.0352	0.0318	0.0216	0.0058	0.0070	0.0067	0.0069
0	0.0224	0.0479***	0.0190	-0.0198	-0.0072	0.0089	0.0086	0.0083
1	0.0192	0.0203	0.0214	-0.0276	0.0072	0.0093	0.0074	0.0079
2	0.0257	0.0328*	0.0272	-0.0312	0.0064	0.0076	0.0064	0.0072
Large Trades: top 20% large trades								
-2	0.0301	0.0119	0.0214	-0.0321**	-0.0022	0.0038	0.0057	0.0049
-1	0.0263	0.0216	0.0372**	0.0287*	0.0031	0.0049	-0.0060	0.0053
0	0.0421***	0.0276	-0.0189	-0.0211	0.0058	0.0058	0.0069	0.0060
1	0.0284	0.0187	-0.0103	-0.0184	-0.0042	-0.0045	0.0072	0.0048
2	0.0319**	0.0152	-0.0218	-0.0205	0.0038	0.0042	0.0061	0.0037

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level

Table 8-B Abnormal trade Imbalance, Reaction Levels (dollar-based)

This table presents coefficient for a regression of abnormal trade imbalance on earnings surprise, where α is the intercept and β is the slope, and the earnings surprises contains all extreme (top and bottom30%) earnings surprises for TEJ samples firms. If a surprise is the first in a series of same-type extreme surprises, it receive a value of N=1. If it is the second in a series, N=2 and so on. The event time columns present the trading day, of the dependable variable trade imbalance. Traders are separated by dollar-based volumes.

Event Time	α				β			
	N=1	**N=2**	**N=3**	**N>=4**	**N=1**	**N=2**	**N=3**	**N>=4**
Small Trades: bottom 20% small trades								
-2	0.0198	0.0217	0.0189	-0.0131	-0.0090	0.0067	0.0074	0.0089
-1	0.0277	0.0299	0.0231	-0.0287	0.0078	0.0084	0.0078	0.0083
0	0.0121	0.0367*	0.0276	-0.0308	0.0078	0.0090	0.0087	0.0090
1	-0.0318*	0.0346*	0.0334*	-0.0265	0.0089	0.0099	0.0089	0.0097
2	0.0387**	0.0321*	0.0301	-0.0342*	0.0065	0.0085	0.0079	0.0083
Middle Trades								
-2	0.0221	0.0192	0.0231	0.0341*	0.0072	0.0071	0.0070	0.0079
-1	0.0189	0.0229	0.0228	0.0395**	0.0072	0.0064	0.0077	0.0082
0	0.0258	-0.0298	0.0376*	0.0389**	0.0078	0.0062	0.0071	0.0087
1	0.0337*	-0.0356*	0.0278	0.0324*	0.0053	0.0059	0.0065	0.0098
2	0.0385**	0.0398**	0.0321	-0.0288	0.0060	0.0060	0.0067	0.0087
Large Trades: top 20% large trades								
-2	0.0265	0.0212	0.0255	0.0302	0.0061	0.0050	0.0065	0.0066
-1	0.0183	0.0219	0.0289	0.0276	0.0069	0.0045	0.0067	0.0073
0	0.0209	0.0367*	-0.0378**	-0.0333*	0.0073	0.0057	0.0075	0.0080
1	0.0376**	0.0332*	-0.0389**	-0.0298	0.0070	0.0059	0.0070	0.0082
2	0.0401**	-0.0421***	-0.0312*	-0.0321*	0.0062	0.0050	0.0066	0.0071

*** Significant at the 0.01 level. ** Significant at the 0.05 level. * Significant at the 0.1 level