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Order Type Selection of Informed Investors around Earning Announcements

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Abstract

We develop a hypothesis that informed investors deliberately choose order types (market vs. limit orders) in buying and selling stocks around earnings announcement and the relative magnitude of two order type has implications on the cross-sectional variation of the post earnings announcement drift. We test the hypothesis using the Korea Exchange (KRX) data set that identifies both order type and investor type (individual, institutional and foreign investors) for all the stocks listed on the Kospi market of the KRX. Consistent with our hypothesis, we find that the information on the order type selection, which is publicly available at the end of each trading day, can explain whether stock prices after earnings announcement would exhibit a drift or a reversal and improves the profitability of well-known post earnings announcement strategy substantially. We also examine the informativeness of the relative magnitude of order types on future stock returns for each investor type.

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1. Introduction

Well known post earnings announcement drift (PEAD) anomaly implies that investors who are aware of this anomaly may earn profit by buying good news stocks and selling bad news stocks. In this paper, we develop a hypothesis that informed investors deliberately choose a certain order type (market and limit orders) in buying and selling shares and their order selection contains information on future stock returns. We test the hypothesis based on the relative magnitude of market and limit orders during 3-day earnings announcement window for firms listed on the Kospi market of the Korea Exchange (KRX) and find evidence that order selection matters for the cross-sectional variation of post earnings announcement stock price change.

Some theoretical models assume that informed investors only submit market orders (Glosten and Milgrom, 1985; Glosten, 1994; Rock, 1996). They assume that the depreciation rate of information is very large (i.e., information horizon is short) and thus market orders are preferred by informed investors for quicker execution despite its price disadvantage to limit orders. On the contrary, others (e.g., Kalay and Wohl, 2009) argue that informed investors would only submit limit orders since market orders are not price sensitive and thus used only by uninformed liquidity traders. Consistent with this, many analyze the limit order submission strategy of rational informed investors (Foucault, Kadan and Kandel, 2005; Goettler, Parlour, and Rajan, 2005; Hollifield, Miller, Sandas, Slive, 2006, Rosu, 2009; Obizhaeva and Wang, 2013).

However, more recent models suggest that that informed investors may use a mixed strategy of using either market or limit orders, depending on information and trading environment they are in (Chakravarty and Holden, 1995; Kumar and Seppi, 1994; Parlour, 1998; Kaniel and Liu, 2006; Goettler, Parlour and Rajan, 2009; and Cont and Kukanov, 2017). These models suggest that the magnitude of mispricing and the information horizon may affect the order type selection of informed investors. If mispricing is deep and if other investors are also aggressively placing market orders due to short information horizon, submitting market orders is superior to submitting limit orders. Since mispricing is deep, despite the adverse price impact of market orders, there still exits a room for future price increases. In addition, market orders submitted by other investors push stock prices away from limit prices, lowering the probability of execution of submitted limit orders. On the contrary, if mispricing is shallow, informed investors may prefer to submit limit orders since it may not be profitable to submit market orders due to the adverse price impact of market orders. Even when there is no mispricing, informed investors may submit limit orders if they could collect liquidity premium by supplying liquidity to non-information driven traders.

These predictions of the models suggest a simple testable hypothesis that the relative magnitude of market buy (sell) to limit buy (sell) orders may contain information on future stock price changes. Market orders will only be placed by informed investors in large amount when these investors are sure that they can still earn profit even after the adverse price impact of market orders. Thus, we may expect that if stocks are purchased (sold) more by market orders than by limit orders, stock prices may exhibit a stronger drift; a continued price change in the direction of the initial price change. However, if stocks are purchased (sold) more by limit orders than by market orders, stock may exhibit a weaker drift or even a reversal if initial price change is due to non-information driven price pressure.

We test this hypothesis using orders submitted during the 3 day window of earnings announcement. We examine whether the normalized difference between market buy and limit buy orders measured during the 3-day earnings announcement window contains information on the future stock price changes during the post-event window. Even though most theoretical models of order selection analyze private information, we choose public information event of earnings announcement for the following reasons. First, private information event is hard to be clearly identified. Second, Kandel and Pearson (1995) and many others show that public information such as earnings announcements engender substantial information heterogeneity among investors (Varian, 1985; Kim and Verrecchia, 1991; Harris and Raviv, 1993; Kandel and Pearson, 1995; Bartov et al., 2000; Hirshleifer et al., 2008; Knyazeva, Knyazeva, and Kostovetsky, 2015), thus creating incentives for informed investors to select order types depending on the relative mispricing after the new release. Third, since the information horizon for public information event is much more similar than that for private information, we can focus on the effect of mispricing in order selection.

In testing our hypothesis, we focus on stocks that experience abnormally high trading volumes during the event window. This is because information-driven market orders or information-driven limit orders may be most active in stocks experiencing large abnormal trading volume. The lower the trading volume, neither market orders nor limit orders could be aggressively placed by informed investors due to the concern for the large price impact or the low execution probability, respectively.

Our hypothesis expands existing literature which examines whether large trading volume is followed by return continuation or reversal. Campbell, Grossman, and Wang (1993) and Llorente *et al*. (2002) show that if trading is mainly driven by private information (liquidity shocks) stock prices exhibit continuation (reversal). However, their approach cannot identify the major driver of trading volume *ex ante*. They can only interpret large trading volume is due to information (liquidity shock) if return continuation (reversal) is observed afterwards (Llorente et al., 2002). On the contrary, our identification, by using additional information based on the relative magnitude of order type, can identify, *ex ante*, whether trading would be followed more likely by return continuation or reversal.

There are existing papers that examine the information contents of order types submitted by subset of investors. They typically examine the price setting order (market order) imbalance which is defined as the normalized difference between market buy and market sell orders (Hvidkjaer, 2008; Barber et al., 2009; Kelley and Tetlock, 2013). These papers either assume that the price setting order imbalance measure captures investor sentiment (Hvidkjaer, 2008; Barber et al., 2009) or information (Kelley and Tetlock, 2013). However, this dichotomy is restrictive since informed investors may select market and limit orders as discussed above. Our hypothesis is different from hypotheses analyzed in these papers in that we allow informed investors can select either market or limit orders based on perceived mispricing and the relative magnitude of order types has an implication on the direction and the magnitude of future stock price changes.[1]

We test our hypotheses using the KRX data which contain all the orders submitted during continuous auctions around 20,293 corporate earnings announcements for 694 common stocks listed on the Kospi market of the KRX between 2000 and 2010. KRX is an electronic order driven market without specialists. This data set identifies order type and three investor types (individual, institutional, and foreign investors). Thus, we do not have to use a proxy, such as trade size, to identify orders submitted by individual investors (Lee, 1992). The data also cover all the investors and thus expand papers that analyze the order type selection of a subset of individual investors using broker data (Hirshleifer et al., 2008; Kelley and Tetlock, 2014).

We examine the relative magnitude of buy order type of a stock as the normalized difference of shares bought by market orders and limit orders.[2] Using this measure, we divide

[1] Unlike other papers, Kelley and Tetlock (2013) also analyze the order imbalance measure constructed using limit orders and find evidence that this variable mainly captures liquidity provision but not information. They also find evidence that the price setting order imbalance predicts future returns. While Kelley and Tetlock (2013) separately analyze two measures, their results suggest that informed investors may use both market and limit orders for information motivated trading and liquidity provision, respectively.

[2] Total amount of limit buy for a stock as a whole is the same as the total amount of market sell orders if a stock market is order-driven market without specialists. Thus, this measure is the same as the price setting order imbalance measure (market

the good news-high abnormal volume firms into two based on whether stocks are purchased more by market orders or by limit orders. Similarly, we divide bad news-high abnormal volume sample into two based on whether stocks are sold more by market orders or by limit orders. Our main findings are summarized as follows.

We find that investors adjust order types substantially during event window when compared with those of pre-event window. Consistent with our hypothesis, while good news high abnormal volume stocks purchased more by market orders than by limit orders have size-book to market adjusted abnormal return of 4.08% over 50 trading days, good news high abnormal volume stocks purchased more by limit orders than by market orders have the abnormal return of only 1.82%. For bad news high abnormal volume stocks, while stocks sold more by market orders than by limit orders exhibit a continued price decrease between event and post-event window, those sold more by limit orders than by market orders exhibit a strong reversal. This is because market buy orders (absorbed by limit sell orders) in this group pushes stock prices up during the event window which reverse later. This implies that interpreting negative post-event returns of bad news stocks are solely driven by the slow information incorporation could be misleading and informed investors are providing liquidity and collect liquidity premium for their service. This expand Kaniel, Liu, Saar, and Titman (2012) and So and Wang (2014), who report that pre-event orders may be subject to huge liquidity premium as stock prices tend to reverse during the event window. Our results show that a similar reversal is observed between event window and post-event window.

Since the information on the normalized difference of shares bought and sold by market and limit orders are publicly available, we can improve the vanilla PEAD strategy of buying good news and selling bad news by buying and selling stocks that are expected to generate strongest drift. In fact, while buying and selling good and bad news stocks generate

order imbalance measure) for a stock as a whole. However, the price setting order imbalance measure of individual investors are not the same as our measure since market sell (buy) orders of individual investors are not the same as limit buy (sell) orders of individual investors.

size and book to market adjusted return of 4.54%, a revised strategy of buying and selling portfolios where drifts are expected to be strongest generates much larger CAR of 7.49%. This result is robust when we use calendar time portfolio analysis with risk adjustment based on widely used factor models.

We run probit regression to identify determinants of dominant order types during event windows and find that pre-event price change and the relative magnitude of bid and ask depths are major determinant. We find that informed investors prefer limit orders to market orders if stock price reflects earnings information in advance, and thus misevaluation at the time of announcement is small, and vice versa. We also find that informed investors prefer market orders to limit orders if the depths of the opposite side of trading are larger so that they could mitigate the negative price impact of market orders. Other variables such as firm size and book to market ratio are insignificant. These results imply that order type selection is not so much driven by firm characteristics as by information environment of earnings announcements.

For good (bad) news high abnormal volume stocks purchased (sold) more by market orders than by limit orders, investors who submit limit buy (sell) orders in this group may be smarter since they buy (sell) stocks at better price due to the bid ask spread. However, we show that the price advantage of limit orders in this portfolio may not be that large as commonly believed. We find that the filled ratio of limit orders, defined as the ratio of executed limit orders to total submitted limit orders, is about 90% on average and thus the dollar return of market order investors of this group is about 1.4 times greater than the dollar return of limit order investors, reflecting the different amount of shares bought by market and limit orders. We also calculate the effective value-weighted average purchase (sale) price (VWAP) considering unfilled limit orders and find that bid ask spread overstates the disadvantage of market orders to limit orders.

Lastly, we examine the information content of the normalized order type difference measure for each investor type. This supplements existing papers which only analyze orders submitted by retail investors based on a subset of broker data of retail investors (Hirshleifer et al., 2008; Kelley and Tetlock, 2013) or on a proxy captured by trade size (Lee, 1992; Hvidkjaer, 2008; Barber, Odean, and Zhu, 2009). We find that the normalized order type difference measures of both domestic individual and domestic institutional investors have independent information on future stock price changes even after controlling other type's measures. However, the order type selection of foreign investors does not contain information on future returns.

The remaining part of the paper is organized as follows. Section 2 describes the data. Sections 3 and 4 report main findings and robustness checks, and Section 5 concludes.

2. Key Variables and Summary Statistics

This section describes the construction of key variables and their summary statistics.

The focus of the paper is to analyze the cross-sectional variation in the PEAD in association with the order type selection by investors around earnings announcements. For this purpose, we define the relative magnitude of buy order type (BOT) for good news stock *i* for quarter *t* as follows.

$$BOT_{it} = \frac{Market\ Buy\ Order_{it} - Limit\ Buy\ Order_{it}}{Market\ Buy\ Order_{it} + Limit\ Buy\ Order_{it}} \quad [1]$$

$Market\ Buy\ Order_{it}$ is the total shares of market buy orders submitted at the Kospi market of the KRX during the 3 day earnings announcement window.[3] KRX data set records every transaction with a flag indicating whether it is a market order or a limit order. Marketable

[3] We only analyze orders submitted during the continuous auction and exclude orders submitted at the opening and closing auctions.

limit orders (a limit order with immediately executable limit price) are also de facto market orders. In this paper, we treat both market orders and marketable limit orders as market orders. The relative magnitude of sell order type (SOT) for bad news stock is similarly defined.

$$SOT_{it} = \frac{Market\ Sell\ Order_{it} - Limit\ Sell\ Order_{it}}{Market\ Sell\ Order_{it} + Limit\ Sell\ Order_{it}} \qquad [2]$$

These variables deserve discussion. For each stock i, if all the market sell orders are absorbed by limit buy orders, BOT_{it} $(= -SOT_{it})$ is the same as the price setting order imbalance measure defined as the normalized difference between market buy orders and market sell orders. The price setting order imbalance measure is analyzed by Hvidkjaer (2008) and Barber et al. (2009). They assume that small trades are done by individual investors and develop a hypothesis that the price setting order imbalance of small trades captures either optimistic (positive BOT_{it}) or pessimistic (negative BOT_{it}) sentiment of individual investors. This is equivalent to assume that market orders are used by uninformed investors only. Empirical results are mixed, though. For example, Barber et al. (2009) find that stocks heavily purchased by individual investors underperform stocks heavily sold by individual investors by 4.4% at annual horizon. However, they find opposite results for weekly returns. Unlike Hvidkjaer (2008) and Barber et al. (2009), we do not impose any restriction whether informed or uninformed investors prefer one order type to another in this paper. In contrast, our hypotheses allow informed investors to choose a particular order type based on their predicted mis-valuation and the information horizon of each stock for a well-defined corporate event and provide implications of the order selection on the patterns of the PEAD.

Second, BOT_{it} and SOT_{it} are different from the net buy measure which is the normalized difference between the total buy and sell orders (Grinblatt and Titman, 1989;

Wermers, 1999; Gompers and Mettrick, 2001; Jackson, 2003; Kumar and Lee, 2006; Kaniel, Sarr and Titman, 2008; Hirshleifer et al., 2008). While net buy measure is important in analyzing the resulting ownership change across different investor type, the measure cannot distinguish whether purchase (sales) of stocks are mainly done by market or limit orders.

Standardized unexpected earnings (SUE_{it}) is defined as the difference between the earnings of the current quarter and the earnings of the same quarter of the previous year normalized by the standard deviation of the earnings growth. For each quarter, if SUE_{it} belongs to the top (bottom) 20% of the SUE distribution of the previous quarter, stock i is defined as good news (bad news) stock, denoted as G (B).

Abnormal return of stock i (AR_{it}) is the difference between the return of stock i and the return of a benchmark portfolio defined using size and book to market matched portfolio. $Size_{it}$ and BM_{it} are measured at the previous year end.

Abnormal trading volume is estimated as follows. First, we run a daily market model of trading volume of Tkac (1996) and Lo and Wang (2000) for each firm using the pre-event window of [-60, -5].

$$V_{it} = \alpha_i + \beta_i MktV_t + \varepsilon_{it} \qquad [3]$$

where V_{it} is the daily trading volume of stock i for day t in the [-60, -5] window and $MktV_t$ is the value weighted trading volume for day t.[4] Using the estimated coefficients from [3] for each stock, we calculate the estimated trading volume for trading day t for stock i as follows.

$$EV_{it} = \hat{a}_i + \hat{\beta}_i MktV_t \qquad [4]$$

[4] Trading volume is measured by share turnover.

The difference between actual trading volume and estimated trading volume is defined as the market adjusted volume. Abnormal volume is defined as the 3-day sum of these values during the event window of [-1,1]. Abnormal trading volumes of stocks for a given quarter are divided into tertiles based on the prior quarter's abnormal volume distribution. Stocks belonging to top (bottom) 30% of the distribution are high (low) volume stocks, denoted as H (L). The rests are denoted as M.

Order submission may also depend on the depth of the opposite side of the market. Informed investors may be reluctant to submit market buy (sell) orders if the ask (bid) depth is relatively shallow and thus price impact is expected to be large. On the contrary, if the depth on the opposite side of the market is thick due to the uninformed liquidity provision, informed investors are more willing to submit market orders since the negative price impact of market orders would be significantly reduced and their information is not fully revealed (Grossman and Stiglitz, 1980). We measure the depth imbalance of the limit order book for each stock at the opening auction. Since BOT and SOT are measured after the opening auction for each trading day, we can examine whether the relative depth at the opening auction affect the relative magnitude of market and limit orders measured during continuous auction. We define the normalized difference between bid and ask depths of a trading day as follows.

$$Dep.Imb_{it} = \frac{Bid\ Depth_{it} - Ask\ Depth_{it}}{Bid\ Depth_{it} + Ask\ Depth_{it}} \qquad [5]$$

The order type selection of rational informed investors may also depend on the trading behavior of irrational investors during the earnings announcement window. Grinblatt and Han (2005) suggest that unrealized capital gains or losses may affect buy and sell behaviors of investors if they are subject to the disposition effect (Shefrin and Statman, 1985). If a stock experience large unrealized capital gains and if a stock receives a good news, irrational investors may submit sell orders to realize gains (Frazzini, 2006; Choi et al., 2010; Li, 2015). On the contrary, if there is unrealized losses, irrational investors may be reluctant to realize losses or, even increase the holding of the stocks with unrealized losses (Grinblatt and Han, 2005). If rational investors can predict whether there will be buy or sell orders by these irrational investors, order type selection by rational investors may be affected. We measure unrealized capital gains as in Grinblatt and Han (2005) who propose a measure, capital gains overhang (CGO), calculated for each stock. CGO for stock *i* is the difference between the current stock price and the reference price. Reference price for stock *i* represents the average purchase price of investors for the stock and defined as follows.

$$R_{it+1} = V_{it} \cdot P_{it} + (1 - V_{it}) \cdot R_{it} \qquad [6]$$

V_{it} and R_{it} are the turn over and the reference price of a stock *i* for a trading day *t*, respectively. If stock price P_{it} changes with large turnover, many investors newly purchase shares and the average reference price of the stock should increase. However, if price changes with no trading volume, reference price remains the same. We simulate this value for each stock from the start of the 1999 and use the CGO measured at five days before the earnings announcement as CGO_{ik} for stock *i* for the earnings announcement made in quarter *k*.

[Table I, Figures 1 and 2 about here]

Table 1 reports summary statistics of key variables. Our sample covers 11 years from 2000 to 2010 for all the stocks traded at the Kospi market of the KRX. There are total of

20,293 earnings announcements for 694 stocks. We divide the sample based on news (G or B), trading volume (H or L) and relative magnitude of order type (MB, LB, MS, LS).

Some of the variables are worth mentioning. The increase in abnormal trading activity of GH (BH) stocks is very large. The average pre-event abnormal trading volume of GH (BH) is very close to zero during the pre-event window but increases to 0.015 (0.020) during the announcement window. A surge in trading activity triggered by the arrival of public information may be due to the reduction of the uncertainty investors face (Tetlock, 2014) or increased heterogeneity in valuation among investors (Kandel and Pearson, 1995). In contrast, GL (BL) exhibits a sharp decrease in abnormal trading activity during event window. GM (BM) experiences relatively small change in abnormal trading activity.

Table 1 also shows how order selection variables change around earnings announcements. We focus on GH and BH in analyzing these changes. GH is divided into two; GHMB (purchased more by Market Buy order) if BOT_{it}>0 and GHLB (purchased more by Limit Buy order) if $BOT_{it} < 0$. For GHMB, BOT changes from -13.86% during pre-event window to 14.29% and the difference of 28.15% between pre-event and event windows is significant at 1% level. For GHLB, BOT changes from -16.26% to -19.78% and the relative small difference of -3.52% is still significant at 1%. The smaller change in the absolute value of BOT for GHLB when compared with that of GHMB may reflect the fact that limit buy orders are executed only when there are market sell orders. If there is short sale constraint and if market sell orders cannot increase as much as market buy orders, we expect smaller change in BOT in absolute value for GHLB portfolio.

Similar significant changes are observed in bad news as well. BH is divided into two; BHMS (sold more by Market Sell order) if SOT_{it}>0 and BHLS (sold more by Limit Sell order) if $SOT_{it} < 0$. For BHMS, SOT changes from 18.24% during pre-event window to

22.74% and the difference is significant at 1% level. For BHLS, SOT changes from 14.75% to -14.57% and the difference is also significant at 1%.

Significant changes in BOT and SOT during event window indicate that investors in these stocks change their buying and selling order types significantly with the arrival of earnings news. This provides us with good opportunities for testing our hypotheses developed in the previous section. In section 4, we also examine these variables by investor type to identify whether there are heterogeneous reactions among investors.

3. Trading Volume, Order Type, and Post Earnings Announcement Drift

3.1 Event time analyses

We define earnings announcement window to be 3 trading days around earnings announcement date. We define good (bad) news sample to be the 5th (1st) quintile based on the previous quarter's SUE distribution. Abnormal return is calculated by subtracting size and book to market matched portfolio. Table II reports stock price changes around earnings announcements for various portfolios.

[Table II and Figure 3 here]

First row of Table II reports size and book to market adjusted returns of good news and bad news portfolios around the announcement window.

Good news portfolio (G) exhibits a significant 0.82% return during the announcement window followed by a significant 2.84% post-event return measured from 2nd trading day to 50th trading day. Bad news portfolio (B) exhibits a significant -0.41% event return followed by a significant -1.70% post-event return. Thus, buying good news and selling bad news stocks from the 2nd day after the announcement generates 4.54% return over 50 trading days.

This is consistent with well-known post earnings announcement drift pattern reported in many studies.

We further divide G and B portfolio based on the abnormal trading activity during the announcement window. High (H), medium (M), and low (L) abnormal trading volume portfolio consist of the top 30%, next 40%, and the bottom 30% of stocks traded at the KRX market based on the previous quarter's abnormal trading volume distribution. To analyze the impact of the choice of orders by investors, we further divide each abnormal volume quintile into two based on which order type (market vs. limit order) is used more in buying and selling stocks after good and bad news, respectively. For a good news stock, if the BOT of the stock is positive, the stock is bought more by market orders (MB) than by limit orders (LB).[5] Thus, if a good news (G)-high abnormal volume (H) stock has positive (negative) BOT, the stock belongs to the GHMB (GHLB) portfolio. Similarly, if a bad news high abnormal volume stock is sold more by market sell orders (MS) than by limit sell orders (LS), the stock belongs to the BHMS. BHLS is similarly defined.

We first examine stocks experiencing high abnormal trading volume. We find that good news high abnormal volume portfolio (GH) generates significant event return of 2.56% followed by significant 2.57% of the post-event return. The drift magnitude of GH portfolio (2.57%) is not very different from that of G portfolio (2.84%). However, a substantial cross-sectional variation emerges among stocks based on whether market or limit orders are used more in buying stocks after good news. When we further divide GH stocks into GHMB and GHLB, the event return of GHMB is very high and significant at 5.33% followed by a significant post-event return of 4.08%. The sum of the two returns (defined as the total return of earnings announcement) is as high as 9.41%, which shows the average valuation change of stocks in the portfolio due to the new information. However, both the event return and post-

[5] MB stands for market buy order and LB stands for limit buy order.

event return of GHLB are much smaller at 0.74% and 1.82%, respectively, which show that the information content of the news is not as large as that of GHMB. This is consistent with our conjecture that when stocks are mostly purchased by market (limit) orders after good news, the valuation change would be larger (smaller).

A striking cross sectional variation in return depending on the order composition becomes much smaller for the case of the medium abnormal volume stocks. The event return of GMMB is very high and significant at 1.75% followed by a significant post-event return of 3.34%. The event return of GMLB is significantly negative at -0.74% and significant at 3.49%. Thus, unlike high abnormal volume stocks, the magnitude of post-event return of GMMB and GMLB is not very different from that of GM (3.27%) and from with each other. However, the directions of the changes of the event window returns of these two portfolios are very different. When we compare the event returns and post-event returns of these two portfolios, we note that while GMMB exhibits a drift, GMLB exhibits a reversal. As a result, the total returns of the two portfolios are very different as well (5.09% vs. 2.75%). Thus, as in the case of high abnormal volume stocks, even in medium abnormal volume stocks, market orders are used more than limit orders when mispricing is deep. The positive post-event return of GMLB does not only reflect the slow information incorporation as in GMMB, but also reflects a price reversal.

For low abnormal volume stocks, GL portfolio generates significant event return of -0.59% followed by significant 3.84% of the post-event return. When we further divide GL stocks into GLMB and GLLB, the event return of GLMB is very high and significant at 2.64% followed by an insignificant post-event return of 0.43%. This implies that no drift is observed in these stocks with low abnormal volume, possibly due to the large price impacts of market orders. However, as in medium abnormal volume stocks, a strong reversal is observed for

GLLB. The event return of GLLB is significantly negative at -1.38% followed by post-event return of 4.64%.

The drift and the reversal pattern found in good news stocks are much more strongly observed in bad news stocks.

We find that bad news high abnormal volume portfolio (BH) generates an insignificant event return of 0.42% followed by a significant -3.74% post-event return. As in good news case, a substantial cross-sectional variation emerges based on whether market or limit orders are mainly used in selling stocks after bad news. When we divide BH stocks into BHMS and BHLS, the event return of BHMS is very high and significant at -1.26%, followed by a significant post-event return of -3.41% (thus, the total return of -4.67%). The event return of BHLS, on the contrary, is positive and significant at 5.86% and followed by a significant reversal of -4.09% (thus, the total return of 1.77%). As in GMLB and GLLB, BHLS stocks exhibit a price reversal during the post-event window, suggesting that when limit sell orders are used more than market sell orders after bad news, those limit orders are submitted by informed liquidity providers.

For medium abnormal volume stocks, BM portfolio generates a significant event return of -0.55% followed by an insignificant -1.22% post-event return. The event return of BMMS is very high and significant at -1.16% followed by an insignificant post-event return of -0.88%. This implies that the price impact of informed market order in BMMS is just enough to reflect the new information. On the contrary, we observe a strong reversal pattern in BMLS. BMLS exhibits the event return of 1.19% followed by a significant reversal of -2.45% during the post-event window. No drift in market sell order driven stocks and a reversal in limit sell order driven stocks observed in BM stocks are similar to those observed in GL stocks. A similar pattern is also found in BL stocks as well. For low abnormal volume stocks, BL portfolio generates a significant event return of -1.19% followed by an insignificant 0.60% post-event return. When we further divide BL stocks into BLMS and BLLS, the event return of BLMS is very high and significant at -1.76% followed by an insignificant 0.50% post-event return, suggesting that event window price change fully reflects the content of the news. The event return of BLLS is significantly positive at 2.32% followed by an insignificant 0.55% post-event return.

Our findings so far can be summarized as follows. For both good and bad news stocks, we show that a post-event return may exhibit not only a drift but also a partial reversal from the event window return and that the order type composition contains valuation information distinguishing the two. If good (bad) news stocks are purchased (sold) more by limit orders than by market orders, future price change contain a partial reversal. However, if good (bad) news stocks are purchased (sold) more by market orders than by limit orders, drift patterns vary depending on the size of abnormal volume. A strong drift is observed in the case of high abnormal volume stocks but no drift in the case of low abnormal volume stocks.

Our exercise complements recent studies by Kaniel, Liu, Saar, and Titman (2012) and So and Wang (2014), who report that pre-event orders may be subject to huge liquidity premium as stock prices tend to reverse during the announcement window. Our results show that even orders submitted during the announcement window may be subject to liquidity premium as evidenced by subsequent price reversals in certain portfolios.

Our results also show that by conditioning on trading volume and order type composition, we may substantially increase the profitability of the existing PEAD strategy. The order composition is publicly available information at the end of each trading day. Thus, we may implement a revised PEAD strategy by concentrating on stocks which may exhibit the strongest drift. A strategy of buying good news (G) and selling bad news stocks (B) during post-event window generates 4.54%. However, our hypotheses show that the strongest drifts for good news and bad news may be observed in GHMB and BHMS stocks. A strategy of buying GHMB and selling BHMS generates a CAR of 7.49%, an astounding 65% improvement from the vanilla PEAD strategy.

3.2 Calendar Time Analyses

Fama (1998) points out that the event study methodology may not correctly address the cross-correlation of event firms. This is potentially a serious problem since there is bunching of earnings announcements in Korea as in the U.S. He also adds that longer horizon post-event returns cause downward biases in standard error estimates, falsely generating high t statistics. He argues that a calendar time analysis based on monthly portfolio return may reduce these problems. While there are debates which methods are better in identifying abnormal returns (Loughran and Ritter, 2000), we test whether our results in the previous section are robust in the monthly calendar time analysis.

We assign each stock to a SUE-abnormal volume-order type portfolio starting on the first trading day of the month following an earnings announcement. It remains in the portfolio until the end of the month when the company made its next earnings announcement or before the end of the fourth month whichever comes first. We calculate the Jensen's alpha for each portfolio using Fama-French's 3 factor model (Fama and French, 1993) and Cahart's 4 factor model (Carhart, 1997).

[Table III, here]

Table III shows the results. First three rows show that the risk adjusted return of the PEAD strategy. Buying good news and selling bad news stocks generates a substantial 1.26% a month four factor risk adjusted return in our data set. The profit is due to the significant negative risk adjusted return for bad news portfolio of -0.80% per month. Good news portfolio, on the contrary, earns positive risk adjusted return of 0.42% but insignificant. This contrasts with the results of event time analysis where both good news and bad news portfolio exhibit significant drifts. The different results can be explained if we consider the lag a stock enters a portfolio in calendar time analysis. Table III shows how long it takes for a stock to enter a calendar time portfolio. It shows the number of days after the announcement window before a stock enters a portfolio. Both for good and bad news stocks, it took about 13 trading days after the announcement window. For comparison purpose, we use event time analyses results to calculate how much abnormal return accrues during the window [2,p-1], where p is the date a stock enters a calendar time portfolio, and how much accrues after the stock enters the portfolio. For good news stock, a significant 1.31% drift happens in [2,p-1] window which amounts to about 45% of the total drift of 2.89% during [2,50] window. On the contrary, for bad news stocks, stock prices react more slowly to the news. During [2,p-1] window, insignificant negative return of -0.36% is observed but significant -1.33% is observed during [p,50] window, which amounts to about 79% of the total drift in [2,50].

When we condition on high abnormal trading volume stocks, significant returns are only observed in bad news stocks. Four factor risk adjusted return of GH stocks is only 0.06% and insignificant but that of BH stocks is -1.25% and significant. When we further divide GH based on order type used, both GHMB and GHLB have insignificant risk adjusted returns while both BHMS and BHLS have significant negative returns. This shows that negative and significant post-event returns of BH stocks reflect both slow information incorporation (BHMS) and reversal (BHLS).

3.3 VWAP

At a given point in time, buying stocks with limit orders is always better than buying stocks with market orders due to bid-ask spread. Despite the obvious price disadvantage of market orders, informed investors may use market orders if he is worried about the execution risk of limit orders.

Price disadvantage of market orders is mitigated in the KRX market since the information on the 10 best quotes of both buy and sell sides is available to investors in real time. This information can be used by informed investors in choosing market or limit orders. He would submit large market orders only when the depth of the opposite side is reasonably deep enough so that he could camouflage his private information even after trading (Grossman and Stiglitz, 1980).

In this section, we show that the bid-ask spread exaggerates the price disadvantage of market orders when we consider the amount of unexecuted limit orders. To analyze this, we calculate the ratio of executed limit orders over total limit orders submitted at the end of each trading day. We define this ratio as the filled limit order ratio. We also calculate the volume weighted average purchase or sell price (VWAP) of each stock each day during the event window. The VWAP of a stock is calculated using transaction level data for all the market and limit orders. The VWAP of stock *i* on day *t* by order type *j* is defined as follows.

$$VWAP_{i,\mathrm{t}}^{j} = \frac{\sum_{k\in t} P_{i,k}^{j} V_{i,k}^{j}}{\sum_{k\in t} V_{i,k}^{j}} \qquad [7]$$

where $P_{i,k}^{j}$ is the price of stock *i* for trade *k* on day *t* for order type *j* and $V_{i,k}^{j}$ is the number of shares of trade for stock *i* for trade *k* on day *t* for order type *j*.

We estimate the price disadvantage of market orders after adjusting filled limit order ratio in two different ways. First, we assume that investors intend to execute any unfilled orders at the closing price at the end of the event window. We define a revised VWAP for limit orders as the weighted average of the VWAP of executed limit orders and the closing price at the end of the event window, with the weights of executed and unfilled limit orders, respectively. Second, we compare the dollar return of investors who buy or sell stocks at the VWAP and hold those stocks until the end of the 50th trading day. The reason why we examine the dollar return is because the amount of shares bought and sold by market or limit orders are different. While returns of market orders may be lower than those of limit orders, dollar returns of market orders may still be higher than those of limit orders due to the unexecuted limit orders.

[Table IV,here]

Table IV shows the results. Numbers in the table shows the average of each variable during the 3 day announcement window. First, for GHMB portfolio, market buy and limit buy orders represent about 58% and 42% of the total buy orders respectively. This implies that if 100 shares are purchased, 58 shares are purchased by market orders and 42 shares are purchased by limit orders. Since the filled limit order ratio is about 90%, limit buyers submit about 47 shares and, out of 47, about 42 shares are executed.

We then calculate the difference between the VWAP of market buy orders and the VWAP of limit buy orders normalized by the closing price of the last day of the event window. The difference is 0.65% for GHMB and statistically significant, showing the price disadvantage of market orders in this portfolio. However, this magnitude may overstate the advantage of limit orders since the filled limit order ratio is less than 1. In fact, when we calculate the normalized difference between the VWAP of market buy orders and the revised VWAP of limit buy orders, the price advantage of limit orders becomes substantially smaller at 0.09% (a seventh of the original difference), even though it still remains significant.

Second, we approximate the dollar return of each order type as follows. We assume that investors buy GHMB stocks during the 3 day window and hold it until the end of the

50th trading day. On the 50th trading day, all the purchased shares are sold at the closing price. In this case, the percentage returns of market buy orders and limit buy orders are 4.08% and 4.73%, respectively. Thus, if 100 shares are purchased (either using market or limit orders) for GHMB portfolio, the gross dollar return of market orders is $60.37 (1.0408*58). On the contrary, the gross dollar return of limit orders is $43.99 (1.0473*42). Thus, dollar return of market buy orders is about 1.4 times larger than that of limit buy orders even though it has a lower percentage return.

These two analyses suggest that for GHMB portfolio, despite inherent price disadvantage, market buy orders may not be a bad choice over limit buy orders considering unfilled ratio of limit orders and dollar returns.

On the contrary, for GHLB, market orders do not perform as well as in GHMB. This is not surprising since, according to our hypotheses, GHLB consists of stocks where market orders are not attractive to informed investors. For GHLB, market (limit) buy orders represent 40% (60%) of total buy orders. VWAP difference between market and limit orders normalized by the closing price is slightly larger than that of GHMB at 0.84%. Filled ratio is about 91% which is about the same as that of GHMB (90%). While the normalized difference between the VWAP of market buy orders and the revised VWAP of limit buy orders is -0.02% and insignificant, dollar return for limit buy orders is about 2.2 times larger than that of market buy orders. The comparison of results between GHMB and GHLB portfolios clearly shows that market orders are used by informed investors when it would be better to do so.

Similar findings are found for bad news as well. For BHMS, market (limit) sell orders represent 61% (39%) of total sell orders. While the normalized VWAP difference between market and limit sell orders is -0.78%, the normalized difference between the VWAP of market sell orders and the revised VWAP of limit sell orders reduces to 0.13%. Dollar return of stocks mainly sold by market orders is about 1.2 times larger than that of limit sell orders.

For BHLS, the opposite is true. Market (limit) sell orders represent 42% (58%) of total sell orders. The normalized VWAP difference between market and limit sell orders is about -0.69% while the normalized VWAP difference between the VWAP of market sell orders and the revised VWAP of limit sell orders becomes -0.003% and insignificant. Dollar return of stocks mainly sold by limit orders is about 1.6 times larger than that of market sell orders in this portfolio.

3.4 What factors affect the selection of order types?

This section investigates what factors are important for a dominant order type during the earnings announcement window.

The pre-event price movement is measured by CAR for the window of [-60,-5]. This interval is divided into two, [-60,-31] and [-30,-5] since the price changes further away from the current earnings announcement (CAR measured during [-60, -31]) may not so much represent the current earnings information as the previous earnings announcement. Another variable is the relative magnitude of bid and ask depths at the opening auction at event date -1. We also include CGO. CGO may affect the buying and selling decisions of investors who are subject to disposition effect (Grinblatt and Han, 2005; Choi et al., 2010). In turn, informed rational investors may respond to these orders in selecting appropriate order types.

We include control variables representing firm-characteristics. While order selection may be driven more by the information environment of a stock around earnings announcement, firm characteristics may be related with order selection as well. Due to higher liquidity, submitting market orders for large stocks may be less costly than submitting market orders for small stocks. We include size and book to market as representative firm characteristics.

We run Probit regressions using firm-quarter data. Dependent variable is a binary variable which takes 1 if $BOT_{it} > 0$ and 0 if $BOT_{it} \leq 0$ for stocks in GH portfolio. For stocks in BH portfolio, dependent variable is a binary variable which takes 1 if $SOT_{it} > 0$ and 0 if $SOT_{it} \leq 0$. Estimation results are reported in Table V.

[Table V, here]

For stocks in GH portfolio, both CAR_{it}[-60,-5] and CAR_{it}[-30,-5] attract negative and significant coefficients while CAR_{it}[-60,-31] is significant only when it is included with CAR_{it}[-30,-5]. This implies that stocks with stronger pre-event drifts are purchased more by limit orders than by market orders. As price incorporates the current earnings news in advance, the price impact of market orders may become a binding constraint.

The coefficients for Depth Imbalance are negative and significant in all the specifications. This implies that stocks are purchased more by market (limit) orders than by limit (market) orders when the depth of the sell side is thicker (thinner) than the buy side. This is consistent with the claim that informed investors submit market buy orders when their information is not fully revealed due to the many uninformed sellers who absorb those orders with uninformed limit sell orders. This finding is inconsistent with Parlour (1998) who emphasizes that if there are many limit buy orders already submitted by other investors, informed investors would submit market orders to avoid execution risk. The concern for this *crowding out effect* suggests that the coefficient for depth to be positive rather than negative.

The coefficient for CGO is positive and significant. This implies that if a stock has large unrealized capital gains, good news stocks are purchased more by market orders than by limit orders. If a subset of investors is subject to the disposition effect, large amount of sell orders would be submitted for stocks with large unrealized capital gains. These sell orders may reduce the concern for the price impact of market orders and may prompt investors to submit market orders. Size attracts positive and significant coefficient. This may be due to the higher liquidity of larger stocks. However, book to market is insignificant.

For stocks in BH portfolio, the coefficient for CAR_{it}[-30,-5] is positive and significant. Thus, as in GH portfolio, pre-event negative drift induces investors to use limit orders rather than market orders. However, coefficients for both CAR_{it}[-60,-5] and CAR_{it}[-60,-31] are insignificant. The coefficients for Depth Imbalance are all positive and significant in all the specifications. Thus, coefficients for CAR and Depth Imbalance in GH and BH portfolios generate results which are consistent with interpretations that preannouncement drift prompts investors to use limit orders, and that the larger depths on the opposite side prompts the use of market orders by informed investors. However, other variables attract inconsistent signs. For CGO, negative and significant results for BH portfolio may be associated with the fact that the effect of large unrealized loss may have two contradicting effects on investors' trading behavior. Investors may keep stocks with large unrealized losses as described in the disposition effect (Shefrin and Statman, 1985). However, investors may eventually realize losses if the possibility of future price increase seems very small (Gomes, 2005). Choi et al. (2010) and Li (2016) find that the tendency of realizing large losses increases with the arrival of bad news, which reduces the possibility of future price increase. If this is the case, irrational investors may submit many sell orders (including limit sell orders) and informed investors may choose to submit market sell orders not to be crowded out by submitting limit sell orders.

Size has negative and significant coefficient for BH portfolio, implying that smaller stocks are sold more by market orders, which defies our earlier liquidity based interpretation on the sign of the size coefficient for GH portfolio. This result may suggest that order type selection is not so much driven by firm characteristic (e.g., market orders are for larger stocks) as by information environment of earnings announcements. Book to market remain insignificant in BH portfolio as well.

Our results for both GH and BH portfolios remain robust to the inclusion of the firm fixed effect.

4. Order Selection By Investor Type and Future Returns

This section examines the order type selection for domestic individual, domestic institutional and foreign investors in the Kospi market of the KRX and the implication of the order type selection of each investor type on future return.

Existing literature mainly focuses on whether a certain investor type is more rational than others. Lee (1992), Daniel, Grinblatt, Titman, and Wermers (1997), Grinblatt and Keloharju (2000), Gompers and Metrick (2001), Cohen, Gompers, and Vuolteenaho (2002), and many others suggest that institutional investors may be more sophisticated than individual investors. Hvidkjaer (2008) and Barber, Odean, and Zhu (2009) use buyer-initiated small trades as a proxy for retail investing and argue that orders from retail investors exert a temporary price pressure, which revert over 60 trading day interval. This implies that retail investors may be noise traders whose trade is not driven by information. Dorn, Huberman, and Sengmueller (2008) arrive at a similar conclusion using a single German retail broker data.

Recent papers, on the contrary, provide different evidence. Lewellen (2011) finds that institutions as a whole cannot beat the market benchmark return and cast doubt whether institutional investors as a whole can be regarded as informed investors. Kaniel, Liu, Saar, and Titman (2012) report informed trading by individual investors around earnings announcement for stocks traded at the NYSE.

However, these papers do not examine the issue in relation with the order type selection of each investor type. One of the exceptions is Kelley and Tetlock (2013) who examine the imbalance measures of market and limit orders of retail investors separately and find that both net order imbalance measures of market and limit orders are positively associated with future return. These results imply that individual investors are both informed traders and informed liquidity providers who collect liquidity premium for their liquidity provision. However, even Kelley and Tetlock (2013) cannot investigate the orders submitted by other investors and thus whether individuals are smarter than other types of investors or not.

In section 4.1, we examine whether all three investor types substantially change order types during earnings announcement windows. Section 4.2 examines which investor type's order selection has stronger future return implication.

4.1 Order Selection By Investor Type

Panel A of Table 6 reports the BOT and SOT for good and bad news respectively for each investor type during the pre-event window of [-30,-5] and during the event window of [-1,1].

[Table VI, here]

For GHMB portfolio, average change in BOT between pre-event window and the event window is very large at 23.10% for the whole sample. The average changes in BOT for both individual and institutional investors are similar at 20.64% and 20.17%. However, that for foreign investors is relatively small at 4.84%. It is interesting to note that institutional investors most aggressively use market orders in this portfolio. This is consistent with Lee

(1992) who argues that institutional investors aggressively and intensively trade during event window when compared with individuals.

For GHLB portfolio, average change in BOT between pre-event window and the event window is relatively small at -7.8%. Unlike GHMB portfolio, BOT has the largest number in absolute value for individual investors. In addition, relative importance of foreign investors is greater in GHLB portfolio than in GHMB portfolio.

For BHMS and BHLS portfolios, we observe larger SOTs in absolute values for BHLS portfolio than BHMS portfolio, possibly due to short sale constraints. As in good news case, institutions are submitting market sell orders more aggressively than others during event window for BHMS portfolio. As in GHLB, for BHLS, foreign investors are more active liquidity providers than aggressive informed traders.

Panels B and C show results for subset of stocks where both individual and institutional investors trade and where all three types trade, respectively. We obtain qualitatively similar results as in Panel A.

4.2 Order Selection By Investor Type and Future Returns

In this section, we examine the future return implication of order type selection for each investor type. First we focus on the informativeness positive BOT (SOT) stocks for each investor type for GH (BH) portfolio (Table 7). Next, we examine the informativeness of negative BOT (SOT) stocks for each investor type for GH (BH) portfolio (Table 8). We run cross-sectional regressions for each quarter where dependent variables are CAR [2,50]. Independent variables are three dummy variables for each investor types. For Table 7 for GH portfolio, dummy for individual investor equals 1 if the BOT of individual investors is positive and 0 if BOT of individual investors is negative. For BH portfolio, dummy for individual investor equals 1 if the SOT of individual investors is positive and 0 if SOT of individual investors is negative. Dummies for institutional and foreign investors are similarly defined. We do not include intercept in each cross sectional regression. Thus, the coefficient for each dummy variable correspond to the average CAR [2,50] for GHMB and BHMS portfolios sorted by BOT or SOT of each investor type, respectively. For Table 8 for GH portfolio, dummy for individual investor equals 1 if the BOT of individual investors is negative and 0 if BOT of individual investors is positive. For BH portfolio, dummy for individual investor equals 1 if the SOT of individual investors is negative and 0 if SOT of individual investors is positive. Dummies for institutional and foreign investors are similarly defined.

[Table VII, here]

Panel A of Table 7 reports the time series averages of estimated coefficients across quarters using full sample when BOT and SOT is positive for GH and BH portfolio, respectively. Panels B and C of Table 7 report subsample results where both individual and institutional investors trade and where all three types trade, respectively.

For GH portfolio for full sample, dummies for individuals and institutional investors are positive and significant when included alone while that for foreign investors is insignificant. When we include dummies for individual and institutional investors together, only the coefficient for individual investor dummy remains positive and significant in both full sample and in a subsample where both individual and institutional investors trade. This implies that the order type selection of individual investors has independent information not contained in the order type selection measure of institutional investor but not vice versa. This result supplements Kelley and Tetlock (2013) who only examine the informativeness of individual's market orders and thus cannot compare the relative strength of individuals over other investor types. When we include all three dummy variables, both individual and institutional dummies are significant. However, coefficient for the dummy of individual investor is larger and more significant. When we restrict our sample to stocks where all three types trade, while both individual and institutional dummies are marginally significant when included alone, no investor type has advantage over others when dummies are included together.

For BH portfolio, the informativeness of SOT measure of individual investors become stronger than those of other investor types. Unlike GH portfolio, for stocks where all three types trade, significance of each dummy variable becomes much stronger when included alone. However, even in this subsample, no investor type has advantage over others when dummies are included together.

[Table VIII, here]

Panel A of Table 8 reports the time series averages of estimated coefficients across quarters using full sample when BOT and SOT is negative for GH and BH portfolio, respectively. Panels B and C of Table 8 report subsample results where both individual and institutional investors trade and where all three types trade, respectively. One notable fact in Table 8 when compared with results in Table 7 is that the informed liquidity provision by foreign investors is strongly observed in the data. Thus, while foreigners do not actively buy or sell on information using market orders for good and bad news stocks respectively, they are actively engaging in liquidity provision by submitting limit orders.

5. Conclusion

This paper shows that by examining the relative magnitude of market and limit orders in buying (selling) good (bad) news stocks during earnings announcement window, we can predict the direction and magnitude of stock price changes during the post-event window. Our hypothesis is based on recent theoretical models that informed investors either submit market or limit orders depending on the trading environment they are in. They would submit market orders if mispricing is deep and if the depth on the opposite side of the market is thick. On the contrary, informed investors would submit limit orders if mispricing is shallow or if there are uninformed investors who are placing market orders aggressively. In the latter case, informed investors can collect liquidity premium.

We test the hypothesis using the KRX data where order types and three investor types (individual, institutional and foreign investors) are identified. Our paper's main contributions to the literature can be summarized as follows.

First, we find that the relative magnitude of order type contains additional information in understanding post-event stock price changes around earnings announcement. Our hypothesis and empirical findings show that the relative magnitude of market and limit orders can be used to identify whether the price change during the event window would continue in the same direction (e.g., a drift) or reverse. The former is the case of delayed information incorporation while the latter is the liquidity shock driven price pressure. We find that a significant portion of stock price change during the post-event window actually represents a reversal rather than a continuation from the price change during the event window. This implies that interpreting the post-event window price change as mostly representing the slow information incorporation (Ball and Brown, 1968; Bernard, 1993) could be misleading. This extends Kaniel, Liu, Saar, and Titman (2012) and So and Wang (2014), who report similar reversal between pre-event window and event window.

Second, when we revise a well known PEAD strategy of buying good news stocks and selling bad news stocks by incorporating information in the relative magnitude of market and limit orders, the profit of the PEAD strategy increases substantially.

Third, our results provide a new identification on the informativeness of trading volume for future price changes. Campbell, Grossman, and Wang (1993) and Llorente *et al*. (2002) show that stock prices of high abnormal volume stocks tend to exhibit either price continuation or reversal depending on whether the trading is initiated by informed investors or liquidity traders. However, their identification is at the stock level. In other words, while one could argue that a stock ‘s trading volume is driven, on average, more by information or liquidity, one is not able to claim a large abnormal trading volume observed at a particular point in time is more likely driven by information or liquidity. We show that we could condition on both news (SUE) and the relative magnitude of order type measure to predict the nature of a large trading volume observed around the public announcement.

Lastly, contrary to a commonly believed assumption that individual investors are noise traders, we find evidence that the relative magnitude of market and limit orders of individual investors contain independent information on the future stock price changes not contained in the same measure of institutional investors. This supplements recent papers which analyze market and limit orders of individual investors find that at least substantial percentage of retail investors in the US are informed investors (Kelley and Tetlock, 2013).

While we focus on the informativeness of the relative magnitude of two order types in this paper, the data set used in this paper contains detailed information on who trade against whom. This implies that one could investigate in great detail on the nature of inter-group and intra-group trading to analyze the propagation of information and the evolution of the temporary price pressure due to liquidity motivated trades. We are working on these topics in separate works.

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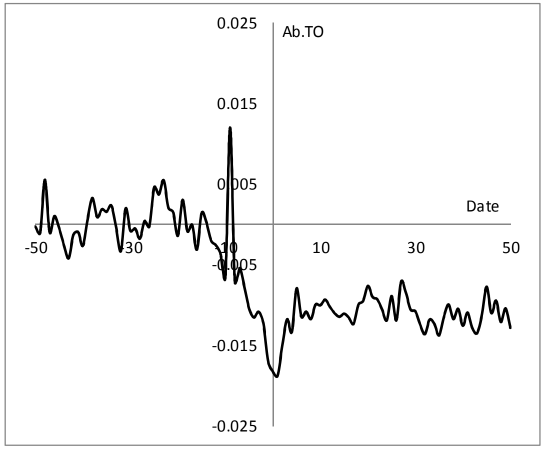
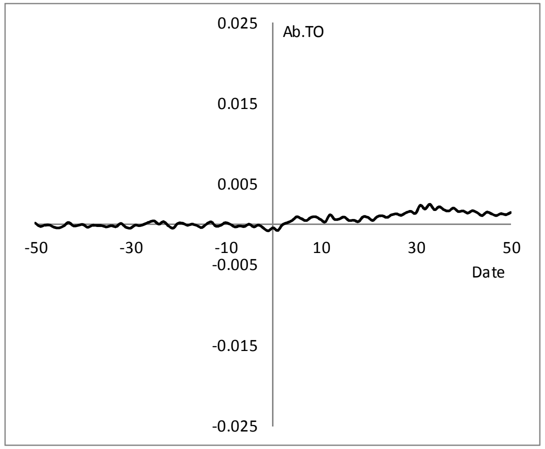
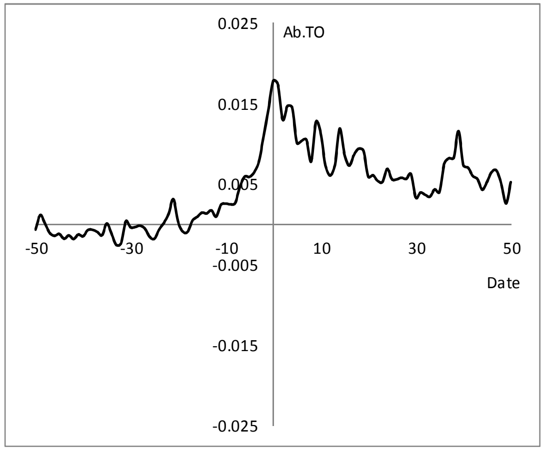
Figure 1. Abnormal Volume Patterns



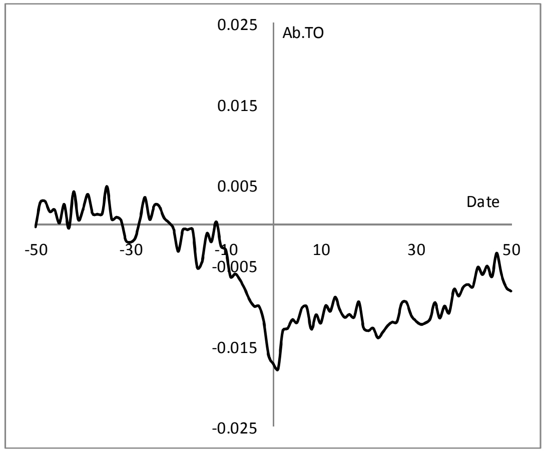
(a) GL



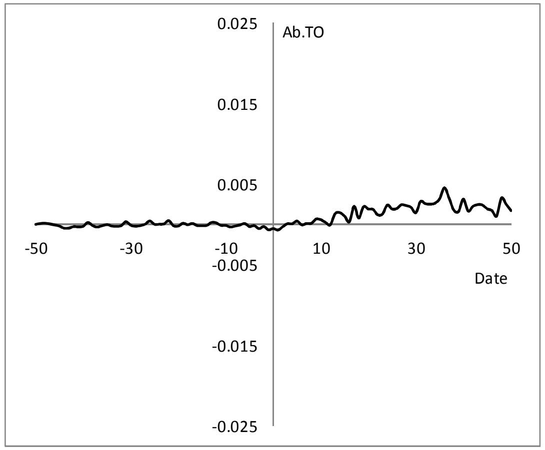
(b) GM



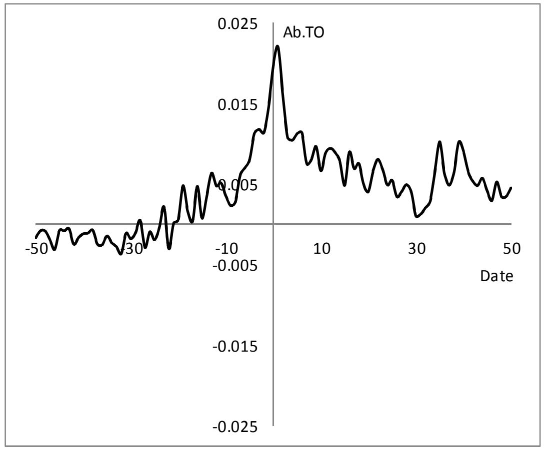
(C) GH



(d) BL

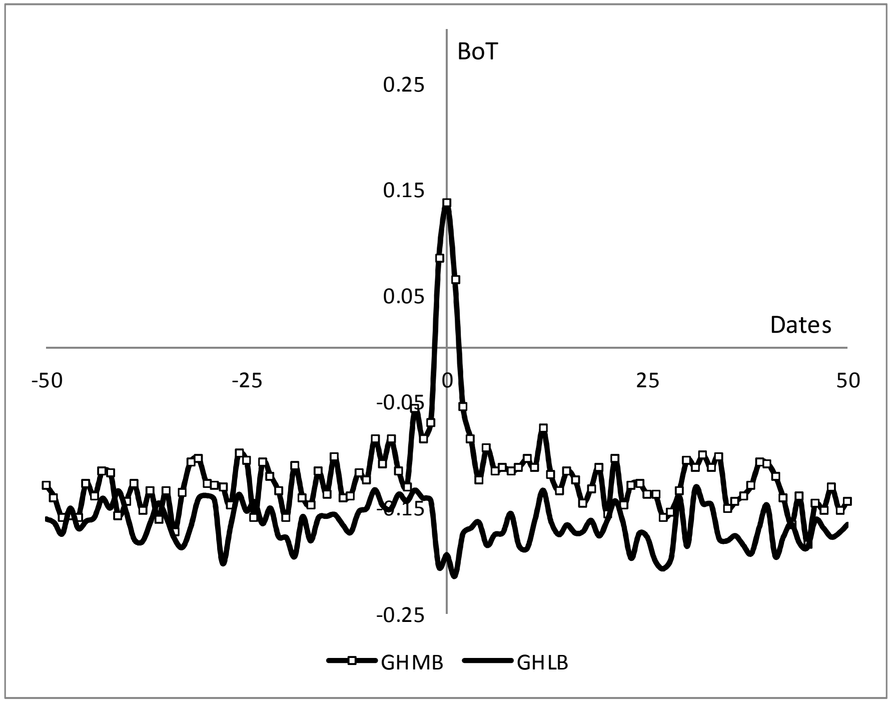


(e) BM

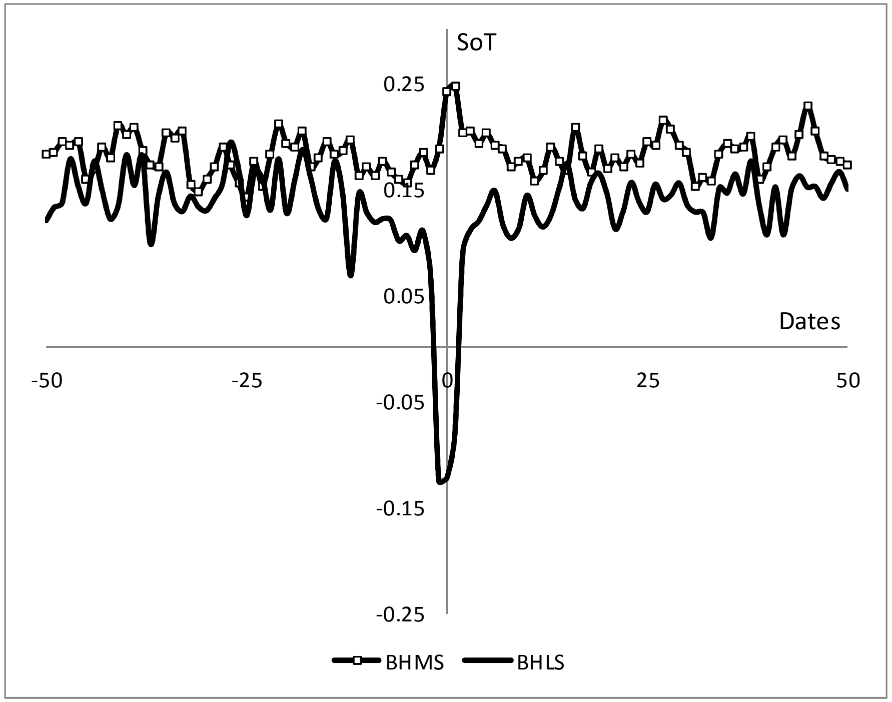


(f) BH

Figure 2. BOT and SOT Patterns



(a) BOT Pattern GHMB and GHLB



(b) SOT Pattern BHMS and BHLS

Figure 3. Cumulative Abnormal Return Patterns

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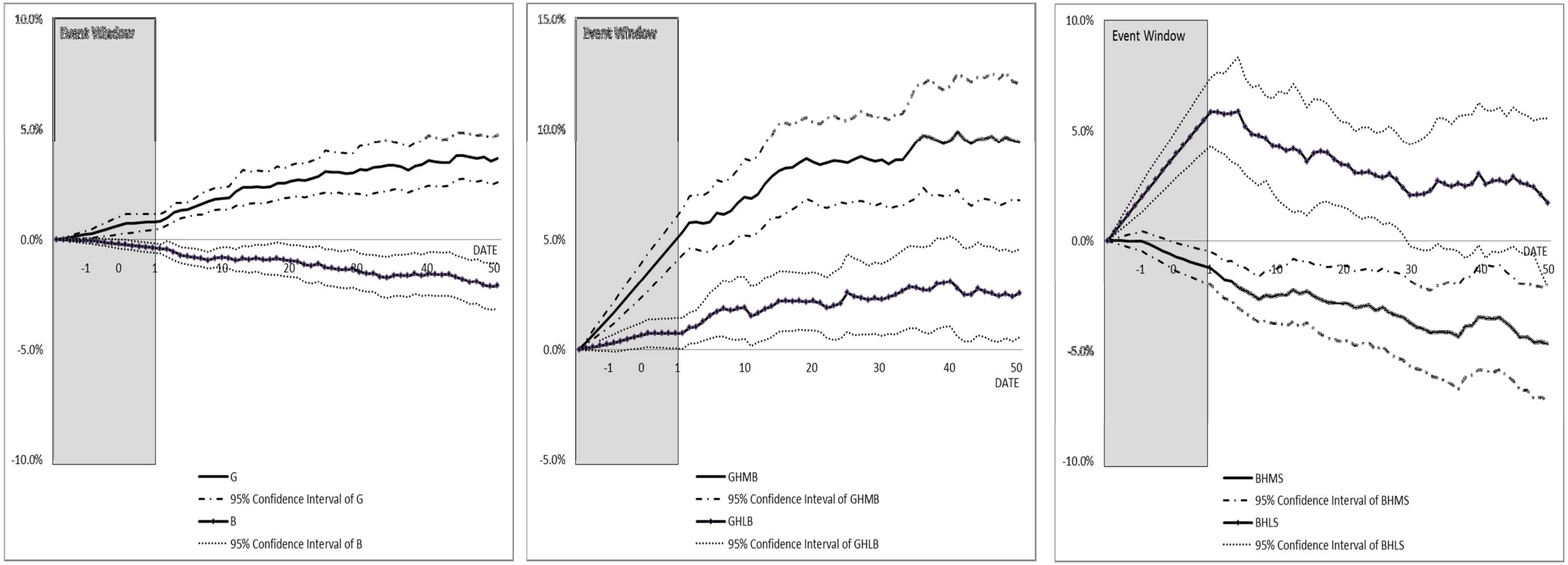

(a) CARs of G (Good News) and B (Bad News) Portfolios **(b) CARs of GHMB and GHLB Portfolios** **(c) CARs of BHMS and BHLs Portfolios**

Table I. Summary Statistics

Panel A. Good News Group Portfolios

		News	Volume			Aggressiveness			Others			
Portfolio	**N**	**SUE**	**Ab.Vol [-1,1]**	**TO [-60,-5]**	**TO [-1,1]**	**BOT [-60,-5]**	**BOT [-1,1]**	**ΔBOT**	**Ln Size**	**BE/ME**	**CGO [-5]**	**Dep.Imb [-1]**
G	4187	1.544	0.0009	0.0164	0.0172	-0.1517	-0.1101	0.0416	11.68	1.801	-0.0174	-0.0003
(Good News)		(18.17)	(0.77)	(11.65)	(12.97)	(-25.48)	(-14.16)	(5.16)	(138.68)	(17.70)	(-0.74)	(-0.02)
GH	1359	1.566	0.0147	0.0150	0.0310	-0.1566	-0.0741	0.0826	11.66	1.758	0.0068	0.0023
(G-High Volume)		(17.41)	(6.97)	(10.33)	(11.54)	(-22.95)	(-8.74)	(9.61)	(123.83)	(16.32)	(0.30)	(0.13)
GM	1618	1.482	-0.0042	0.0050	0.0042	-0.1304	-0.1044	0.0261	11.93	1.941	-0.0117	-0.0389
(G-Middle Volume)		(17.10)	(-6.66)	(12.74)	(12.32)	(-18.17)	(-8.19)	(2.22)	(135.17)	(17.54)	(-0.40)	(-2.28)
GL	1210	1.601	-0.0103	0.0355	0.0181	-0.1733	-0.1731	0.0002	11.32	1.649	-0.0649	0.0526
(G-Low Volume)		(16.92)	(-5.36)	(9.29)	(11.01)	(-26.98)	(-20.63)	(0.02)	(96.92)	(15.81)	(-2.73)	(2.36)
GHMB	505	1.603	0.0073	0.0115	0.0236	-0.1386	0.1429	0.2815	11.86	1.798	0.0310	-0.0366
(GH-Market Buy)		(11.42)	(2.94)	(7.11)	(8.29)	(-22.13)	(16.19)	(31.54)	(95.82)	(13.59)	(1.28)	(-1.19)
GHLB	854	1.534	0.0181	0.0166	0.0344	-0.1626	-0.1978	-0.0352	11.54	1.783	-0.0116	0.0140
(GH-Limit Buy)		(17.91)	(6.24)	(10.10)	(10.07)	(-20.21)	(-25.05)	(-2.93)	(104.14)	(15.96)	(-0.50)	(0.67)
GMMB	561	1.424	-0.0023	0.0043	0.0038	-0.0966	0.2078	0.3044	12.22	1.776	0.0560	-0.0849
(GM-Market Buy)		(12.88)	(-5.57)	(10.75)	(8.94)	(-12.95)	(16.70)	(22.38)	(99.56)	(18.04)	(1.94)	(-3.24)
GMLB	1057	1.484	-0.0049	0.0054	0.0044	-0.1480	-0.2630	-0.1149	11.80	1.966	-0.0399	-0.0163
(GM-Limit Buy)		(17.23)	(-6.46)	(12.43)	(11.21)	(-20.47)	(-32.19)	(-11.61)	(124.12)	(14.95)	(-1.31)	(-0.84)
GLMB	230	1.574	-0.0079	0.0294	0.0178	-0.1440	0.1260	0.2700	11.74	1.640	-0.0181	0.0575
(GL-Market Buy)		(12.46)	(-2.29)	(6.74)	(7.92)	(-14.45)	(11.84)	(17.07)	(51.23)	(10.56)	(-0.60)	(1.33)
GLLB	980	1.594	-0.0115	0.0365	0.0181	-0.1797	-0.2424	-0.0628	11.21	1.644	-0.0738	0.0500
(GL-Limit Buy)		(15.62)	(-5.05)	(9.49)	(10.46)	(-27.68)	(-34.67)	(-8.61)	(97.75)	(15.33)	(-3.10)	(2.48)

Table I. (Continued)

Panel B. Bad News Group Portfolios

Portfolio	N	News	Volume			Aggressiveness			Others			
		SUE	Ab.Vol [-1,1]	TO [-60,-5]	TO [-1,1]	SOT [-60,-5]	SOT [-1,1]	ΔSOT	Log Size	BE/ME	CGO (D-5)	Dep.Imb (D-1)
B	4242	-1.378	0.0010	0.0158	0.0167	0.1678	0.1615	-0.0063	11.42	1.956	-0.1221	0.0323
(Bad News)		(-18.42)	(0.72)	(12.22)	(10.31)	(31.49)	(17.83)	(-0.68)	(144.22)	(22.15)	(-4.35)	(2.65)
BH	1380	-1.420	0.0204	0.0173	0.0361	0.1742	0.1291	-0.0451	11.42	1.878	-0.1032	0.0610
(B-High Volume)		(-14.02)	(4.67)	(7.13)	(7.24)	(28.26)	(12.27)	(-4.06)	(135.26)	(18.87)	(-3.93)	(3.72)
BM	1635	-1.317	-0.0038	0.0046	0.0040	0.1469	0.1533	0.0064	11.64	2.086	-0.1219	-0.0084
(B-Middle Volume)		(-16.74)	(-7.50)	(10.96)	(8.86)	(18.08)	(12.56)	(0.55)	(136.79)	(19.88)	(-3.34)	(-0.59)
BL	1227	-1.405	-0.0122	0.0337	0.0167	0.1849	0.2105	0.0257	11.108	1.829	-0.1356	0.0496
(B-Low Volume)		(-18.26)	(-6.18)	(11.25)	(10.38)	(32.06)	(18.95)	(2.36)	(98.10)	(16.96)	(-5.11)	(2.80)
BHMS	979	-1.453	0.0226	0.0177	0.0387	0.1824	0.2274	0.0451	11.25	1.925	-0.1165	0.0826
(BH-Market Sell)		(-11.97)	(3.99)	(6.65)	(6.38)	(27.89)	(28.38)	(4.26)	(138.02)	(17.40)	(-4.06)	(4.29)
BHLS	401	-1.337	0.0176	0.0155	0.0322	0.1475	-0.1457	-0.2932	11.81	1.737	-0.0659	-0.0175
(BH-Limit Sell)		(-13.03)	(3.63)	(6.31)	(6.07)	(24.02)	(-13.59)	(-27.55)	(80.76)	(15.69)	(-2.44)	(-0.49)
BMMS	1175	-1.288	-0.0042	0.0050	0.0042	0.1601	0.3045	0.1444	11.54	2.097	-0.1428	0.0104
(BM-Market Sell)		(-16.21)	(-7.26)	(10.34)	(8.14)	(18.99)	(26.93)	(11.93)	(124.47)	(20.59)	(-3.90)	(0.54)
BMLS	460	-1.349	-0.0027	0.0037	0.0034	0.1215	-0.2408	-0.3623	11.84	2.056	-0.0611	-0.0611
(BM-Limit Sell)		(-15.55)	(-6.55)	(10.59)	(8.11)	(11.44)	(-16.94)	(-19.08)	(103.35)	(15.34)	(-1.39)	(-2.81)
BLMS	1044	-1.408	-0.0123	0.0352	0.0175	0.1909	0.2686	0.0777	11.04	1.860	-0.1477	0.0559
(BL-Market Sell)		(-17.37)	(-5.89)	(11.64)	(9.90)	(32.89)	(31.63)	(9.49)	(99.40)	(15.70)	(-5.20)	(3.25)
BLLS	183	-1.341	-0.0105	0.0250	0.0127	0.1494	-0.1301	-0.2795	11.38	1.688	-0.0690	0.0042
(BL-Limit Sell)		(-11.41)	(-2.75)	(6.07)	(5.19)	(14.75)	(-10.16)	(-20.53)	(49.71)	(11.18)	(-2.43)	(0.09)

Table II. Cumulative Abnormal Returns around Earning Announcements

Good News						Bad News					
Portfolio	N	Pre [-60,-5]	Event [-1,1]	Post [2,50]	Event + Post	Portfolio	N	Pre [-60,-5]	Event [-1,1]	Post [2,50]	Event + Post
G	4187	0.0403	0.0082	0.0284	0.0366	**B**	4242	-0.0128	-0.0041	-0.0170	-0.0211
		(4.52)	(4.90)	(5.26)	(6.69)			(-2.25)	(-3.99)	(-3.41)	(-3.98)
GH	1359	0.0460	0.0256	0.0257	0.0513	**BH**	1380	0.0020	0.0042	-0.0374	-0.0331
		(4.57)	(7.96)	(2.96)	(5.36)			(0.19)	(1.35)	(-4.04)	(-3.45)
GM	1618	0.0231	0.0016	0.0327	0.0344	**BM**	1635	-0.0281	-0.0055	-0.0122	-0.0177
		(3.07)	(1.12)	(6.64)	(7.04)			(-4.30)	(-4.51)	(-1.72)	(-2.52)
GL	1210	0.0730	-0.0059	0.0384	0.0325	**BL**	1227	-0.0033	-0.0119	0.0060	-0.0059
		(5.75)	(-2.68)	(3.57)	(2.87)			(-0.33)	(-7.05)	(0.59)	(-0.57)
GHMB	505	0.0276	0.0533	0.0408	0.0941	**BHMS**	979	0.0126	-0.0126	-0.0341	-0.0467
		(1.71)	(10.12)	(3.40)	(7.01)			(0.91)	(-3.25)	(-2.75)	(-3.63)
GHLB	854	0.0600	0.0074	0.0182	0.0256	**BHLS**	401	-0.0308	0.0586	-0.0409	0.0177
		(5.05)	(2.05)	(1.92)	(2.52)			(-2.02)	(7.41)	(-2.39)	(0.91)
	Difference	-0.0395	0.0470	0.0210	0.0680		**Difference**	0.0377	-0.0717	0.0085	-0.0633
		(-2.04)	(7.69)	(1.97)	(6.00)			(1.72)	(-7.39)	(0.37)	(-2.48)

Table II. (Continued)

Good News						Bad News					
Portfolio	N	Pre [-60,-5]	Event [-1,1]	Post [2,50]	Event + Post	Portfolio	N	Pre [-60,-5]	Event [-1,1]	Post [2,50]	Event + Post
GMMB	561	0.0264	0.0175	0.0334	0.0509	**BMMS**	1175	-0.0312	-0.0116	-0.0088	-0.0204
		(1.96)	(7.29)	(3.63)	(5.71)			(-4.42)	(-8.67)	(-1.19)	(-2.82)
GMLB	1057	0.0203	-0.0074	0.0349	0.0275	**BMLS**	460	-0.0205	0.0119	-0.0245	-0.0126
		(2.60)	(-4.07)	(5.95)	(4.96)			(-2.09)	(5.21)	(-2.46)	(-1.25)
	Difference	0.0061	0.0249	-0.0015	0.0234		**Difference**	-0.0108	-0.0234	0.0135	-0.0099
		(0.49)	(9.08)	(-0.14)	(2.19)			(-1.10)	(-9.47)	(1.50)	(-1.13)
GLMB	230	0.0669	0.0264	0.0043	0.0307	**BLMS**	1044	-0.0079	-0.0176	0.0050	-0.0126
		(2.55)	(4.01)	(0.17)	(1.19)			(-0.69)	(-10.85)	(0.47)	(-1.18)
GLLB	980	0.0720	-0.0138	0.0464	0.0326	**BLLS**	183	0.0454	0.0232	0.0055	0.0287
		(5.05)	(-6.17)	(3.74)	(2.57)			(2.28)	(5.48)	(0.24)	(1.31)
	Difference	-0.0009	0.0393	-0.0468	-0.0076		**Difference**	-0.0561	-0.0404	-0.0067	-0.0471
		(-0.03)	(5.33)	(-1.56)	(-0.26)			(-2.31)	(-8.73)	(-0.28)	(-2.03)

Table III. Calendar Time Analysis

Portfolio	N	Jensen's Alpha		Portfolio Entrance Event Date		CAR Decomposition by Portfolio Entrance Event Date		
		FF3	FF4	Mean	CAR[2,12]	CAR[2,P-1]	CAR[P,50]	CAR[2,50]
G	4094	0.0042	0.0042	12.61	0.0136	0.0131	0.0158	0.0289
		(1.44)	(1.45)	(168.03)	(5.80)	(6.15)	(3.64)	(5.43)
B	4018	-0.0080	-0.0080	12.52	-0.0053	-0.0036	-0.0133	-0.0169
		(-2.37)	(-2.40)	(173.78)	(-2.11)	(-1.46)	(-3.18)	(-3.40)
G-B		0.0130	0.0126					
		(3.37)	(3.53)					
GH	1314	0.0006	0.0006	12.66	0.0142	0.0178	0.0085	0.0263
		(0.15)	(0.13)	(99.14)	(3.08)	(3.70)	(1.41)	(3.08)
BH	1282	-0.0126	-0.0125	12.67	-0.0165	-0.0126	-0.0249	-0.0376
		(-2.51)	(-2.50)	(101.52)	(-2.65)	(-2.10)	(-3.34)	(-4.06)
GH-BH		0.0122	0.0119					
		(2.32)	(2.35)					
GHMB	490	0.0077	0.0075	12.84	0.0172	0.0272	0.0153	0.0425
		(1.36)	(1.37)	(59.59)	(2.91)	(3.93)	(1.89)	(3.57)
GHLB	824	0.0002	0.0001	12.55	0.0091	0.0118	0.0064	0.0182
		(0.03)	(0.01)	(79.30)	(1.80)	(2.37)	(0.83)	(1.92)
BHMS	903	-0.0117	-0.0117	12.80	-0.0123	-0.0108	-0.0235	-0.0343
		(-2.18)	(-2.19)	(92.43)	(-1.77)	(-1.65)	(-2.19)	(-2.76)
BHLS	379	-0.0100	-0.0100	12.36	-0.0178	-0.0119	-0.0293	-0.0412
		(-1.25)	(-1.24)	(46.69)	(-1.97)	(-1.14)	(-2.24)	(-2.41)

Table III (continued)

Portfolio	N	Jensen's Alpha		Portfolio Entrance Event Date		CAR Decomposition by Portfolio Entrance Event Date		
		FF3	FF4	Mean	CAR[2,12]	CAR[2,P-1]	CAR[P,50]	CAR[2,50]
GHMB-GHLB		0.0032	0.0032					
		(0.52)	(0.52)					
GHMB-BHMS		0.0151	0.0150					
		(2.24)	(2.31)					
GHMB-BHLS		0.0208	0.0205					
		(2.20)	(2.18)					
GHLB-BHMS		0.0119	0.0118					
		(2.02)	(2.07)					
GHLB-BHLS		0.0177	0.0173					
		(2.06)	(2.02)					
BHMS-BHLS		-0.0067	-0.0069					
		(-0.78)	(-0.79)					

Table IV. VWAP Analysis

Portfolio	N	Market Order Proportion	Filled Limit Order Ratio	(VWAP(M)-VWAP(L))/P[1]	(VWAP(M)-VWAP(L*))/P[1]
GHMB	505	0.575	0.898	0.0065	0.0009
		(129.82)	(202.97)	(12.27)	(6.17)
GHLB	854	0.398	0.909	0.0084	-0.0002
		(106.81)	(313.23)	(15.82)	(-0.76)
BHMS	979	0.614	0.874	-0.0078	0.0013
		(152.90)	(217.14)	(-17.52)	(9.22)
BHLS	401	0.424	0.907	-0.0069	0.0000
		(81.08)	(188.59)	(-9.88)	(-0.21)

Table V. Probit Regression Result

Dependent Variable	Intercept	CAR [-60,-5]	CAR [-60,-31]	CAR [-30,-5]	Ln Size	BE/ME	CGO [-5]	Dep.Imb [-1]	Psuedo.RSQ
Among GH, GHMb=1, GHLb=0 (N=1359)	-12.43	-0.6490						-0.4272	0.096
	(-0.03)	(-2.46)						(-2.66)	
	-12.40		-0.4966					-0.3967	0.090
	(-0.03)		(-1.29)					(-2.47)	
	-12.30			-0.7602				-0.4092	0.095
	(-0.03)			(-2.16)				(-2.56)	
	-13.71				0.1163			-0.3678	0.100
	(-0.03)				(3.27)			(-2.29)	
	-12.28					-0.0169		-0.3972	0.092
	(-0.03)					(-0.41)		(-2.47)	
	-12.32						0.9939	-0.3360	0.104
	(-0.03)						(3.65)	(-2.08)	
	-13.88		-0.5376	-0.7586	0.1200	0.0154		-0.3804	0.10.6
	(-0.03)		(-1.36)	(-2.07)	(3.17)	(0.35)		(-2.33)	
	-13.48		-0.8627	-1.2753	0.0796	0.0174	1.3055	-0.3267	0.124
	(-0.03)		(-2.09)	(-3.19)	(2.03)	(0.39)	(4.19)	(-1.98)	

Table V. (Continued)

Dependent Variable	Intercept	CAR [-60,-5]	CAR [-60,-31]	CAR [-30,-5]	Ln Size	BE/ME	CGO [-5]	Dep.Imb [-1]	Psuedo.RSQ
Among BH BHMs=1 , BHLs=0 (N=1380)	11.23	0.3632						0.5188	0.107
	(0.04)	(1.22)						(3.20)	
	11.30		-0.4662					0.5136	0.104
	(0.04)		(-1.16)					(3.17)	
	11.18			0.9211				0.5136	0.111
	(0.04)			(2.47)				(3.16)	
	14.03				-0.2364			0.5657	0.140
	(0.05)				(-5.97)			(3.45)	
	11.22					0.0229		0.5478	0.110
	(0.04)					(1.05)		(3.34)	
	11.19						-0.6180	0.5025	0.112
	(0.04)						(-2.61)	(3.10)	
	13.80		-0.2831	0.8412	-0.2288	0.0218		0.5699	0.147
	(0.05)		(-0.64)	(2.11)	(-5.51)	(0.56)		(3.41)	
	13.48		-0.0703	1.1118	-0.2117	0.0199	-0.5944	0.5438	0.152
	(0.04)		(-0.16)	(2.65)	(-5.03)	(0.51)	(-2.23)	(3.24)	

Table VI. Relative magnitude of market buy (BOT) and market sell (SOT)

Panel A. All Samples

Portfolio	N	Market			Individual			Domestic Institution			Foreign		
		[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff
GHMB	505	-0.0881	0.1429	0.2310	-0.1246	0.0817	0.2064	0.0240	0.2369	0.2017	-0.0041	0.0741	0.0484
		(-8.59)	(16.19)	(22.23)	(8.59)	(-16.19)	(-22.23)	(-10.68)	(8.25)	(12.45)	(0.69)	(6.53)	(3.54)
GHLB	854	-0.1198	-0.1978	-0.0780	-0.1565	-0.2092	-0.0527	0.0492	-0.0628	-0.1261	-0.0202	-0.0913	-0.0478
		(-15.16)	(-25.05)	(-7.03)	(15.16)	(25.05)	(7.03)	(-23.85)	(-19.88)	(-4.63)	(2.09)	(-2.51)	(-4.33)
BHMS	979	0.1426	0.2274	0.0848	0.1378	0.2122	0.0744	0.1756	0.2923	0.1346	0.0880	0.1495	0.0451
		(-2.89)	(-1.37)	(0.50)	(20.33)	(24.19)	(8.53)	(6.39)	(9.43)	(3.14)	(3.48)	(4.27)	(1.19)
BHLS	401	0.1051	-0.1457	-0.2508	0.0866	-0.1358	-0.2224	0.2659	0.0792	-0.1765	0.0995	-0.1821	-0.2316
		(-1.71)	(2.29)	(2.96)	(8.00)	(-14.87)	(-18.62)	(8.17)	(2.07)	(-4.74)	(3.62)	(-3.10)	(-3.85)

Panel B. Individual and Institutional Investors Trading Samples

Portfolio	N	Market			Individual			Domestic Institution			Foreign		
		[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff
GHMB	474	-0.0734	0.1375	0.2109	-0.1134	0.0628	0.1762	0.0204	0.2369	0.2017	-0.0042	0.0510	0.0413
		(-4.10)	(15.93)	(13.69)	(4.10)	(-15.93)	(-13.69)	(-5.74)	(3.99)	(5.34)	(0.61)	(6.53)	(3.54)
GHLB	750	-0.1144	-0.1876	-0.0732	-0.1556	-0.1999	-0.0443	0.0648	-0.0628	-0.1261	-0.0176	-0.0955	-0.0699
		(-14.47)	(-22.57)	(-6.33)	(14.47)	(22.57)	(6.33)	(-22.97)	(-18.16)	(-3.70)	(2.94)	(-2.51)	(-4.33)
BHMS	858	0.1364	0.2180	0.0816	0.1313	0.2043	0.0730	0.1618	0.2923	0.1346	0.0770	0.1499	0.0569
		(-2.45)	(-1.14)	(0.53)	(19.14)	(21.65)	(7.67)	(6.13)	(9.43)	(3.14)	(2.88)	(4.35)	(1.51)
BHLS	343	0.1012	-0.1340	-0.2352	0.0805	-0.1240	-0.2045	0.2663	0.0792	-0.1765	0.0835	-0.1646	-0.2024
		(-1.58)	(2.41)	(3.02)	(7.62)	(-15.53)	(-19.27)	(8.11)	(2.07)	(-4.74)	(2.36)	(-2.77)	(-3.45)

Table VI. (Continued)

Panel C. All Investor Type Trading Samples

Portfolio	N	Market			Individual			Domestic Institution			Foreign		
		[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff	[-30,-5]	[-1,1]	diff
GHMB	384	-0.0600	0.1184	0.1784	-0.1132	0.0423	0.1554	0.0330	0.1781	0.1422	-0.0039	0.0510	0.0413
		(-3.39)	(13.63)	(11.45)	(3.39)	(-13.63)	(-11.45)	(-5.67)	(2.67)	(4.68)	(1.05)	(4.32)	(2.42)
GHLB	560	-0.1013	-0.1764	-0.0751	-0.1547	-0.1975	-0.0429	0.0809	-0.0477	-0.1297	-0.0321	-0.0955	-0.0699
		(-10.47)	(-16.24)	(-5.97)	(10.47)	(16.24)	(5.97)	(-19.27)	(-15.82)	(-3.39)	(3.90)	(-1.65)	(-3.72)
BHMS	647	0.1239	0.1846	0.0607	0.1105	0.1700	0.0596	0.1789	0.2696	0.0958	0.0766	0.1499	0.0569
		(-2.53)	(-1.14)	(0.53)	(15.47)	(18.73)	(5.67)	(7.83)	(9.01)	(2.23)	(2.74)	(4.35)	(1.51)
BHLS	267	0.0939	-0.1129	-0.2068	0.0649	-0.1137	-0.1785	0.2641	0.0992	-0.1664	0.0493	-0.1646	-0.2024
		(-1.84)	(2.41)	(3.02)	(6.38)	(-13.27)	(-15.36)	(8.49)	(2.84)	(-4.37)	(1.45)	(-2.77)	(-3.45)

Table VII. Decomposition of CAR[2,50] contributed by Investors Type

Panel A. All Samples

GH (n=1359)				BH (n=1380)			
IND. BOT>0	INS. BOT>0	FOR. BOT>0	RSQ	IND. SOT>0	INS. SOT>0	FOR. SOT>0	RSQ
0.0378			0.0625	-0.0387			0.1299
(3.51)			(3.64)	(-2.81)			(3.80)
	0.0300		0.0999		-0.0340		0.0997
	(2.49)		(6.40)		(-3.18)		(3.49)
		0.0119	0.0647			-0.0429	0.1188
		(0.77)	(4.52)			(-2.21)	(3.89)
0.0289	0.0181		0.1489	-0.0331	-0.0098		0.1715
(2.53)	(1.36)		(7.25)	(-1.98)	(-0.72)		(4.85)
0.0375		-0.0054	0.1148	-0.0378		-0.0113	0.1860
(3.04)		(-0.30)	(5.98)	(-2.74)		(-0.53)	(5.34)
	0.0321	-0.0038	0.1382		-0.0294	-0.0200	0.1808
	(3.08)	(-0.28)	(7.35)		(-2.65)	(-0.92)	(5.48)
0.0317	0.0227	-0.0138	0.1842	-0.0333	-0.0087	-0.0066	0.2359
(2.38)	(1.98)	(-0.85)	(8.58)	(-2.01)	(-0.62)	(-0.30)	(6.09)

Panel B. Individual and Institutional Investors Trading Samples

GH (n=1224)				BH (n=1201)			
IND. BOT>0	INS. BOT>0	FOR. BOT>0	RSQ	IND. SOT>0	INS. SOT>0	FOR. SOT>0	RSQ
0.0367			0.0625	-0.0371			0.1299
(3.58)			(3.64)	(-2.57)			(3.80)
	0.0300		0.0999		-0.0340		0.0997
	(2.49)		(6.40)		(-3.18)		(3.49)
		0.0135	0.0647			-0.0413	0.1188
		(0.87)	(4.52)			(-2.03)	(3.89)
0.0280	0.0189		0.1489	-0.0270	-0.0149		0.1715
(2.12)	(1.37)		(7.25)	(-1.58)	(-1.20)		(4.85)
0.0315		0.0009	0.1148	-0.0364		-0.0118	0.1860
(2.65)		(0.05)	(5.98)	(-2.71)		(-0.53)	(5.34)
	0.0306	-0.0027	0.1382		-0.0317	-0.0162	0.1808
	(2.87)	(-0.20)	(7.35)		(-2.80)	(-0.69)	(5.48)
0.0283	0.0216	-0.0079	0.1842	-0.0275	-0.0142	-0.0074	0.2359
(1.98)	(1.76)	(-0.52)	(8.58)	(-1.71)	(-1.02)	(-0.32)	(6.09)
		(0.87)	(4.52)			(-2.03)	(4.83)

Table VII. (Continued)

Panel C. All Investor Type Trading Samples							
GH (n=944)				BH (n=914)			
IND. BOT>0	INS. BOT>0	FOR. BOT>0	RSQ	IND. SOT>0	INS. SOT>0	FOR. SOT>0	RSQ
0.0214			0.0625	-0.0345			0.1064
(1.63)			(3.64)	(-2.03)			(4.17)
	0.0250		0.0999		-0.0332		0.0753
	(1.73)		(6.40)		(-2.89)		(4.92)
		0.0135	0.0647			-0.0413	0.0950
		(0.87)	(4.52)			(-2.03)	(4.83)
0.0106	0.0140		0.1489	-0.0151	-0.0254		0.1492
(0.77)	(0.88)		(7.25)	(-0.70)	(-1.85)		(5.30)
0.0145		0.0069	0.1148	-0.0279		-0.0193	0.1640
(1.09)		(0.40)	(5.98)	(-1.80)		(-0.96)	(5.91)
	0.0244	0.0010	0.1382		-0.0273	-0.0202	0.1586
	(1.84)	(0.07)	(7.35)		(-2.13)	(-0.85)	(6.32)
0.0082	0.0134	0.0022	0.1842	-0.0150	-0.0196	-0.0149	0.2153
(0.54)	(0.95)	(0.15)	(8.58)	(-0.84)	(-1.28)	(-0.71)	(6.40)

Table VIII. Decomposition of CAR[2,50] contributed by Investors Type

Panel A. All Samples

GH (n=1359)				BH (n=1380)			
IND. BOT<0	INS. BOT<0	FOR. BOT<0	RSQ	IND. SOT<0	INS. SOT<0	FOR. SOT<0	RSQ
0.0200			0.0446	-0.0278			0.0270
(1.97)			(4.27)	(-2.57)			(4.32)
	0.0259		0.0372		-0.0438		0.0600
	(2.70)		(5.22)		(-2.48)		(3.30)
		0.0339	0.0514			-0.0379	0.0448
		(3.49)	(6.12)			(-3.95)	(5.94)
0.0109	0.0164		0.0840	-0.0186	-0.0371		0.0854
(0.92)	(1.45)		(6.57)	(-1.56)	(-1.99)		(4.24)
-0.0066		0.0366	0.0848	-0.0030		-0.0344	0.0702
(-0.50)		(3.03)	(7.00)	(-0.22)		(-2.94)	(7.29)
	0.0014	0.0354	0.0748		-0.0186	-0.0329	0.0903
	(0.15)	(3.89)	(7.53)		(-0.91)	(-3.06)	(5.04)
-0.0059	0.0032	0.0351	0.1146	-0.0056	-0.0188	-0.0287	0.1152
(-0.40)	(0.31)	(3.12)	(8.63)	(-0.41)	(-0.92)	(-2.43)	(5.81)

Panel B. Individual and Institutional Investors Trading Samples

GH (n=1224)				BH (n=1201)			
IND. BOT<0	INS. BOT<0	FOR. BOT<0	RSQ	IND. SOT<0	INS. SOT<0	FOR. SOT<0	RSQ
0.0184			0.0516	-0.0211			0.0296
(1.82)			(4.51)	(-1.89)			(4.82)
	0.0246		0.0338		-0.0361		0.0521
	(2.51)		(6.44)		(-1.91)		(2.84)
		0.0312	0.0533			-0.0340	0.0442
		(3.20)	(5.24)			(-3.59)	(6.24)
0.0123	0.0140		0.0957	-0.0136	-0.0301		0.0796
(0.94)	(1.09)		(6.59)	(-1.14)	(-1.55)		(3.89)
0.0002		0.0274	0.0958	0.0006		-0.0320	0.0705
(0.01)		(2.11)	(7.07)	(0.04)		(-2.69)	(7.33)
	0.0019	0.0329	0.0780		-0.0121	-0.0322	0.0892
	(0.21)	(3.47)	(7.36)		(-0.57)	(-2.84)	(4.84)
0.0014	0.0035	0.0260	0.1327	0.0003	-0.0126	-0.0298	0.1145
(0.08)	(0.29)	(2.04)	(8.86)	(0.02)	(-0.60)	(-2.37)	(5.55)
(0.63)	(-0.03)		(6.06)	(-1.95)	(-1.18)		(4.46)
0.0032		0.0096	0.1230	-0.0201		-0.0242	0.1046
(0.21)		(0.65)	(7.03)	(-1.22)		(-1.61)	(4.85)
	-0.0006	0.0184	0.0970		-0.0173	-0.0291	0.1282
	(-0.06)	(1.51)	(6.85)		(-0.78)	(-2.03)	(4.32)

Table VIII. (Continued)

Panel C. All Investor Type Trading Samples

GH (n=944)				BH (n=914)			
IND. BOT<0	INS. BOT<0	FOR. BOT<0	RSQ	IND. SOT<0	INS. SOT<0	FOR. SOT<0	RSQ
0.0066			0.0614	-0.0313			0.0368
(0.60)			(4.70)	(-2.42)			(5.18)
	0.0085		0.0342		-0.0353		0.0540
	(0.87)		(3.80)		(-1.84)		(2.95)
		0.0159	0.0702			-0.0318	0.0651
		(1.32)	(5.34)			(-2.48)	(3.19)
0.0095	-0.0004		0.1147	-0.0284	-0.0240		0.0898
(0.63)	(-0.03)		(6.06)	(-1.95)	(-1.18)		(4.46)
0.0032		0.0096	0.1230	-0.0201		-0.0242	0.1046
(0.21)		(0.65)	(7.03)	(-1.22)		(-1.61)	(4.85)
	-0.0006	0.0184	0.0970		-0.0173	-0.0291	0.1282
	(-0.06)	(1.51)	(6.85)		(-0.78)	(-2.03)	(4.32)
0.0066	-0.0021	0.0095	0.1652	-0.0208	-0.0127	-0.0226	0.1610
(0.36)	(-0.16)	(0.66)	(8.58)	(-1.32)	(-0.59)	(-1.48)	(5.16)