Are order imbalances related to information?

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Key words: order imbalance, information, market efficiency

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1. Introduction

How is information reflected in the price of securities? This simple question has not received the attention it deserves. Researchers study whether and to what extent prices reflect news, but they spend relatively little time in studying the mechanism by which information is reflected in the price. If information is public, it will (in an efficient market) immediately be reflected in the prices as traders attempt to trade on the information. On the other hand, if information is private, it is reflected in the price by trading. Good news will cause informed traders to purchase shares and drive up the price, and bad news will cause informed traders to sell shares and drive down the price. In other words, the imbalance in orders, which is a reflection of the private information, will push prices to reflect the information. The occurrence of an order imbalance does not, however, imply that an information event has occurred. Order imbalances may arrive randomly or may reflect non-informational trading needs and may have a price effect due to the price pressure of the imbalance, not associated with any news. It is perfectly possible that imbalances occur without any news.

It is relatively easy to acquire order imbalances data in these days. For example, Wall Street Journal provides order imbalances data on its website. The order imbalances are estimated using standard Lee and Ready (1992) method. Suppose the researcher observes a purchase imbalance in a particular stock. What can he infer? One possibility is that informed traders are trading on their private information. The stock price would increase to reflect the private information. A second possibility is that the imbalance is simply a random liquidity event that puts pressure on the inventories of dealers and other suppliers of liquidity. The stock price would increase to reflect the trading pressure and would return once the trading pressure abated. To distinguish the information and trading pressure sources of the imbalance one can examine the association of imbalances with the information. The elements of the market are depicted in Figure 1 – imbalance, return, and imbalance.

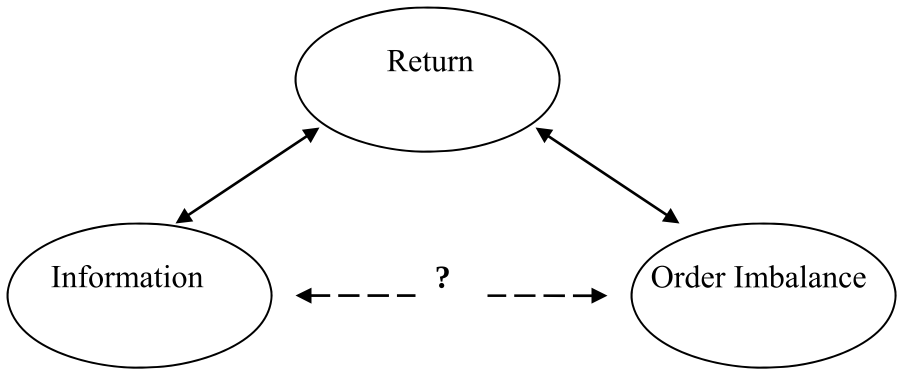

Figure 1. Triangular relation among return, information, and order imbalance

The relation between order imbalances and information can be inferred from the models of the bid-ask spread. Adverse information theories of the spread (Kyle 1985, Glosten Milgrom 1985, Easley O'Hara 1987) determine the spread so that the losses to informed traders are offset by the gains from the uninformed. In these models the spread is wider the greater the probability of informed trading. Easley and O'Hara (1997) provide an elegant and simple model of this process and test it empirically with the PIN variable. PIN is directly related to the imbalance between buys and sells. Easley, Engle, O'Hara, and Wu (2008) document similarity between two variables. If the only source of the imbalance were private information, a finding that the spread is correlated with PIN would support the adverse information theory of the spread. However, the imbalance may also come from non-informational sources. Duarte and Young (2009) find that the imbalance reflects liquidity and they conclude that the liquidity effect is priced. Andrade, Chang and Seasholes (2008) model the effect of non-informational imbalances on prices. In a comprehensive study of order imbalances, Chordia and Subrahmanyan (2004) show that there are price effects of imbalances, but they remain agnostic on the sources of the price effects.

In this study, we examine order imbalances around earnings announcements. Since Bernard and Thomas (1990), earnings surprise – the difference between actual earnings and predicted earnings – has been selected as a proxy of information. Recently, Kaniel, Liu, Saar, and Titman (2010) use earnings announcements to study the correlation between individual trading and private information. Campbell, Ramodorai, and Schwartz (2009) analyze institutional trading around earnings announcements. While these papers use private on trading patterns[1], we use order imbalance data estimated from Lee and Ready (1992) method, which is publicly available trading information. The publicity of order imbalance data would make order imbalances behave differently from private data driven measures, because market participants can adjust their trades according to observed order imbalances. Order imbalances data is publicly available information and weak-form market efficiency hypothesis tells that publicly available trading data cannot predict future stock returns, which would be affected by forthcoming information. Meanwhile, order imbalances may not exist at all if market is completely efficient, because trades that are not based on information should not have a direction. Therefore, order imbalances not only captures a direction of trades but also the reaction of stock prices. Thus, a study on the relation between order imbalances and information reveals current price discovery process of the market, and the relation can be used as a test of market efficiency. Our analysis on order imbalances would shed light on the question how information and trading activities are transferred to stock prices. We use 8 years of order imbalances data to provide a comprehensive picture of the relation among order imbalances, information, and price.

Our findings on the triangle relation among information, return, and imbalance may be summarized as follows: (1) Order imbalances weakly predict future earnings announcements. Stocks that had large positive (negative) order imbalances show positive (negative) earnings surprises afterwards, but the difference in stock returns predicted by order imbalances is not large enough to allow constructing a feasible investment strategy. Order imbalances aggregated over long period are better indicators of earnings information than short term order imbalances. This result shows that informed orders are stealthily placed over a long period of time.

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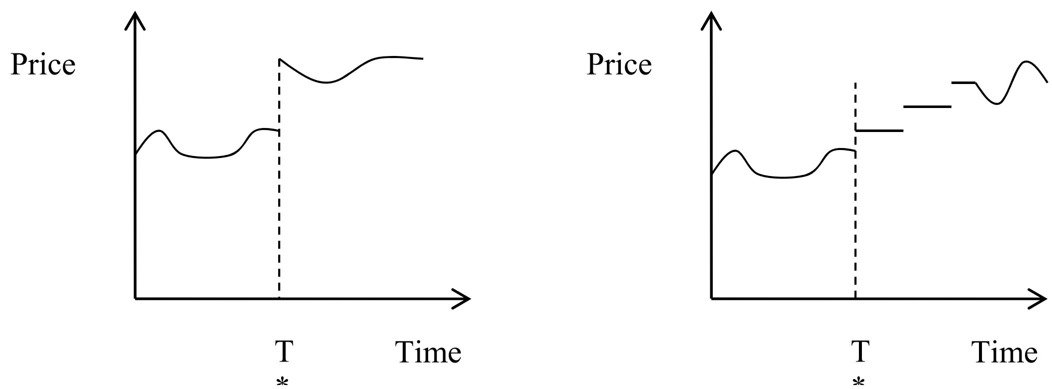
[1] Kaniel, Liu, Saar, and Titman (2010) acquire private trading data from NYSE. Campbell, Ramadorai, and Schwartz (2009) develop regression techniques to estimate institutional trading patterns from order imbalances and institutional holdings data.

(2) While result (1) indicates an efficient market and rational investors, we find a contradicting pattern after earnings announcement dates. Order imbalances trail both past earnings information and past stock returns. The correlation is much stronger than that before the announcements. This result shows that there is a considerable amount of momentum trading after earnings announcements. We find the trailing continues for at least 20 business days after earnings announcements. This strange trading activity may contribute to post-earnings-announcement-drift (PEAD), a market anomaly. This result is consistent with Liu, Kaniel, Saar, and Titman (2010) and Campbell, Ramodorai and Schwertz (2009) who find institutional investors are trading based on the past earnings information, but given the fact that order imbalances represent the difference between trades and prevailing quote level, it is a puzzle why market participants let the abnormal trades to persist. We find that the trailing of order imbalances is stronger in more recent periods, indicating that market is not absorbing this publically observable trading pattern for nearly a decade.

(3) The relationship between order imbalances and earnings information is detectible only when the sensitivity of stock prices to order imbalances are taken into account. This result is consistent with Kyle (1985), who shows that traders place smaller orders when their trades easily move stock prices. Intuitively, order imbalances measure alone does not tell how much impact the stock price will receive. One has to control for the sensitivity of stock price to observe the true price effect of order imbalances. The control is especially important when order imbalances are negatively correlated with the sensitivity of stock prices. Therefore, an analysis of trading patterns should include a sensitivity measure.

2. Hypotheses on Order Imbalance and Information

Following standard procedure of Lee and Ready (1992), order imbalance is calculated by subtracting the trades in bid side (selling pressure) from the trades in ask side (buying pressure). There will be relatively more bid side transactions when current quotes are above market’s consensus price, and vice versa. Therefore, order imbalance captures the dispersion of opinion between market makers (who sets quotes) and other investors. Even if there is highly positive information, order imbalance can be negative if market makers post their quotes above the consensus price. The following figure compares two cases: when market makers change their quotes according to positive information and when they do not. Order imbalance will not reflect the value of public information if market makers change their quotes quickly.



Stock A – fast moving quotes (No order imbalance)

Stock B – slow or not moving quotes (High order imbalance)

Figure 2. Quote speed and order imbalance.

2.1. Order imbalance and private information

Order imbalances depend on the current quote level. If market makers fail to adjust their quotes instantly, order imbalances will follow the direction of information. When market makers do not know the information that some other investors do, the informed investors would trade based on their *private* information, and their trade will generate order imbalance. If the private information is to be announced later, the order imbalance pattern would predict the forthcoming announcement.

We use the framework in Kyle (1985) as a basis for our empirical test of the relation between order imbalance and private information.[2] As our starting point, consider Kyle's (1985) equation (3.11):

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[2] Back and Bruch (2004) extend Kyle (1985) model to show that the model's implications also hold in

$$\Delta\tilde{x}_n = \beta_n(\tilde{v} - \tilde{p}_{n-1})\Delta t_n \quad , \tag{1}$$

where

Δx is order placement of informed investors,

β_n is a decreasing function of Kyle's lambda λ (market depth), i.e. $\beta = \dfrac{1}{f(\lambda)}$ where $f(\lambda)$ is increasing in λ,

v is value of stock based on private information,

p is stock price,

t is the time left until information is publicly announced. We let $\Delta t=1$.

n is the number of trades before the information is announced.

Letting $\Delta t=1$, and noting that $\beta = \dfrac{1}{f(\lambda)}$, we can rewrite (1) to get

$$\tilde{v} = \Delta\tilde{x}_n \cdot f(\lambda_n) + \tilde{p}_{n-1} \tag{2}$$

Equation (2) states that the informed trader's stock value is related to informed order placement Δx, market depth λ, and previous price p. If there is no informed order flow, there is no private information, and $\tilde{v} = \tilde{p}_{n-1}$. Equation (2) is also empirically testable, because all the variables can be obtained from the stock market. Although informed order placement is not observable to the public, the average order imbalance will be proportional to Δx, because other orders have no direction. All investors observe aggregate order flow $\Delta x + \eta$, where η is order flow with zero mean. Hence, order imbalance is an unbiased estimator of informed order placement Δx. Using standard regression techniques, one can filter out the effect of η, because the mean of η is zero. Equation (3) substitutes informed order placement Δx with observed order imbalance $\Delta x + \eta$:

$$\tilde{v} = (\Delta\tilde{x}_n + \eta)\cdot f(\lambda_n) + \tilde{p}_{n-1} = (\Delta\tilde{x}_n)\cdot f(\lambda_n) + \tilde{p}_{n-1} + \eta \cdot f(\lambda_n) \tag{3}$$

By taking average of equation (3), we get:

$$\overline{\tilde{v}} = (\Delta\overline{\tilde{x}}_n)\cdot f(\lambda_n) + \overline{\tilde{p}}_{n-1} + \overline{\eta}\cdot f(\lambda_n) = (\Delta\overline{\tilde{x}}_n)\cdot f(\lambda_n) + \overline{\tilde{p}}_{n-1} \tag{4}$$

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continuous trading. Chordia and Subrahmanyam (2004) uses Kyle (1985) model to explain serial correlation of order imbalance.

Where $\Delta\bar{\bar{x}}_n$ can be interpreted as the average order imbalance and $\bar{\bar{v}}$ as the average value of the asset given the private information contained in the imbalance. Equation (4) states that the value of information is increasing in the order imbalance and Kyle's lambda. Because Kyle's lambda and previous price level can be estimated using past data, we can use (4) to test if there is a direct link between order imbalance and information.

To assess the link between information and order imbalance we use the regression (5) based on (4). For stock *i*, information announcement at day *t*,

$$v_{it} = \alpha + \delta_1 \cdot (OI_{it-j}) \cdot (\lambda_{it-j}) + \delta_2 \cdot r_{i,t-j-1} + \varepsilon_{it} \ , \qquad (5)$$

where

v_{it} is the value of the information announcement for stock *i* on day *t.* Our information event is the surprise component in company earnings announcements.

OI_{it} is the average order imbalances in stock *i* on day *t*.

$r_{i,t-j-1}$ is the stock's return on the prior day, and lagged days. This variable is used instead of the price because it better captures the extent to which upcoming information is reflected in the price.

j indicates the time between the forthcoming information announcement and current order imbalance.

We test the following null hypothesis:

H1(Null): Order imbalance is uncorrelated with the value of forthcoming information.

The null is rejected if δ_1 in equation (5) is positive and significant, in which case we accept the alternative hypothesis that order imbalance is correlated with the value of forthcoming information.

There are two things to note in equation (5). First, the relationship between order imbalances and forthcoming information, if any, would be affected by Kyle's Lambda. Large order imbalances itself does not necessarily mean there is information. Rather, one should also consider Kyle's Lambda to find a link between order imbalances and information. Second, order imbalances have to be aggregated over time to see true abnormal trading activities. Equation (5) is derived by taking averages of abnormal trading activities. It would be easier to capture abnormal trading activities when we look at the long term trend of order imbalances. We will study how these factors affect the relationship between order imbalances and forthcoming information.

2.2. Order imbalance and public information

Although order imbalance can be a function of *private* information, order imbalance reacts differently to *public* information. When there is a public announcement, market makers also know the information. Order imbalance may still reflect the direction of a public information announcement, when market makers fail to adjust their quotes quickly enough to the announcement. However, in an efficient market, quote adjustment should be faster than any trades. Suppose a company makes a positive announcement. If market makers do not change their quotes quickly, they would sell their stocks at a discount, and some investors may make profit from the public announcement. This violates semi-strong efficiency, which requires a public announcement to have no investment value. Hence, in a semi-strong efficient market, quotes should move before any trade comes in.[3]

This argument implies that in any semi-strong efficient market, public information will be converted to price in a 2-step procedure. In step one, public information arrives and quotes first adjust according to the information. Trades occur in the second step to trade based on the quote level. Such 2-step procedure means that without any help from trading, investors can successfully estimate the unbiased price from public information. Fleming and Remolona (1999) find such 2-step pattern in Treasury Bill market. So our second hypothesis is:

H2(Null): Order imbalance is independent of contemporaneous or past public announcement.

Order imbalances themselves being public information makes the test complicated. Suppose order imbalances indeed contain private information. Then other investors

[3] Fama (1970) explains the definition of semi-strong efficiency. In such market, no investor should be able to profit from public information.

would trade according to order imbalances. This trading will reduce the relationship between order imbalances and private information. For example, Atkas, de Bodt, Declerck, and Van Oppens (2007) find no significant correlation between trading activity before M&A announcements. We will see if our equation (5) captures hidden earnings surprise information embedded in order imbalances.

3. Data and Method

We use Trade and Quote (TAQ) data for ordinary common shares from 1997 to 2004 to construct order imbalance data. The construction method is in appendix A, and it closely follows the method of Chordia, Roll, and Subrahmanyam (2002). Their method is based on Lee and Ready (1992), but it imposes additional filters to reduce problems from infrequent trading. We report the results using order imbalance in shares. We acquire qualitatively similar results using order imbalance in dollars, and number of trades. In our dataset, share order imbalance and dollar order imbalance have 99% positive correlation, while order imbalance of trades has 83% positive correlation with other two measures. The order imbalance is normalized by dividing by the corresponding total daily volume (in shares, dollars, or number of trades, as appropriate).

As in Chordia and Subrahmanyam (2004), we use mid-quote stock returns to take out the effect of bid-ask bounce. The mid-quotes data comes from Market Microstructure Database constructed by the Financial Markets Research Center at Vanderbilt University. The database contains average trade weighted bid price and ask price during a day. We take the mid-quote between the daily average bid and ask prices and calculate a continuously compounded return using two consecutive mid-quote prices (taking natural logarithm of the ratio).

In order to measure the value of information, we choose earnings announcements. For each earnings announcement, there are analyst forecasts for earnings per share. The earnings surprise, which is the difference between the forecasted earnings (analyst consensus) and the actual earnings, represents the value of information to the stock market. Earnings surprise data comes from IBES database. We use quarterly earnings announcements. We use the most recent earnings per share (EPS) forecasts for each analyst. If the forecast is more than 90 days old or less than 15 days prior to the actual earnings announcement, we drop the forecast. We require stocks to have more than 5 recent forecasts. We use the forecast of the analyst with the most recent forecast because some analysts are slow to adjust their forecast to the latest information. The earnings surprise for a firm, *i*, in quarter, *q*, is then calculated as the difference between actual earnings and the latest forecast of earnings divided by the forecasted earnings:[4]

$$v = \frac{Actual\ EPS - Expected\ EPS}{\left|Expected\ EPS\right|}. \tag{7}$$

We report regression results where the earnings surprise is measured directly as in (7), but we also use earnings ranks as recommended by Bernard and Thomas (1990) to account for non-linearity and outlier problems. Mendenhall (2004) suggests ranking earnings surprise into 11 ranks and then dividing by 11 and subtracting 0.5 from the variable. The ranked earnings surprise variable has its mean around 0, and 0.1 is the difference between two close ranks. The results were unaffected by the use of ranks and are not reported here. Summary statistics for the variables are in Table 1.

The following figures, 3a and 3b, show average, non-cumulative order imbalances and mid-quote returns for three ranks of earnings surprise. Figure 3 shows order imbalance pattern differs much from that of stock return. Since order imbalances do not have zero mean around earnings announcements (Table 1), we normalize order imbalances by subtracting market-wide average of order imbalances. First, order imbalance is on average positive around earnings announcements. This pattern indicates that absolute size of daily order imbalance number cannot be an indicator of earnings surprises. We should aggregate the order imbalances over time and see the relative size of

[4] We used other measures of earnings surprise, but the results were unaffected. For example, Mendenhall (2004) and other earnings surprise related papers define earnings surprise as follows: Earnings surprise is difference between actual earnings and average analyst EPS forecasts, divided by standard deviation of the forecasts: $Surprise_{i,q} = \frac{Actual\_Earnings_{i,q} - \overline{Exp\_Earnings_{i,q}}}{STD(Exp\_Earnings_{i,q})}$ where *i* is one firm and *q* is one quarter.

order imbalances. Second, which may be related to the first point, stock return has a large announcement day effect, but order imbalance does not show a significant announcement day reaction.

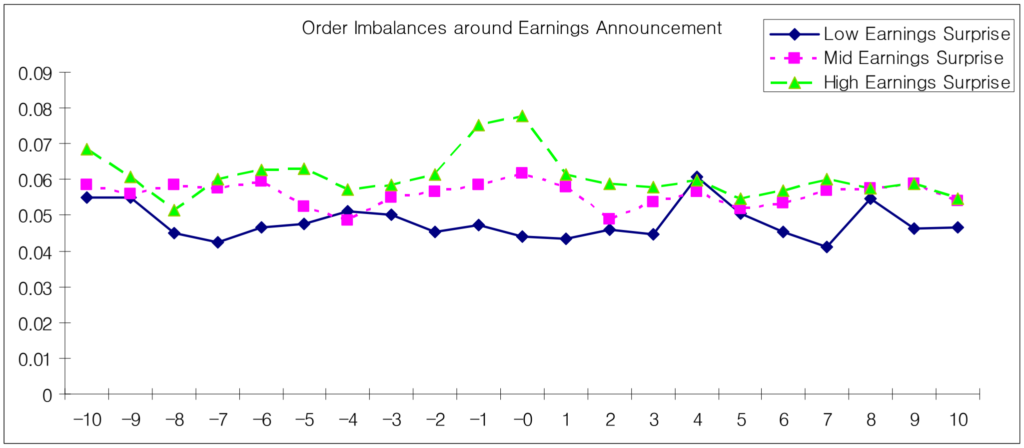

Figure 3a. Order imbalances around earnings announcements

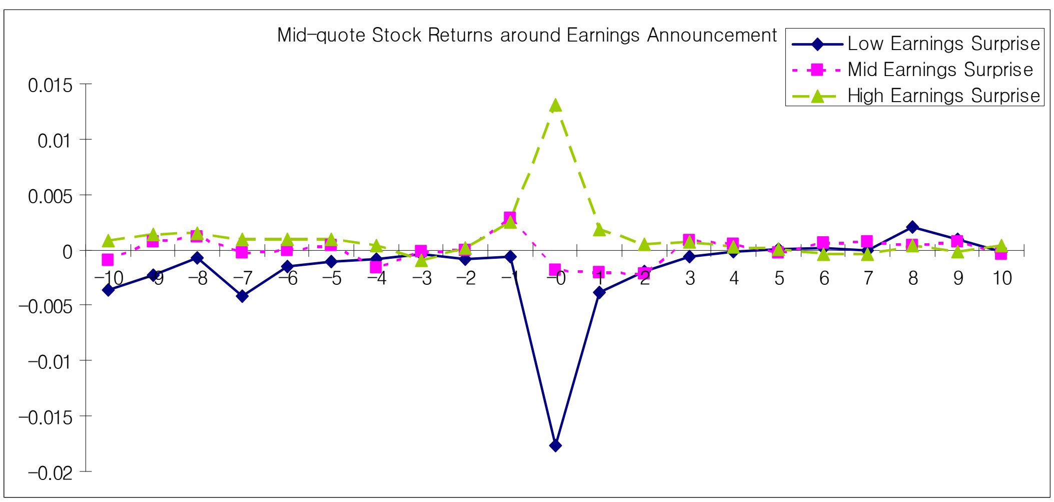

Figure 3b. Stock returns around earnings announcements

In figure 4a, we plot cumulative order imbalances around earnings announcement dates by earnings surprise rank (Low, 2, 3, 4, High). We use 5 ranks and (-30, +30) business day windows for visual convenience. Here we do not find a monotonic relation between order imbalances and earnings surprises. Low earnings surprise stocks indeed have negative cumulative order imbalances, but high earnings surprise stocks also show negative numbers. We observe the highest order imbalances from earnings surprise rank 3. However, before making a quick conclusion that order imbalances are not correlated with information, we add Kyle's lambda variable. As we show from Kyle's model, order imbalances are meaningful when the sensitivity of stock price to order imbalances is included.

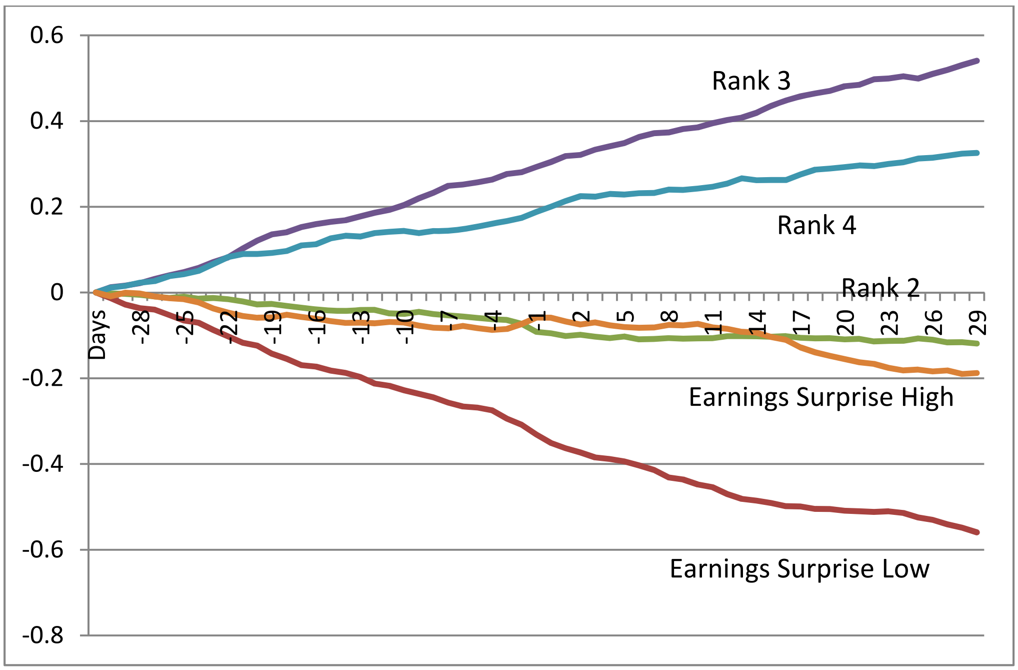

Figure 4a. Cumulative order imbalances around earnings announcements

Figure 4b plots the *product* of order imbalances and Kyle's lambda by earnings surprise rank (Low, 2, 3, 4, High). Now we see a clear monotonic relation with earnings surprises. This result shows that Kyle's lambda is an important variable to understand the effects of trading activities. In other words, information based trades tend to 'hide' – there are less informed orders when stock prices are more sensitive to orders. We find that an analysis on trading activity must include the sensitivity of stock prices, because large trading activity is often offset by small sensitivity of stock prices. Intuitively, one cannot analyze trading pressure alone, because what eventually affects stock price is the interaction between trading activities and the sensitivity of stock prices.

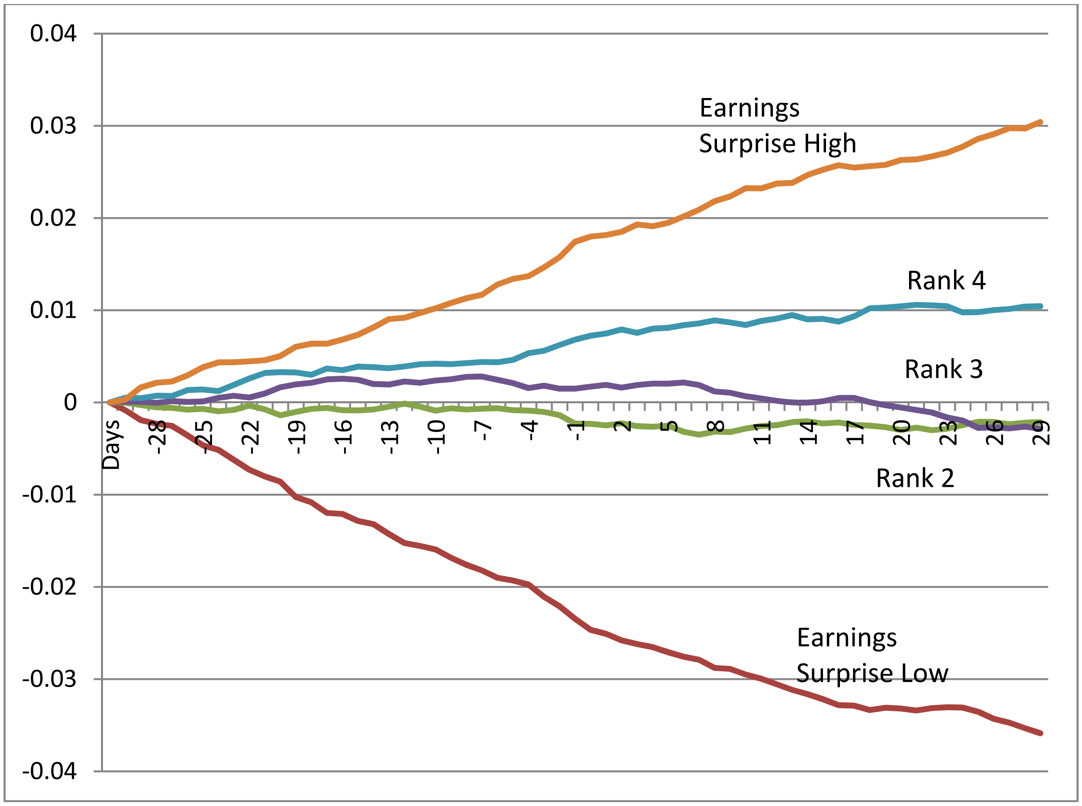

Figure 4b. Cumulative (order imbalances x Kyle's lambda) around earnings announcements

4. Are order imbalances related to information?

If order imbalance reflects trading of informed investors, one would expect an imbalance to predict subsequent information. The information event we analyze is an earnings announcement. We examine whether the order imbalances before the announcement have statistically significant prediction power for the earnings information, as specified in equation (5).

$$v_{it} = \alpha + \delta_1 \cdot (OI_{it-j}) \cdot (\lambda_{it-j}) + \delta_2 \cdot r_{i,t-j-1} + \varepsilon_{it} \qquad (5)$$

Note that this equation controls for the effect of Kyle's lambda. If the coefficient δ_1 is statistically significant and economically meaningful, the order imbalance would be a useful variable to predict the effect of upcoming earnings announcement. The regression method is OLS with clustering and heteroskedasticity controlled error structure. We control for clustering by firm, year, and quarter. Petersen (2009) shows that such correction yields consistent estimators for panel data sets. Since we do not know when informed investors might establish a position, we examine in separate regressions the association between the earnings surprise and the imbalance for lags of 5, 10, and 20 business days.[5] The results are in Table 2.

Table 2 shows that most of the coefficients are significant, especially when order imbalances are aggregated over long time. 20-day moving sum of order imbalances has higher significance than 10-day or 5-day moving sum of order imbalances. This result shows that informed trading is placed in small amounts over a long period of time. Order imbalances do not directly indicate informed trading, but order imbalances do contain some informed trading.

We also report regression results without Kyle's lambda variable in Panel B. We find that the t-statistics of order imbalances decrease without Kyle's lambda. If Kyle's Lambda variable is not related to informed trading, Panel B results should be more significant because of less noise in the model, but we see the opposite. This result confirms that Kyle's lambda variable helps to identify informed trading. As in Kyle (1985), order imbalances would contain more informed trading when stock prices are less sensitive to order imbalances. Therefore, informed trading would be a function of both order imbalances and Kyle's lambda.

Our results point that order imbalances are weakly correlated with forthcoming information. Informed investors seem to place orders according to their private information (earnings surprises). However, models' overall R-squares are low, indicating that it is difficult to clearly identify information related to order imbalances.

5. Can Investors Use Order Imbalances to Earn Extra Stock Returns?

[5] Results from other lags resemble the result of their close neighbors. For example, the result of lag 6 is similar to that of lag 5.

In this section, we test the relation between order imbalances and future stock returns. If informed trading is detectible using order imbalances, and informed trading predicts future stock returns, a non-informed investor may want to use order imbalances to earn extra stock returns. However, if this strategy works, it violates weak-form market efficiency. If the market is to be weak-form efficient, the order imbalances data should be so noisy that it is hard to use the data to predict future stock returns.

We first test whether earnings surprise is related to abnormal stock returns around earnings announcement days. In section 3, we see the stock returns show the highest variation around earnings announcement dates. So we test whether order imbalances predict cumulative abnormal stock return around earnings announcement days. The abnormal stock return is measured as the difference between a stock return and the average stock return of the firms within the same firm size deciles. We cumulate the abnormal return in (-1, +1) and (-5, +5) business day event windows.

Table 3 shows the cumulative abnormal return is correlated with earnings surprises – information. Someone who accurately knows the true earnings in advance may earn extra return. The difference between lowest earnings surprise stocks and highest earnings surprise stocks is 5%. Now we see if past order imbalances predict the cumulative abnormal stock returns. Suppose an investor does not know the true earnings information in advance, but she uses order imbalances to estimate the forthcoming earnings surprise. We rank the product of order imbalances and Kyle′s lambda into deciles and report the cumulative abnormal stock returns by deciles. We include Kyle′s lambda because it accounts for the effect of order imbalances on stock prices. Even if two stocks have the same order imbalances, the stock with higher sensitivity to order imbalances (Kyle′s lambda) would receive a bigger shock from the order imbalance.

Table 4 shows that an investor cannot use order imbalances to predict stock returns. We do not see as clear pattern as the case with earnings surprises, and the difference between the lowest deciles and the highest deciles is statistically insignificant. Thus, trading on order imbalances does not guarantee better future returns. This result is consistent with weak-form market efficiency that publically observable trading pattern cannot predict future returns. We tried different specifications such as omitting Kyle′s lambda variable, changing the measure of earnings surprise, and aggregating order imbalances in a different way. But none of the specifications show that order imbalances can predict the stock returns associated with earnings surprises.

In sum, we find order imbalances are weakly correlated with information. The correlation is better detectible when we aggregate order imbalances over time and control for Kyle′s lambda. However, the relation between order imbalances and information is so noisy that one cannot use order imbalances to earn extra stock returns around earnings announcement dates.

6. Order imbalance and public information: empirical evidence

In the previous section, we see that order imbalances cannot predict a meaningful difference in event returns. But figure 4b shows order imbalances by earnings surprise rankings diverge even after earnings announcement dates. Order imbalances may be trailing the past earnings information and cause post-earnings-announcement-drift (PEAD). PEAD is a market anomaly that the stocks that had positive (negative) earnings surprise continue to have positive (negative) returns. Recent papers on PEAD have found that several market microstructure variables are related to PEAD. Mendenhall (2004) shows that PEAD is related to bid-ask spread, Sadka (2006) argues that stock liquidity plays an important role in PEAD, and Garfinkel and Sokobin (2006) find that abnormal trading volume around announcement dates is linked to PEAD. Vega (2006) reports several factors that affect the correlation between PEAD and information. Order imbalances could be another variable related to PEAD, if it follows the past earnings surprise information. On the other hand, Trueman, Wong, and Zhang (2003) find order imbalances do not always follow the past earnings surprise but move stock returns regardless.

When we derive our equation (5), we show that past information should have no correlation with current order imbalances. To test this empirically, we summarize (order imbalances x Kyle's lambda) after earnings announcements by the size of past earnings surprise.[6] Table 5 shows that the product of order imbalances and Kyle's lambda is significantly and positively correlated with past earnings surprises. Average order imbalances are positive in general, but when compared side-by-side, stocks with low earnings surprises have lower order imbalances than stock with high earnings surprises. In all cases, the difference between the lowest deciles and the highest deciles is significant. 5-day moving sum of order imbalances have significant difference at 21 days after announcements, which means order imbalances continue to follow the past earnings information even after several weeks are past from the announcement dates. Overall, the positive correlation between earnings information and order imbalances are much stronger compared to the case before announcement dates. In other words, order imbalances trail past information. In an un-tabulated result, we test the correlation between raw order imbalances (not multiplying Kyle's lambda) and past earnings information. We find raw order imbalances are not correlated with past earnings information. This result shows that the effect of order imbalances cannot be measured without including Kyle's lambda variable.

We also check if past event day stock returns around earnings announcement dates are related to order imbalances. Campbell, Ramadorai, and Schwartz (2009) and Kaniel, Liu, Saar, and Titman (2010) find institutional investors trade based on the past returns. We check if that pattern is captured by order imbalances data. We take abnormal cumulative stock returns around earnings announcements and report order imbalances by the stock returns. Figure 5 plots the product of order imbalances and Kyle's lambda by event date returns.

[6] We measure aggregate order imbalances after 11 and 21 days after earnings announcement dates, when earnings announcement dates do not overlap order imbalance measurement dates.

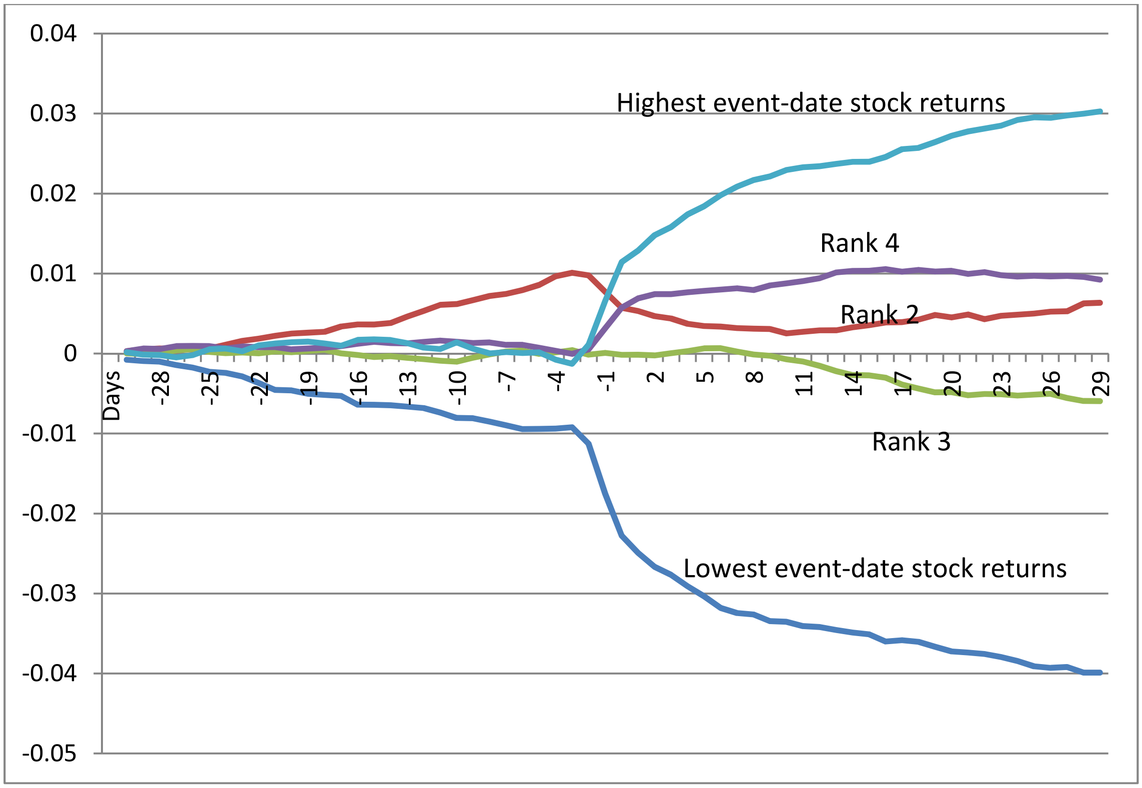

Figure 5. Cumulative (order imbalances x Kyle's lambda) around earnings announcements by (-1, +1) event window abnormal stock returns

Figure 5 shows that while order imbalances are not correlated with event window returns before earnings announcement dates, the difference between the highest rank and lowest rank quickly diverges around earning announcement dates (day 0). The pattern indicates order imbalances follow event day returns after announcement dates. In Table 6, we report statistical significance between the order imbalances of the highest stock return decile and the order imbalances of the lowest stock return decile. We can see order imbalances are significantly correlated with past stock returns.[7] The difference between the lowest return deciles and the highest return deciles is more than 4 times of standard error, which is highly significant in 1% level. T-statistics also indicates the relation between earnings announcement returns and order imbalances is stronger than the relation between earnings surprise and order imbalances. This result is consistent with

[7] Here we use 12 and 22 days after earnings announcement dates to prevent overlapping because the ranking is based on the stock return in (-1, +1) event window.

Campbell, Ramadorai, and Schwartz (2009) and Kaniel, Liu, Saar, and Titman (2010) who find that institutional investors trade according to the past returns around earnings announcements.

Our result is still surprising, because order imbalances are not a pure measure of trading activities. Order imbalances technically measure the difference between current quote level and actual trade price. That is, order imbalances are generated only when most of trades are above or below the prevailing quote level. Market makers may adjust their quote level to absorb the 'irregular' trades, as we showed in section 2. Also, order imbalances measure itself is publicly available information compared to the data used by Campbell, Ramadorai, and Schwartz (2009) or Kaniel, Liu, Saar, and Titman (2010). We find the trailing pattern by pairing order imbalances with Kyle's lambda, which means stock prices actually receive larger positive trading shocks when the past earnings surprise is higher. Investors can even observe stock return patterns to identify the direction of trades. Thus, the irregular pattern of order imbalances raises not only the question why some investors trade on the past information, but also the question why other investors do not fully take the advantage of the trades.

We test if those trailing order imbalances have smaller effect on stock prices. We compare the relation between order imbalances and stock returns before earnings announcements and after the announcements. The rationale of this test is that stock returns should be more sensitive to order imbalances when earnings information is forthcoming, and less sensitive when order imbalances are trailing the past earnings information.

We do the test of Chordia and Subrahmanyam (2004) in two different samples. We divide the sample into two: before earnings announcements and after earnings announcements. The former dataset has stock returns between [-10, -1] days of announcements and the latter dataset has stock returns between [6, 15] days of announcements.[8] We estimate the correlation between daily order imbalances and stock

[8] We find similar results when we use different time windows.

returns using 5 lagged days of order imbalances, which is a method used in Chordia and Subrahmanyam (2004).

$$r_{it} = \alpha + \sum_{j=1}^{5} \delta_j \cdot (OI_{it-j}) + \varepsilon_{it}$$

where r_{it} is the mid-quote stock return of firm i at day t, OI_{it} is the order imbalance of firm i at j days before the day t.

We do not include contemporaneous order imbalances in order to see the prediction power of order imbalances. If the coefficient δ_j are statistically significant and economically meaningful, the order imbalance would predict upcoming stock returns. The regression method is OLS with clustering and heteroscedasticity controlled error structure. We control for clustering by stock, year, and quarter. Petersen (2009) shows that such correction yields consistent estimators for panel data sets. We estimate the equation separately before earnings announcement dates and after earnings announcement dates.

The results are in Table 7. We find that daily order imbalances are significantly correlated with stock returns, which is consistent with Chordia and Subrahmanyam (2004). There is no material difference between the estimation results before earnings announcements and after earnings announcements. The similarity indicates that order imbalances move stock prices regardless of the major information arrival. Even if order imbalances follow the past information, stock prices will drift according to these 'irregular' order imbalances. This pattern shows that PEAD is likely to be caused by order imbalances that trail the past earnings information and stock returns. It is a puzzle why there is such a strong trading activity that follows the past information, and why the trading activity is not absorbed by the market.

Another possible answer to the puzzle may be that there was a temporary disturbance to the US stock market, and either some investors stopped trading based on past order imbalances, or other investors learned to take the advantage of the trailing. We separate the sample into two parts: 1997 ~ 2000 and 2001 ~ 2004. If other investors learned from past order imbalance patterns we would observe a weaker trailing of order imbalances in recent years. Note that Campbell, Ramadorai, and Schwartz (2009) have data period from 1993 to 2000, and Liu, Kaniel, Saar, and Titman (2010) have data period from 2001 to 2003.

Figure 6 shows the product of cumulative order imbalances and Kyle's lambda by past stock returns around earnings announcement dates. The stock return is the cumulative abnormal return in (-1, +1) day event window. We can see from two figures that the trailing phenomenon is similar, or even stronger in recent period. In 1997 ~ 2000 period, the highest return quintile does not have the highest order imbalances. Rank 4 instead has the highest order imbalances. In 2001 ~ 2004 period, on the other hand, we see almost monotonic correlation between past stock returns and order imbalances.

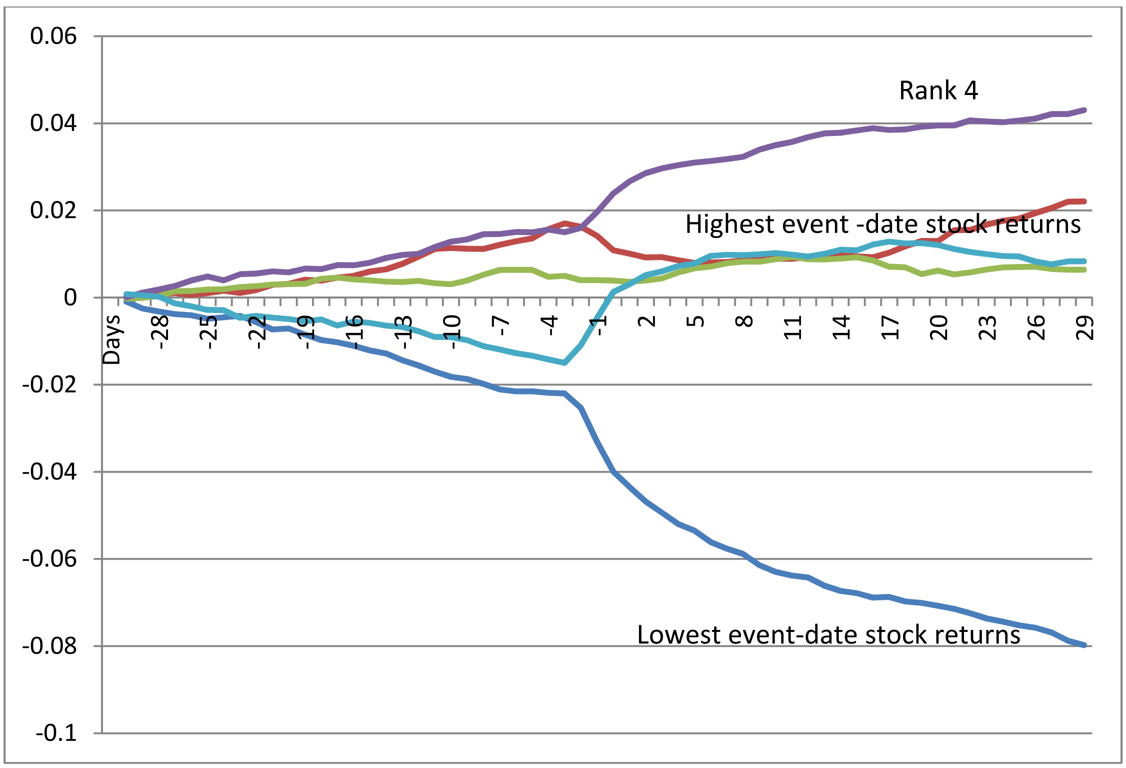

Figure 6a. Cumulative (order imbalances x Kyle's lambda) around earnings announcements; 1997 ~ 2000

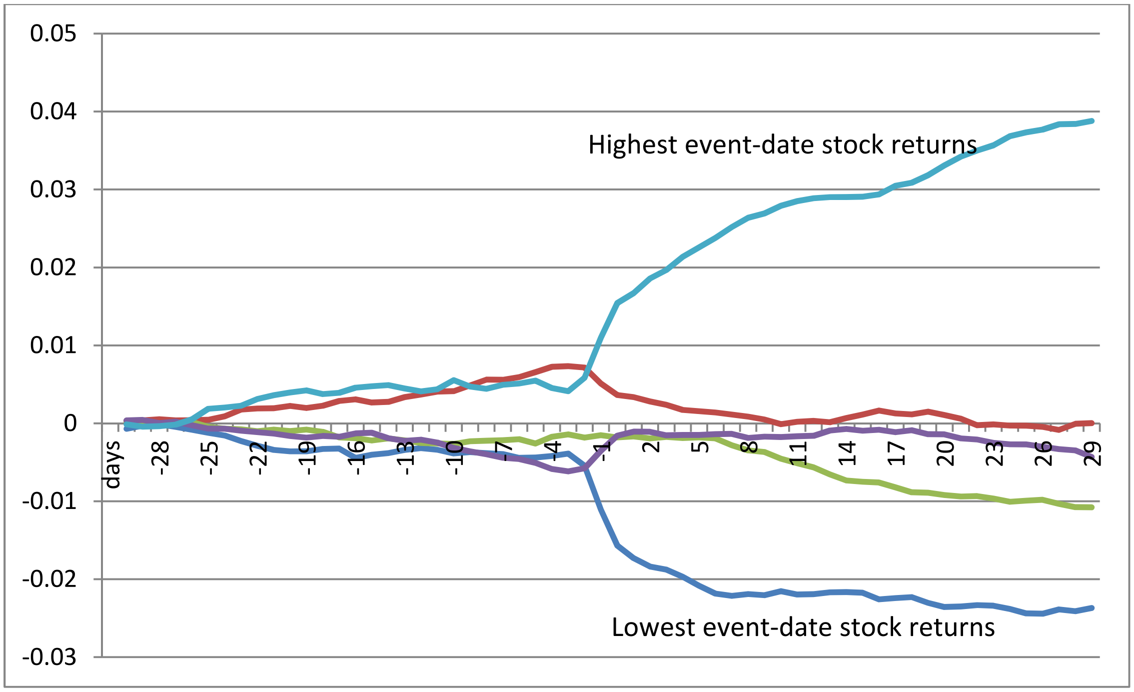

Figure 6b. Cumulative (order imbalances x Kyle's lambda) around earnings announcements; 2001 ~ 2004

In sum, we find order imbalances trail the past information. The degree of trailing is actually stronger in more recent periods. Since we do not find the trailing pattern when we look at only raw order imbalances, this result can be stated that stocks receive more positive trading pressure when past earnings surprise was more positive. This result is contradictory to our finding that it is difficult to construct a feasible investment strategy based on order imbalances before earnings announcement dates. It is a puzzle why such publicly observable trading pattern is not absorbed by the stock market.

7. Conclusion

In this study the relation between order imbalances and information is studied, using earnings announcements as the information source. We find order imbalances are weakly related with forthcoming earnings news. Although there is a positive correlation between cumulative order imbalances and stock returns, the relation is not strong enough to allow a feasible investment strategy based on order imbalances.

On the other hand, we find order imbalances trailing the past information and stock returns. Stocks that have more positive earnings surprise and higher stock returns around announcement dates have larger order imbalances afterwards. The trailing of order imbalances would be related to post-earnings-announcement-drift (PEAD). While our finding is consistent with institutional trading pattern found by Campbell, Ramadorai, and Schwartz (2009) and Liu, Kaniel, Saar, and Titman (2010), the fact that order imbalances are publicly available information makes the trailing of order imbalances as a serious challenge to market efficiency hypothesis.

We find order imbalances can be better analyzed when paired with Kyle's lambda, which is the sensitive of stock prices to trading. While we do not see a clear relation between raw order imbalances and information, we find the product of order imbalances and Kyle's lambda has significant positive correlation with earnings information and stock prices. This pattern is consistent with Kyle (1985), who shows observed trading activities are influenced by the sensitivity of stock prices to trading. Information embedded in order imbalances would be better identified when order imbalances are paired with the sensitivity measure.

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Appendix A – The Construction of Order Imbalance Data

1. Criteria for stock selection are:

- Data source comes from Trade and Quote (TAQ) data.
- Data period is from January 1996 to December 2004.
- We exclude Certificates, ADRs, shares of beneficial interest, units, Americus Trust components, closed-end funds, preferred stocks and REITs from the dataset.
- We delete the stock is from the sample year if the price at any month-end during the year was greater than $999.
- We eliminate non-synchronous trading issue by marking stock return as missing if there was no trade on today or previous day.

2. When constructing order imbalance variable, we only use quotes and trades such that:

- Quotes and trades are in regular market trading times (from 9:30 to 16:00)
- There is no special settlement conditions
- All bid-ask spreads are positive

3. Method to calculate order imbalance is (Lee and Ready (1992) method):

- A trade is buyer (seller) initiated if it is closer to the ask (bid) of the prevailing quote.
- Prevailing quote should be at least 5 seconds old.

If the trade is at the midpoint of the quote, the trade is buyer (seller) initiated if prior stock price change was positive (negative).

Table 1: Summary statistics.

Daily order imbalance is estimated using Lee and Ready (1992) method, and we impose additional filters used in Chordia, Roll, and Subrahmanyam (2002). For every trading day, we use 250 prior business days of order imbalance data to estimate Kyle's lambda. Earnings surprise measure *v* is derived from the difference between actual earnings and average analyst forecasts. Here we rank the earnings surprise into 11 ranks, divide it by 10, and subtract 0.5 to make it symmetric around zero. Daily mid-quote returns are derived from daily trade weighted average bid prices and ask prices.

	Sample Description
Data Period	From Jan 1997 to Dec 2004
Number of firms	1,364
Number of earnings announcements	8,095
Average number of analyst reports per earnings announcement	10.38

Main Variables Summary	Mean	Median	Standard Deviation
Order Imbalance of Shares	0.054	0.055	0.207
Earnings Surprise	-0.001	0.000	0.316
Mid-quote Returns	-0.018%	-0.004%	3.139%

Table 2: Order imbalances and earnings surprises.

The regression is:

$$v_{it} = \alpha + \delta_1 \cdot (OI_{it-j}) \cdot (\lambda_{it-j}) + \delta_2 \cdot r_{i,t-j-1} + \varepsilon_{it} \quad , \qquad (5)$$

where v_{it} is the value of the information announcement for stock *i* on day *t*. OI_{it} is the cumulative order imbalances in stock *i* on day *t*. $r_{i,t-j-1}$ is the stock's return on the prior day, and lagged days. *j* indicates the time between the forthcoming information announcement and current order imbalance.

We use OLS regression with clustering and heteroscedasticity controlled error structure. We control for clustering by stock, year, and quarter. t-values are in the parenthesis. Coefficients significant in 1%, 5%, and 10% level are marked with a, b, and c.

Panel A: Kyle's Lambda included in the equation

Using 5-day moving sum of order imbalances

	Regression at 20 business days before earnings announcements	Regression at 10 business days before earnings announcements	Regression at 5 business days before earnings announcements
5-day moving sum of order imbalances * Kyle's Lambda (δ_1)	3.049[b] (2.12)	2.611[c] (1.74)	5.542[b] (2.61)
Stock return (δ_2)	0.832[b] (2.31)	0.211 (0.38)	-0.488 (-0.89)
Observations	7,798	7,811	7,811
Adj. R-square	0.1%	0.1%	0.2%

Using 10-day moving sum of order imbalances

	Regression at 20 business days before earnings announcements	Regression at 10 business days before earnings announcements	Regression at 5 business days before earnings announcements
10-day moving sum of order imbalances * Kyle's Lambda (δ_1)	7.532[a] (4.56)	5.945[a] (3.39)	5.833[a] (2.74)
Stock return (δ_2)	0.854[b] (2.38)	0.208 (0.39)	-0.375 (-0.71)
Observations	7,798	7,811	7,811
Adj. R-square	0.4%	0.2%	0.2%

Using 20-day moving sum of order imbalances

	Regression at 20 business days before earnings announcements	Regression at 10 business days before earnings announcements	Regression at 5 business days before earnings announcements
20-day moving sum of order imbalances * Kyle's Lambda (δ_1)	8.876[a] (4.50)	9.070[a] (4.63)	8.121[a] (3.85)
Stock return (δ_2)	0.913[b] (2.53)	0.222 (0.42)	-0.327 (-0.62)
Observations	7,798	7,811	7,811
Adj. R-square	0.4%	0.3%	0.3%

Panel B: Kyle's Lambda not included in the equation

In this table, we report the result without Kyle's Lambda variable.

$$v_{it} = \alpha + \delta_1 \cdot OI_{it-j} \cdot + \delta_2 \cdot r_{i,t-j-1} + \varepsilon_{it} \ , \qquad (5)'$$

Using 5-day moving sum of order imbalances			
	Regression at 20 business days before earnings announcements	Regression at 10 business days before earnings announcements	Regression at 5 business days before earnings announcements
5-day moving sum of order imbalances (δ_1)	0.136 (1.35)	0.144 (1.32)	0.256[b] (2.38)
Stock return (δ_2)	0.818[b] (2.28)	0.300 (0.55)	-0.315 (-0.60)
Observations	8,019	8,030	8,031
Adj. R-square	0.1%	0.0%	0.1%

Using 10-day moving sum of order imbalances			
	Regression at 20 business days before earnings announcements	Regression at 10 business days before earnings announcements	Regression at 5 business days before earnings announcements
10-day moving sum of order imbalances (δ_1)	0.360[a] (3.11)	0.392[a] (2.82)	0.298[b] (2.21)
Stock return (δ_2)	0.797[b] (2.22)	0.280 (0.53)	-0.152 (-0.51)
Observations	8,019	8,030	8,031
Adj. R-square	0.2%	0.2%	0.1%

Using 20-day moving sum of order imbalances			
	Regression at 20 business days before earnings announcements	Regression at 10 business days before earnings announcements	Regression at 5 business days before earnings announcements
20-day moving sum of order imbalances (δ_1)	0.416[a] (3.28)	0.534[a] (3.58)	0.472[a] (2.86)
Stock return (δ_2)	0.834[b] (2.32)	0.299 (0.57)	-0.239 (-0.46)
Observations	8,019	8,030	8,031
Adj. R-square	0.2%	0.2%	0.2%

Table 3: Cumulative abnormal stock returns around earnings announcements.

We define abnormal stock returns as the difference between a stock return and average stock return of the stocks in the same size deciles. We cumulate the abnormal returns in (-1, +1) day window or (-5, +5) day window around earnings announcements. We rank earnings surprises into deciles and report average cumulative abnormal return by the deciles. Standard errors are in the parentheses. The last row compares the lowest decile and the highest decile. Significant difference in 1%, 5%, and 10% level is marked with small a, b, and c respectively.

Earnings surprises rank	(-1, +1) cumulative abnormal return	(-5, +5) cumulative abnormal return
Low (most negative)	-2.89% (0.40%)	-3.26% (0.56%)
2	-1.65% (0.30%)	-2.31% (0.38%)
3	-0.80% (0.27%)	-1.42% (0.37%)
4	-1.01% (0.26%)	-1.53% (0.33%)
5	-0.94% (0.26%)	-1.49% (0.34%)
6	0.94% (0.25%)	-0.04% (0.36%)
7	0.94% (0.27%)	0.83% (0.36%)
8	1.59% (0.31%)	1.60% (0.44%)
9	1.72% (0.35%)	1.72% (0.47%)
High (most positive)	2.65% (0.37%)	2.98% (0.53%)
Difference between Highest and Lowest	5.54%[a] (0.54%)	6.24%[a] (0.79%)

Table 4: Order imbalances and cumulative abnormal returns around earnings announcements.

We define abnormal stock returns as the difference between a stock return and average stock return of the stocks in the same size deciles. We cumulate the abnormal returns in (-1, +1) day window or (-5, +5) day window around earnings announcements. We rank the product of 20-day moving sum of order imbalances and Kyle's Lambda into deciles. We report average cumulative abnormal return by the deciles. We measure order imbalances at 3 and 6 business days before earnings announcements. Standard errors are in the parentheses. The last row compares the lowest decile and the highest decile. Significant difference in 1%, 5%, and 10% level is marked with small a, b, and c respectively.

Panel A: 3 days before earnings announcements

20-day moving sum of order imbalances * Kyle's Lambda	(-1, +1) cumulative abnormal return	(-5, +5) cumulative abnormal return
Low (most negative)	-0.53% (0.39%)	-0.72% (0.52%)
2	-0.30% (0.35%)	-1.08% (0.48%)
3	-0.07% (0.29%)	-0.22% (0.39%)
4	0.29% (0.29%)	-0.34% (0.36%)
5	0.13% (0.28%)	-0.33% (0.35%)
6	0.20% (0.29%)	0.12% (0.38%)
7	-0.36% (0.28%)	-1.10% (0.36%)
8	0.27% (0.27%)	-0.13% (0.38%)
9	0.31% (0.33%)	-0.56% (0.44%)
High (most positive)	-0.03% (0.34%)	0.07% (0.51%)
Difference between Highest and Lowest	0.50% (0.52%)	0.79% (0.73%)

Panel B: 6 days before earnings announcements

20-day moving sum of order imbalances * Kyle's Lambda	(-1, +1) cumulative abnormal return	(-5, +5) cumulative abnormal return
Low (most negative)	-0.60% (0.40%)	-0.51% (0.52%)
2	-0.44% (0.34%)	-0.92% (0.43%)
3	0.05% (0.29%)	-0.40% (0.37%)

4	0.43% (0.30%)	0.36% (0.37%)
5	0.15% (0.26%)	-0.54% (0.36%)
6	0.38% (0.32%)	0.36% (0.48%)
7	-0.30% (0.27%)	-0.90% (0.35%)
8	-0.18% (0.29%)	-0.92% (0.37%)
9	0.52% (0.28%)	0.07% (0.42%)
High (most positive)	-0.06% (0.36%)	-0.25% (0.49%)
Difference between Highest and Lowest	0.54% (0.53%)	0.26% (0.72%)

Table 5: Past earnings surprises and order imbalances.

We rank earnings surprises into deciles and calculate aggregate order imbalances after earnings announcements. We measure the cumulative order imbalances at 11 and 21 days after earnings announcements. The last row compares the lowest decile and the highest decile. Significant difference in 1%, 5%, and 10% level is marked with small a, b, and c respectively.

Panel A: Order imbalances at 11 days after earnings announcements

Earnings surprises rank	5-day moving sum of order imbalances x Kyle's Lambda	10-day moving sum of order imbalances x Kyle's Lambda	20-day moving sum of order imbalances x Kyle's Lambda
Low (most negative)	1.415 (0.195)	2.713 (0.322)	
2	1.483 (0.170)	2.808 (0.280)	
3	1.647 (0.169)	3.316 (0.290)	
4	1.617 (0.133)	3.146 (0.225)	
5	1.464 (0.138)	2.999 (0.249)	
6	1.703 (0.129)	3.507 (0.222)	
7	1.807 (0.142)	3.563 (0.241)	
8	1.705 (0.163)	3.429 (0.291)	
9	2.015 (0.184)	3.749 (0.312)	
High (most positive)	1.981 (0.176)	3.820 (0.296)	
Difference between Highest and Lowest	0.566[b] (0.262)	1.107[b] (0.438)	

Panel B: Order imbalances at 21 days after earnings announcements

Earnings surprises rank	5-day moving sum of order imbalances x Kyle's Lambda	10-day moving sum of order imbalances x Kyle's Lambda	20-day moving sum of order imbalances x Kyle's Lambda
Low (most negative)	1.220 (0.201)	2.490 (0.336)	5.230 (0.561)
2	1.790 (0.179)	3.220 (0.287)	6.022 (0.477)
3	1.640 (0.161)	3.345 (0.263)	6.669 (0.479)
4	1.574 (0.131)	3.337 (0.218)	6.479 (0.381)
5	1.516 (0.150)	2.956 (0.240)	5.984 (0.429)

6	1.726 (0.125)	3.320 (0.218)	6.825 (0.382)
7	1.843 (0.162)	3.535 (0.261)	7.111 (0.434)
8	1.725 (0.158)	3.357 (0.282)	6.803 (0.508)
9	1.657 (0.190)	3.141 (0.321)	6.885 (0.559)
High (most positive)	1.850 (0.203)	4.016 (0.332)	7.887 (0.552)
Difference between Highest and Lowest	0.630[b] (0.292)	1.526[a] (0.490)	2.657[a] (0.818)

Table 6: Past stock returns and order imbalances.

We rank cumulative abnormal stock return around earnings announcements (-1, +1 window) into deciles and calculate aggregate order imbalances after earnings announcements. We measure the cumulative order imbalances at 12 and 22 days after earnings announcements to prevent overlapping. The last row compares the lowest decile and the highest decile. Significant difference in 1%, 5%, and 10% level is marked with small a, b, and c respectively.

Panel A: Order imbalances at 12 days after earnings announcements

Cumulative abnormal stock return (-1, +1)	5-day moving sum of order imbalances x Kyle's Lambda	10-day moving sum of order imbalances x Kyle's Lambda	20-day moving sum of order imbalances x Kyle's Lambda
Low (most negative)	1.579 (0.186)	2.535 (0.320)	
2	1.149 (0.176)	1.844 (0.306)	
3	1.642 (0.163)	3.086 (0.280)	
4	1.464 (0.152)	2.835 (0.251)	
5	1.482 (0.138)	3.125 (0.241)	
6	1.699 (0.143)	3.427 (0.247)	
7	1.782 (0.132)	3.668 (0.223)	
8	1.678 (0.146)	3.284 (0.258)	
9	1.955 (0.152)	4.233 (0.257)	
High (most positive)	2.512 (0.201)	5.051 (0.329)	
Difference between Highest and Lowest	0.933[a] (0.275)	2.516[a] (0.459)	

Panel B: Order imbalances at 22 days after earnings announcements

Cumulative abnormal stock return (-1, +1)	5-day moving sum of order imbalances x Kyle's Lambda	10-day moving sum of order imbalances x Kyle's Lambda	20-day moving sum of order imbalances x Kyle's Lambda
Low (most negative)	1.459 (0.211)	3.157 (0.341)	5.731 (0.566)
2	1.623 (0.180)	2.879 (0.302)	4.723 (0.531)
3	1.591 (0.163)	3.195 (0.268)	6.300 (0.476)
4	1.472 (0.134)	3.072 (0.238)	5.905 (0.430)

5	1.620 (0.144)	3.027 (0.243)	6.138 (0.416)
6	1.442 (0.157)	2.953 (0.253)	6.348 (0.436)
7	1.614 (0.141)	3.339 (0.220)	7.018 (0.377)
8	1.618 (0.161)	3.257 (0.252)	6.566 (0.443)
9	1.829 (0.157)	3.591 (0.260)	7.853 (0.438)
High (most positive)	2.196 (0.204)	4.067 (0.353)	9.146 (0.603)
Difference between Highest and Lowest	0.737[b] (0.293)	0.910[c] (0.491)	3.415[a] (0.827)

Table 7: Daily order imbalances and stock returns.

We divide the sample into two: before earnings announcements and after earnings announcements. The former dataset has stock returns between [-10, -1] days of announcements and the latter dataset has stock returns between [6, 15] days of announcements. We run the following equation in each sample to test how order imbalances affect stock returns.

$$r_{i,t} = \alpha + \sum_{j=0}^{5} \gamma_j \cdot OI_{i,t-j} + \varepsilon_{i,q}$$

r_{it} is daily mid-quote stock return of stock *i* at day *t* and OI_{it} is daily order imbalance of stock *i* at day *t-j*.

We use OLS with heteroskedasticity corrected errors accounting for clustering by stock or month. t-values are in the parenthesis. Coefficients significant in 1%, 5%, and 10% level are marked with a, b, and c.

	Before earnings announcements	Before earnings announcements	Before earnings announcements	After earnings announcements	After earnings announcements	After earnings announcements
Order Imbalance$_t$	0.040[a] (57.40)	0.041[a] (58.75)		0.034[a] (60.60)	0.035[a] (60.46)	
Order Imbalance$_{t-1}$		0.012[a] (22.38)	0.020[a] (32.50)		0.010[a] (23.40)	0.017[a] (34.46)
Order Imbalance$_{t-2}$		-0.010[a] (-16.48)	-0.005[a] (-9.26)		-0.009[a] (-19.13)	-0.006[a] (-11.91)
Order Imbalance$_{t-3}$		-0.006[a] (-10.34)	-0.002[a] (-4.48)		-0.005[a] (-11.12)	-0.002[a] (-5.17)
Order Imbalance$_{t-4}$		-0.005[a] (-9.35)	-0.002[a] (-3.92)		-0.004[a] (-9.18)	-0.002[a] (-3.78)
Order Imbalance$_{t-5}$		-0.005[a] (-9.10)	-0.003[a] (-4.99)		-0.004[a] (-9.18)	-0.002[a] (-3.98)
Observations	78892	78869	78869	77400	77400	77400
Adj. R-square	6.4%	7.6%	1.5%	7.0%	8.3%	1.6%