Small and Large Trades Around Earnings Announcements:
Does Trading Behavior Explain Post-Earnings-Announcement Drift?

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Abstract

This paper analyzes trade-initiation by small and large traders for one year following earnings announcements and examines the predictive ability of event-time trading for future returns. With earnings surprises based on a seasonal random walk expectations model, small traders react slightly more weakly than large traders, during the event window, to the first surprise in a series of similar surprises, but more strongly than large traders to the later surprises. With earnings surprises based on analyst forecasts, small traders react more weakly than large traders regardless of the past series. Large traders trade in the direction of the earnings surprise for one month after the earnings announcement, while small traders do not. Starting in month two this switches and small traders trade in the direction of the surprise, while large traders do not. The strength of the small trade event-time reaction is a weak positive predictor of returns in the first month after the announcement and a weak negative predictor of drift after the first month. Large trade reaction is generally a negative predictor of future drift. The collection of evidence points to both small and large trader underreaction to earnings announcements, with small trader underreaction more severe in the first month. In month one, large traders capitalize on drift, but after that small traders seem to correct and possibly overreact.

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I. Introduction

Post-earnings-announcement drift is a well-documented, long-standing and consistent anomaly. Even in Fama (1998), a paper that criticizes evidence of many market anomalies, the author describes post-earnings-announcement drift as an anomaly "above suspicion." There are many theories about the cause of post-earnings-announcement drift, and virtually all of the theories involve investors who underreact or overreact to the announcement. This paper looks directly at trading as a measure of investor reaction in an attempt to test different explanations of post-earnings-announcement drift.

On the date of an earnings surprise, stock prices move dramatically. If an announcement is a positive surprise, the associated price normally moves up. If it is a negative surprise, the price normally moves down. Post-earnings-announcement drift is an anomaly by which the price continues to move in the same direction for the next few months. Trading strategies based on earnings surprises earn consistently positive excess returns, even after taking trading costs into account (Bernard (1993)). Bernard and Thomas (1989) set out to show that post-earnings-announcement drift would disappear once other factors were accounted for. Instead, they simply provided more evidence for the phenomenon. Chan, Jagadeesh and Lakonishok (1996) show that post-earnings-announcement drift survives after controlling for momentum, market risk, size and book-to-market effects. Because earnings announcements are important quarterly informational events, and because they are immediately public, the continued existence of post-earnings-announcement drift is particularly puzzling. While market frictions, risk and uncertainty may all contribute to the continued existence of post-earnings-announcement drift, the underlying cause of the drift is still uncertain.

There are three main explanations of post-earnings-announcement drift in the literature. The traditional view is that investors underreact initially and then later correct their reactions – causing drift. Barberis, Shleifer and Vishny (1998) predict initial investor underreaction and eventual overreaction. Daniel, Hirshleifer and Subrahmanyam (1998) predict initial overreaction, which increases over time. The key motivating question for this paper is: What is the actual behavior around earnings announcements? Few people would believe that every investor underreacts to earnings information. A more likely explanation is that certain investors underreact, and others are unable to take full advantage of this mistake at the time of the announcement. A natural question is: Who underreacts? Does a particular class of investors underreact? Does drift occur as these investors correct their mistake, or as other investors continue to take advantage of the drift? Since almost all explanations of post-earnings-announcement drift have the same predictions for returns, we need to look beyond returns to gain a deeper understanding of what drives post-earnings-announcement drift.

This paper focuses on measures of net investor trade-initiation, based on data from the NYSE Trades and Quotations (TAQ) database, to determine reactions to earnings news. If abnormal net buying is significantly positive after an announcement, then traders are reacting positively to that announcement. We can measure the degree of reaction by a measure of abnormal net trading, controlling for the information in the announcement. The paper examines the trading of both small and large traders to gain a better understanding of their behavior around and after earnings announcements. In addition, we test whether the trading behavior of small and large traders predicts returns, directly testing the relationship between trading and post-earnings-announcement drift.

We find mixed results for reactions immediately surrounding the earnings announcement. When we use an earnings expectations model based on a seasonal random walk to calculate earnings surprises, we find that small traders react slightly more weakly than large traders to the first surprise in a series of similar surprises, but more strongly than large traders to the later surprises. With earnings surprises based on analyst forecasts, small traders react more weakly than large traders, whether the surprise differs from the previous quarters' surprise or not. Looking at trading behavior beyond the event period, large traders trade in the direction of the earnings surprise for one month after the earnings announcement, while small traders do not, which seems to suggest that large traders are trading to take advantage of the post-earnings-announcement drift. Starting in month two this switches and small traders trade in the direction of the surprise, while large traders do not. This could be a small trader correction or, if prices have already corrected, an overreaction. The strength of the small trade event-time reaction is a weak positive predictor of returns in the first month after the announcement and a weak negative predictor of drift after the first month. Large trade reaction is generally a negative predictor of future drift, which suggests that while small traders may be underreacting relative to large traders, large traders themselves are underreacting during the event period.

There are several reasons to suspect that small traders are more likely to display sub-optimal behaviors than large traders. In particular, larger traders are more often professional investors and professional investment advisors, who are likely to have greater financial education, more experience and more time to make investing decisions. Most strongly, there is a growing empirical behavioral finance literature that has repeatedly shown that individuals make basic trading mistakes which institutions do not make. (See Barberis and Thaler (2003) for a summary.)

The two benchmarks used to evaluate small-trade reactions are based on information and large-trade behavior. Based on post-earnings-announcement drift, we can use the type of earnings surprise to construct a simple benchmark. Reactions to negative information should be negative and reactions to positive information should be positive. Such reactions would earn positive abnormal returns, on average, as shown in prior literature (Bernard (1993)). For the second benchmark, based on the existing empirical evidence, we posit that large traders are likely to interpret the earnings announcement more accurately. The analysis compares trading during the event period to determine if there is an initial underreaction, and for several months following the announcement to determine if there is eventual overreaction. Finally, we test the predictive ability for future returns of the event-time trading of both groups, to test whether initial underreaction is driving post-earnings-announcement drift. This section also allows us to draw conclusions about whether large traders underreact to earnings announcements.

The traditional explanation of post-earnings-announcement drift is that investors underreact to earnings information initially, and later correct their mistakes. The correction must take about six months to a year to explain post-earnings-announcement drift, as a majority of the drift occurs within the first year (Bernard (1993)). This leads to several clear predictions for trading behavior. First, investors should underreact to the earnings announcement initially. Second, their reactions should correct themselves within approximetely one year. Third, the level of underreaction should be a positive predictor of drift, since underreaction is the only factor in determining the degree of drift. Section 4 reports tests of the first prediction, Section 5 reports tests of the second prediction and Section 6 reports tests of the third prediction.

Both Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) predict eventual overreaction to the earnings surprise. Both of these behavioral models predict that reactions to later announcements in a same-sign sequence should be stronger than reactions to earlier announcements. The key difference between these two behavioral models is with respect to the initial reaction. Daniel, Hirshleifer and Subrahmanyam (1998) predict initial overreaction, but Barberis, Shleifer and Vishny (1998) predict initial underreaction. Shanthikumar (2004) shows that small traders display increasing reactions in their trading behavior, but that paper does not examine whether the initial reaction is an underreaction or overreaction. This paper does, potentially allowing us to differentiate between these two models.

This paper looks at three elements of investor reactions to earnings surprises, the first two dealing with the trading reactions themselves. The findings point to initial underreaction by both small and large traders, and an eventual overreaction by small traders. First, we look at the initial reaction to the surprise. We find that small traders buy after a negative surprise, but buy more after a positive surprise. They also buy more than large traders around all types of earnings surprises. This evidence suggests that investor reactions to the actual earnings surprise reflect an attention effect, such as those described in Barber and Odean (2002). Alternatively, the higher buying levels could be driven by investor heterogeneity combined with higher short-sale costs. We do not attempt to separate the possible explanations. Once we control for the pattern of higher small trade buying levels, it appears that small traders overreact to earnings surprises, relative to large traders, but the overreaction is driven entirely by later announcements in a series of similar earnings surprises. We repeat these tests using analyst forecast errors as a proxy for earnings surprises, and find that large traders consistently react more strongly than do small traders to the analyst-based measure of surprise. Second, we look at lagged trading behavior to determine whether drift is driven by small trader correction or overreaction, or by large traders continuing to trade to take advantage of the drift. We regress abnormal trade imbalances during the months following an earnings surprise on the earnings surprise decile values to measure reaction coefficients. During the first month, large trade imbalances depend positively on the earnings surprise, while small trade imbalances do not, suggesting that large traders may be attempting to profit from post-earnings-announcement drift during that period. Our results suggest that small traders overreact in the second month and beyond. Small-trader behavior is significantly dependent on an earnings announcement for over a year after the event date, while large trader behavior does not depend on the earnings surprise more than a month beyond the announcement. The differences in the estimated regression coefficients, comparing results using small trader imbalances and results using large trader imbalances, are also significant.

Finally, we examine whether event-time trading behavior predicts post-event returns. Controlling for the "correct" price reaction, the traditional underreaction-correction hypothesis would predict that the strength of event-time price reactions should be a negative predictor of drift: The more prices adjust initially, the weaker will be the drift. In Section 6, we make additional assumptions to extend this relationship to trade imbalance, as does Hirshleifer, Myers, Myers and Teoh (2003). We use trade imbalance as a measure of reaction, and earnings surprise level as a control for the "correct" reaction. For example, we posit that if there is a positive surprise, a more positive initial trade reaction should be related to weaker future drift, that is, a more positive initial reaction is related to less positive future returns. We find, however, that small-trader buying is a positive predictor of returns for the first month after the earnings announcement, and only a weakly negative predictor in the next five months. We find that large-trader buying is a significantly negative predictor of returns over many horizons, suggesting that large traders are underreacting.

Several recent empirical papers address the topic of trading behavior surrounding informational events. This literature is described in Section 2. The existing literature makes an important contribution in showing that individuals and small traders trade differently than do institutions and large traders. Individuals and small traders seem to trade less rationally, generally buying firms with predictably negative returns. The recent literature has established that trading behavior around informational events is an important topic, but there is a great deal for this work to add.

Section 2 reviews related literature. Section 3 describes the data and empirical methodology used, while Sections 4, 5 and 6 describe the results. Section 4 looks at trading reactions to earnings surprises around the event date and Section 5 examines trading behavior further from the announcement date. Section 6 reports results regarding the predictive ability of event-time trading for future returns. Section 7 concludes.

II. Related Literature

Post-earnings-announcement drift is a well-documented and long-standing market anomaly. Bernard (1993) provides a survey of the founding papers in this area. In particular, Bernard and Thomas (1990) find that the returns response to earnings is consistent with use by investors of a naïve random-walk earnings-expectations model. Earnings surprises based on a random-walk model have, on average, positive correlations at lags of one to three quarters and negative correlations at four-quarter lags. Bernard and Thomas (1990) find that the three-day price reactions, surrounding earnings announcements, reflect a failure of investors to account for these autocorrelations, as if investors incorrectly relied upon the random-walk model. This leads to two natural questions. First, which investors use this simple model? And second, do more sophisticated investors trade against them? Several papers attempt to answer these questions. Bhattacharya (2001) and Battalio and Mendenhall (2003), written concurrently with this paper, focus on the first question, using data similar to the data used in this paper. Bhattacharya (2001) finds that small traders' trading behavior around earnings announcements is strongly related to the seasonal random-walk-based earnings surprise, while the large trader response is not. Battalio and Mendenhall (2003) find that small traders react more strongly to random walk surprises, while large traders react more strongly to analyst-based surprises. Bartov, Radhakrishnan and Krinsky (2000) and Ke and Gowda (2004), also written concurrently with this chapter, attempt to answer the second question by focusing on quarterly institutional ownership. Several other papers examine the relationship between other earnings-announcement-related variables and institutional ownership (see Ke and Petroni (2004) for a summary.) Bartov, Radhakrishnan and Krinsky (2000) find that post-earnings-announcement drift is decreasing in institutional ownership, suggesting that non-institutional, and potentially less sophisticated, investors are driving the drift. Ke and Gowda (2004) focus on institutional investors who trade actively to maximize shorter-term profits, and find evidence that these institutions trade to exploit the drift, with a strong relationship between quarterly ownership changes and the contemporaneous random-walk-based earnings surprise.

Lee (1992) is the first paper to look at trade imbalances around earnings announcements, displaying an intra-day focus and looking at a three-day window around the earnings announcement. He finds that small traders buy after earnings surprises, whether the surprise is good or bad, and that they react later than large traders. In a related paper, Hirshleifer, Myers, Myers and Teoh (2002) attempt to relate trading behavior to post-earnings-announcement returns. Hirshleifer, Myers, Myers and Teoh (2002) look only at individual investor behavior, but then relate the trading to future returns. They find that individual investors are net buyers after both positive and negative earnings surprises, and that individual trading is a weakly negative predictor of returns in the following three quarters.

The three empirical papers most directly related to our work are Lee (1992), Hirshleifer, Myers, Myers and Teoh (2003), and Battalio and Mendenhall (2003). The current paper makes several additional contributions. First, we look at trading beyond the event period, and second, we control for the previous earnings information by doing additional analyses for a subsample of earnings surprises, which eliminates earnings later in a series of similar (top 30% or bottom 30%) earnings surprises. Both of these additions to previous methods yield new results, regarding the ways in which small and large traders react to different types of earnings announcements. In addition, we look at reactions to analyst forecast surprises, which reveals specific differences in the reactions to analyst forecast surprises and the reactions to random-walk surprises. Perhaps most significantly, this paper examines whether both small and large trade behavior around the earnings event has predictive ability for future returns, showing that both trader types seem to underreact to earnings information.

III. Data and Empirical Approach

There are three primary data elements required for this paper. To examine trading reactions to earnings surprises we need a measure for earnings surprises, and we need a measure for trading reactions. To determine whether trading predicts returns, we need returns data as well. Overall, an event-study methodology is used, with earnings announcements as the key event. Earnings surprises are calculated using two alternate approaches. Trading reactions are based on trade-by-trade data from the New York Stock Exchange. This section describes the raw data and the methods used for this paper.

The basic sample is restricted to ordinary common shares trading on the New York Stock Exchange between January 1, 1993 and December 31, 2002, excluding foreign companies, Americus trust components, closed-end fund shares and REITs.[1] We do not require data on the company for the entire period in order for it to be in the sample, but certain minimum data

[1] Because most existing work on post-earnings announcement drift uses earlier samples, a sample of earnings announcements from 1974-1986 is also used to compare the post-announcement drift of our sample and to ensure that our measurement of earnings surprise is accurate. As with Johnson and Schwartz (2000), we find that post-earnings-announcement drift has declined between the earlier and later periods, but is still significant in the later period, and with our specific sample.

requirements do limit the data. As described below, the primary limit is that we require enough of a history to estimate earnings expectations. The final sample includes 2,723 firms.

Returns data are obtained from CRSP. Earnings announcements and firm characteristics are taken from Compustat, and analyst earnings forecasts are taken from the Institutional Brokers Estimates System (I/B/E/S). Trading measures are calculated from the New York Stock Exchange Trades and Quotations database (TAQ). This database reports every round-lot trade and every quote from 1993 onwards on the New York Stock Exchange, American Stock Exchange and Nasdaq.

In calculating returns, we use cumulative abnormal returns (CARs), which are the sums of daily abnormal returns, and are defined as

$$CAR^i_{t_0,t_1} = \sum_{t=t_0}^{t_1} \left(AR^i_t \right), \qquad (1)$$

where AR^i_t is the CRSP beta-adjusted abnormal return for security *i* on day *t*. Fama (1998) summarizes theoretical and statistical reasons that CARs are preferable to buy-and-hold returns.

3.1 Earnings Models

The event of interest to us in this paper is the quarterly earnings announcement. Quarterly earnings announcement dates are taken from Compustat.[2] If an announcement is made on a holiday or weekend, the first trading day following the announcement date is used as the event date. Our final sample of earnings surprises, for which we have all the necessary data, contains 59,658 earnings announcements for the primary earnings surprise measure.

Our primary measure of earnings surprise is based on expectations built from prior earnings announcements. We use the standardized unexpected earnings measure commonly used in the post-earnings-announcement drift literature. Bernard and Thomas (1990) show that stock returns patterns around earnings announcements correspond to this naïve earnings expectations model. This allows us to use a measure that is both consistent with observed behavior in general, and independent of announcement-specific behavior. In order to calculate standardized

[2] Shanthikumar (2004) finds that with a small sub-sample of 125 earnings announcements for NYSE listed firms, with the announcement falling in the years 1993 through 2002, Compustat earnings announcement dates are accurate to within one day in 97% of the cases.

unexpected earnings (SUE), we assume that earnings expectations are based on a seasonal random-walk model. Our primary measure uses a seasonal random walk with drift, but we also repeat the study using a seasonal random walk without drift, and our results are robust to this variation. Expected earnings are

$$E\left(e_t^i\right) = e_{t-4}^i + \delta^i , \tag{2}$$

where δ^i is the expected change in earnings from the same quarter's earnings of the prior year, and is referred to as the earnings drift for firm *i*. For each stock, we estimate the drift using up to twenty quarters of previous data. The estimated drift is

$$\hat{\delta}^i = \frac{1}{n}\sum_{j=1}^{n}\left(e_{t-j}^i - e_{t-j-4}^i\right) , \tag{3}$$

where *n* is the number of intervals used to calculate the drift, where one interval requires earnings information for a given quarter and the same quarter in the prior year. *n* is the maximum of the number of intervals with available data and 16, so that no more than 5 years of earnings data are used. We use less data if the full period is not available, although we require at least one year's worth of data. This does introduce a slight survivorship bias into the sample, but eliminates only 5.34% percent of the earnings announcements, and 2.97% of firms. We then standardize the unexpected earnings measure by dividing each firm's surprise by the standard deviation of that firm's earnings, as measured by the available subset of the preceding 20 announcements. As a robustness check, we also normalize the unexpected earnings measure by dividing by the standard deviation of earnings changes rather than the standard deviation of earnings. Results are similar. The primary earnings surprise measure is

$$SUE_t^i = \frac{e_t^i - e_{t-4}^i - \hat{\delta}^i}{\sqrt{Var(e_t^i)}} , \tag{4}$$

where $Var(e_t)$ is estimated using the previous 20 announcements. Earnings announcements are then ranked by the SUE within each year, and placed into deciles 0-9, where the most negative surprises are in decile 0 and the most positive in decile 9.[3] Earnings announcements in deciles 4 and 5 are not strong surprises.

The second measure of earnings surprises is based on analyst forecasts. The surprise is the difference between announced earnings-per-share and the analyst forecast as reported by I/B/E/S, normalized by stock price. We use two measures of the consensus forecast. The first measure is taken from the I/B/E/S summary file. The consensus forecast is defined as the most recent monthly median forecast before the earnings announcement, when there are at least four earnings forecasts for the firm. The consensus forecasts occur a mean of 15.8 days and median of 13 days before the earnings announcement dates, so they tend to be approximately two weeks old. The mean and median forecasts are similar, with a correlation coefficient of 0.998. The second measure of consensus is constructed from the I/B/E/S detail files, and uses the median forecast occurring at least one week before the earnings announcement, but no more than two months before the announcement, when there are at least four earnings forecasts during that period. With both consensus measures, the earnings surprise is taken to be the difference between announced earnings-per-share and the consensus, divided by the price on the date of the consensus forecast. Using the monthly consensus measure, our sample of surprises contains 29,649 earnings announcements. The sample using the daily measure contains 14,505 earnings announcements.

3.2 Creating the trading database

Trading reaction is measured using variables based on net directional trading or net order flow. Following established algorithms, first proposed by Lee and Ready (1991), for each trade on the NYSE for our sample stocks, we determine which side of the trade represents the "initiating" side, that is, which side demands more immediacy of execution. An abnormally high level of "buyer-initiated" trades indicates an overall buying pressure and a positive reaction, while an abnormally high level of "seller-initiated" trades indicates a selling pressure and a negative reaction.

[3] This choice is equivalent to alternate decile-labeling methods, such as deciles 1 through 10, or deciles -0.5 through 0.5, but each corresponds to a different interpretation of regression coefficients. In this case, a simple intercept-slope regression will result in a slope that indicates the expected difference in corresponding dependant variable value from one decile to the next. The difference between the most negative and most positive surprises will be ten times this slope. The intercept will approximate the expected dependant variable value for the most negative surprises, decile 0. The alternate labeling of deciles 1-10 would result in the same slope coefficient, but the intercept would now be one unit of estimated slope below the approximate dependant variable value for the most negative surprise.

The raw trade initiation variables are normalized to determine abnormal levels and adjust for standard differences between small and large trade initiation patterns. Prior work has compared our trade-initiation data with two other measures of small (individual) and large (institutional) trading – quarterly institutional ownership from CDA Spectrum (Malmendier and Shanthikumar (2004)) and individual trading in accounts from a large discount retail brokerage firm (Shanthikumar (2004)). In each case, the correlations between trade initiation and changes in ownership or trading were significant in the expected directions.

In order to determine which side initiated a given trade, we use the modified Lee and Ready (1991) algorithm recommended in Odders-White (2000). This algorithm is commonly used in the empirical market microstructure literature (see Odders-White (2000) for a list of papers using the Lee-Ready algorithm). The algorithm involves matching a trade to the most recent quote, which precedes the trade by at least 5 seconds. If a price is nearer the bid price it is classified as seller initiated and if it is closer to the ask price it is classified as buyer initiated. If a trade is at the midpoint of the bid-ask spread, we classify based on the previous price. In this case, a "tick test" is used – if the trade occurs at a price that is higher than the price of the previous trade it is classified as buyer initiated. Similarly, a trade that occurs at a price lower than the previous trade is classified as seller initiated.

To separate small and large trades we use two cutoffs, with a buffer in between small and large trades to reduce noise. The primary cutoffs of $5,000 and $50,000 are chosen based on evidence from Lee and Radhakrishna (2000), and we use alternate cutoffs of $10,000 and $20,000 as well. Lee and Radhakrishna (2000) show that dollar based cutoffs create less noise in separating individuals from institutions than share-based cutoffs and suggest using two cutoffs, with a buffer zone separating small and large trades. They also analyze which particular cutoffs work best for their three-month sample from 1990-1991, and their results indicate that a very low cutoff such as $5,000 or less does the best job separating out individuals while a high cutoff of $50,000, or even $100,000, does the best job separating out institutions. While our aim is not specifically to discriminate between individuals and institutions, this interpretation is useful. Even if trades of $50,000 and above are being made largely by individuals, these individuals are likely to take advantage of professional investment advice. A difference in the behavior of small and large traders is interesting in and of itself, regardless of mapping to individuals and institutions. Once the trades are classified, we then aggregate the trade-by-trade data to find daily trading measures for each stock. Our final database is based on over 640 million classified trades.

Throughout the paper, we focus on the \$5,000 and \$50,000 trade-size cutoffs, but results are similar using \$10,000 or \$20,000 cutoffs.

3.3 Calculating abnormal trading measures

In order to aggregate across firms, and to be able to make clearer conclusions regarding the comparison of event-time trading and non-event time trading, we calculate abnormal trading measures. Our primary variable of interest is a measure of trade imbalance. Intuitively, if every trade after an announcement were being initiated by the buy side, then the trading reaction to that announcement is extremely positive. Similarly, if all trades were being initiated by the sell side, then the reaction is strongly negative. To capture this concept, the raw trade imbalance measure is calculated as follows, for firm *i*, investor type *x*, and date *t*:

$$IMB_{i,x,t} = \frac{buys_{i,x,t} - sells_{i,x,t}}{buys_{i,x,t} + sells_{i,x,t}} \quad . \tag{5}$$

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

$$IMB_{i,x,t}^{abnormal} = \frac{IMB_{i,x,t} - E\left(IMB_{i,x,year(t)}\right)}{\sqrt{Var(IMB_{i,x,year(t)})}} . \tag{6}$$

This controls for systematic differences in trading behavior. We calculate the sample mean and variance of trade imbalance in each year, for the given firm and investor type, excluding days that are close to an earnings announcement. The event period that is excluded in calculating $E\left(IMB_{i,x,year(t)}\right)$ and $Var(IMB_{i,x,year(t)})$ consists of days –5 through 5 in event time; the eleven trading days centered on any earnings announcement date. This period is chosen to be large enough to allow event-time trade variation to remain. This allows us to aggregate across firms without concerns for general, not-event-time, differences in the trading behavior associated with them. Normalizing the measures by the standard deviation allows us to make qualitative comparisons of our final values that would be impossible to make if the values were not normalized. It controls for systematic differences in the volatility of large trades and small trades or in the volatility of the stocks large and small traders invest in.

We also use a return adjusted abnormal trade imbalance measure as a robustness check. This measure accounts for prior returns over varying horizons and is particularly important in ensuring that lagged trading behavior is due to the information in the earnings surprise, and not a naïve response to the drift in the intervening period. In order to come up with our adjusted measure, we estimate the equation

$$IMB_{i,t}^{abnormal} = \alpha_0 + \alpha_1 AR_{t-1}^{i} + \alpha_2 CAR_{t-5,t-2}^{i} + \alpha_3 CAR_{t-20,t-6}^{i} + \alpha_4 CAR_{t-60,t-21}^{i} + \varepsilon_{i,t} \tag{7}$$

for each size-based category of trade imbalances. This equation essentially groups prior returns into day, week, month and quarter. Return adjusted abnormal trade imbalance is the residual from the above equation – the abnormal trade imbalance that is not accounted for by the previous day, week, month and quarter returns. We run all of our long-term tests using this measure as well as the unadjusted measure. Results are similar, and are actually slightly stronger for the return-adjusted measure, but only the results using our unadjusted abnormal trade imbalance are reported.

An alternate, more general, normalization procedure is used as an additional robustness check. Based on the evidence in Chordia, Roll and Subrahmanyam (2002), we perform a normalization controlling for calendar-effects, serial correlation in the trade imbalance variable, and dependence of trade imbalance on prior returns, similar to Frieder (2004). The first step involves regressing raw trade imbalance on indicators for month (January, February,…) and day-of-week (Monday, Tuesday,…). This regression is run for each security separately, using the entire sample period. The residual is used in the second step, where the calendar-adjusted imbalance is regressed on the previous fifteen trading-days' calendar-adjusted imbalance and security return. Again, these regressions are run for each stock separately. The residuals from these regressions are used in the final step. In order to ensure that the final abnormal trade imbalance values are comparable across trade size groups, the final step is similar to our primary normalization, removing the mean and standard deviation effects for each firm and trade-size group from the residuals from step 2. In this third step, the mean of the imbalance measure resulting from step 2, for a particular security and trade-size group, is subtracted from that groups' step 2 residual and the resulting mean-adjusted imbalance is divided by the standard deviation of the step 2 residual for that security and trade-size group. Step 1 adjusts for calendar effects. Step 2 adjusts for prior returns and prior imbalance measures. Step 3 normalizes the imbalance measure to have a mean of zero and standard deviation of one for each security and trade-size group.

IV. Trading Around the Event Day

One of the key differences between alternate explanations of post-earnings-announcement drift is whether investors underreact or overreact at the time of the earnings announcement. In this section, we focus on trading around the event day, for days –1 through 1. Based on the evidence in Shanthikumar (2004), we calculate reactions for both the whole sample, and for a subsample of surprises which differ from the preceding surprise type. By doing this, we can see how the different types of investors react, both in general and to the first surprise of a given type.

Full Sample

Figure 1 displays small- and large-trader reactions to each earnings surprise decile. As one can see, the abnormal buying of small traders is stronger around an earnings surprise, regardless of the type of earnings surprise. Small traders buy even for the most negative earnings surprises, while large traders sell. The bottom two deciles alone would suggest that small traders underreact to earnings announcements. But, when we look at the whole picture, we see that small traders buy even more at positive earnings surprises, and that the gap between small- and large-trader reactions is higher for the most positive surprises. This seems to point to a small trader overreaction. The two results are easily reconciled by considering the possibility of attention buying. Barber and Odean (2002) finds that individuals buy an abnormally high amount of a company's stock after news about the company – whether the news is good or bad. Thinking of the "curve" of abnormal trade imbalance reaction on the vertical axis and earnings surprise decile on the horizontal axis, attention buying would shift the entire curve up for the traders who are most susceptible to the attention effect, increasing the reactions to each earnings surprise, and causing the intercept to be higher for small trades than for large trades.

By fitting this data to a linear model, we can estimate the difference in the slopes of the small trader reaction and the large trader reaction. Using ordinary least squares, we estimate the equation:

$$VolMeas_{t,e,x} = \alpha_t^S \mathrm{I}(x=S) + \alpha_t^L \mathrm{I}(x=L) + \beta_t^S \mathrm{I}(x=S) SurpDec_e$$
$$+ \beta_t^L \mathrm{I}(x=L) SurpDec_e + \varepsilon_{t,e,x}, \qquad (8)$$

where t is the trading day in event time, that is, the number of trading days between event e and the date of the trading data observation, e is the earnings announcement event, x is the trade size category, S for small trade, L for large trade, and $SurpDec_e$ is the surprise decile for event e. In equation (8), α is the intercept for the reaction to the earnings announcement, which is roughly the reaction to an extremely negative surprise (decile 0), and helps control for the attention buying effect. The β coefficient reflects the way in which the given volume measure depends on the surprise decile. Essentially, β measures the strength of the reaction. Table 1 presents the coefficient estimates for these regressions, with t-statistics for tests of $\alpha^S = \alpha^L$ and of $\beta^S = \beta^L$. One can see that α^S is significantly higher than α^L during the entire event period. The relationship between β^S and β^L is not as consistent through the event period as the relationship between α^S and α^L. Before the announcement date, β^S is less than β^L but on and after the announcement date, β^S is much higher than β^L . It seems as if large traders are learning more about the earnings value in the few days before the announcement is made, but once the earnings are made public, small traders are reacting more strongly than large traders. Overall, these regression results seem to confirm the interpretation of Figure 1, that small traders exhibit some sort of attention buying and react more strongly to the type of earnings surprise than do large traders.

When we use the earnings-surprise measure based on analysts' earnings forecasts, we find that small traders actually react more weakly to the earnings surprise than do large traders, in that β^S is less than β^L throughout the event period. With only these two sets of results it is unclear whether small traders are underreacting or overreacting to earnings surprises.

Subsample – eliminating surprises that are late in a series

A key prediction of the models of Daniel, Hirshleifer and Subrahmanyam (1998) and Barberis, Shleifer and Vishny (1998) is that investors react differently to different surprises in a series. For example, investors react differently to the third negative surprise in a row than to the first negative surprise. Shanthikumar (2004) provides evidence that small traders exhibit this behavior in the market. Because of this, we might see overreaction when we pool all earnings surprises together, when in fact investors underreact to the first surprise in a series and overreact only to the later ones. Due to the importance of this prediction to the models, and based on the empirical evidence, in this section we condition on past surprises by looking at the first surprise in any given series. We use the same methods as in the above section, but we restrict ourselves to a subset of the earnings surprises. In particular, we assign an earnings surprise a value of N=0 if it is a mild surprise, that is, in deciles 3, 4, 5 or 6. We assign it a value of N=1 if it is a very negative surprise (decile 0, 1 or 2) and if the preceding surprise for that firm was not strongly negative. Similarly a surprise gets a value of N=1 if it is very positive (deciles 7,8 or 9) and the preceding surprise was not positive. The surprise has a value of N=2 if it is the second surprise of the same type, strongly negative or strongly positive, N=3 if it is the third, and so on. Since both the model of Daniel, Hirshleifer and Subrahmanyam (1998), and the model of Barberis, Shleifer and Vishny (1998), predict that investor reactions will depend on N values, N is an important variable in the analysis of these models. For this section, we limit the sample to surprises with N=0 or N=1.

Figure 2 displays average reactions to the different earnings surprise deciles. The large-trade reaction does not change much between the full sample and the $N \in \{0,1\}$ subsample. As expected, since small traders react more strongly to each consecutive surprise, in that their reaction slope increases with N, their reaction is weaker when we limit the sample to the first surprise in each sequence. The small trade reaction to positive surprises is lower for this subsample, and their reaction to negative surprises is higher. Overall, their reaction does not seem as extreme as with the full earnings surprise sample. Regression results show that the significant overreaction observed for the full sample does not occur for the $N \in \{0,1\}$ subsample. Table 2 displays results from regressions of the form of equation (8), with the $N \in \{0,1\}$ sample.

The results regarding β change dramatically when we limit our sample to firm-events with $N \in \{0,1\}$. With the whole sample, small-trader slope is over twice as high as the large-trader slope for four days surrounding the earnings announcement. With the $N \in \{0,1\}$ subsample, the slope coefficients are about the same for the two groups, from day 0 through day 3. Surrounding this period, small trades actually depend less on the earnings surprise than do large trades, with $\beta^S < \beta^L$. These results provide weak support for a small trader underreaction to the first surprise in a series, as the slope is significantly negative during the weeks surrounding the earnings surprise. While the results are insignificant on days 0-3, and based on these four days alone it seems possible that small traders are reacting correctly with the added effect of attention buying, these results do provide strong evidence against the proposition that less sophisticated investors will display an event-time overreaction.

Analyst-Based Earnings Surprise

Panels B of Table 1 and Table 2 present results using the earnings-surprise measure based on monthly analyst consensus forecast, calculated as described in Section 3. Our measure of earnings surprises using analyst forecasts as a proxy for earnings expectations yields similar results, with the one key difference pointed out in Section 4, Full Sample, regarding the difference between β^S and β^L. Specifically, for the whole sample, we find that small traders have a weaker reaction than large traders, that is $\beta^S < \beta^L$ when we use analyst-based earnings surprises, in contrast with the SUE based results for which small traders have a stronger reaction than large traders, with $\beta^S > \beta^L$. As with the SUE results, the difference between small and large trade slope, $(\beta^S - \beta^L)$, is more negative when we limit the sample to events with $N \in \{0,1\}$. In particular, the small trader reaction on days 1 through 8 is much lower if we limit the sample to only firms with $N \in \{0,1\}$, when we measure earnings surprises using analyst forecasts. Overall, small traders react more weakly to the analyst-based surprises, providing more support for theories proposing that small traders underreact.

V. Lagged Trading Behavior

One of the key differences between traditional explanations of post-earnings-announcement drift and behavioral explanations is the implied reaction in the months after the earnings announcement. According to traditional explanations, the reaction corrects itself. According to both of the two behavioral models we focus on, the models of Daniel, Hirshleifer and Subrahmanyam (1998) and Barberis, Shleifer and Vishny (1998), investors overreact. In addition, we would like to know whether post-earnings-announcement drift occurs as one group's reaction changes or as a second group trades against them. For example, if the market as a whole underreacts and corrects – does it correct because the underreacting investors realize their mistake, or because other investors are able to correct prices over time? In order to answer these questions, we look at trading behavior for several months after the earnings announcement date.

Figure 3 displays the slope coefficients from estimation of equation (8) using a moving five-day window for roughly two years following the earnings announcement, and with the sample limited to earnings surprises with $N \in \{0,1\}$. Table 3 displays the coefficients from regressions of the form of equation (8), where the dependent variable is the sum of daily abnormal trade imbalances over the given period in event-time. The particular periods shown in the table are each of the first twelve months following the earnings announcement.

First, if we focus on the large traders, we can see from the figure that their trading is strongly positively related to the earnings surprise in the first month surrounding the surprise. The slope coefficient is significantly positive for 18 of the 22 days from day –1 through day 20. Although the coefficient is positive again during portions of months two and three, it is only significant for three days during those months. The regression results displayed in Table 3 confirm that the large trader reaction is only significantly positive during the first month following the earnings surprise. If these trading results are representative of the large trader strategies, it seems that the large traders trade in such a way as to take advantage of the potential post-earnings-announcement drift during the entire first month, but after that their trading ceases to depend strongly on the earnings announcement.

Focusing on the small traders, there is a significantly positive reaction during four days surrounding the earnings announcement, but the reaction is roughly zero, or significantly negative during the remainder of the first month. The small trader slope is significantly positive two to three months after the earnings announcement and remains significantly positive for at least ten months after that. Interpreting these results in terms of trading strategies, the small traders do not seem to be trading to take advantage of the potential drift in the same way that the large traders are. If anything, they are trading in the opposite direction during the second and third weeks following the earnings surprise. But during the second and third months, the small traders seem to react to the earnings announcement, potentially taking advantage of any remaining drift, or overreacting if prices have already corrected.

Figure 4A displays the difference between the slopes of small and large trade response to earnings surprises, using the SUE measure and a moving five-day window to estimate equation (8), as for Figure 3. Figure 4B displays the t-statistics for this difference. As the figure indicates, small traders exhibit significantly lower sensitivity to the earnings announcement than do large traders, in the weeks surrounding the earnings announcement. But in the months following the earnings surprise, their reaction slowly increases relative to the large trader reaction, and becomes stronger than that of large traders. We can interpret the significantly positive small-trader slope in months 3-12 as "oversensitivity" based on two assumed benchmarks. First, the small-trader slope would represent an "oversensitivity" if, because the information has been publicly available for some time, there is no need to significantly hinge a trading strategy on the old information.

Second, the small-trader slope would be "oversensitivity" if we use the large trader reaction as a benchmark. There may be other stock characteristics associated with the earnings announcement, or investor heterogeneities, which make the small trader behavior optimal, but the results provide preliminary support of the proposition that small traders exhibit a lagged overreaction to the earnings announcement, as predicted by the models of Daniel, Hirshleifer and Subrahmanyam (1998) and Barberis, Shleifer and Vishny (1998). While the apparent oversensitivity develops during the first six months, it takes longer to decrease, staying generally positive for a year and a half after the event date. The pattern is similar using analyst-forecast surprises.

The lagged trading behavior is also consistent with attention buying triggered by earnings announcements. For small traders, the intercept term is positive about every 60 trading days and is negative the remainder of the time, suggesting that small traders are buying more around the time of each subsequent earnings announcement. Again, the results are similar using the analyst-forecast surprises.

When looking at a long horizon of trade imbalances such as these, combined with the established returns pattern of post-earnings-announcement drift, we must be particularly concerned with controlling for prior returns and prior values of trade-imbalance. Table 4 reports robustness checks of the lagged trading behavior, reporting the estimated ($\alpha^S - \alpha^L$) and ($\beta^S - \beta^L$), for regressions estimating equation (8) with the dependant variable, trade imbalance, measured in each of the first twelve months following the earnings announcement. The table reports results from regressions using abnormal trade imbalance measures which have been adjusted for prior returns using equation (7), as well as using the alternate normalization of trade imbalance, which corrects for calendar-time effects and prior 15-day trade-imbalances and returns as described in Section 3. The table also reports estimated coefficients using the primary abnormal trade-imbalance measure with alternate earnings surprise measures. The table displays results for a modified version of Standardized Unexpected Earnings which does not include earnings drift and earnings-surprises calculated from analyst forecasts. All of these modifications confirm that $\beta^S > \beta^L$ during months 4-11. Although the difference is not statistically significant in each month for each variation, the difference is positive for each month, and significant for at least half of the months in each variation. In unreported regressions, we estimate equation (8) using three other measures of earnings-surprises, and the results are similar. We use earnings-surprises based on an analyst consensus seven days prior to the earnings announcement, constructed from daily analyst forecast data, and SUE-based surprises where the change in earnings, with or without a drift adjustment, is normalized by the standard deviation of earnings changes.

Together, the trading results seem to suggest that small traders underreact initially, although this evidence is mixed, and subsequently over-correct, causing an overreaction. Large traders seem to be trading in the same direction as the earnings announcement in the first month after the earnings announcement, suggesting that their trading may be increasing the post-earnings-announement drift during this period, but the lack of a relationship between large-trade imbalance and earnings surprises after the first month after the announcements suggests that large traders are not driving drift during the later period.

VI. Relationship Between Event-time Trading and Future Returns

In order to test whether event-time trading behavior predicts returns, we regress future CARs on event-time (days –1, 0 and 1) trade imbalance, controlling for the earnings surprise. We control for the earnings surprise by looking at positive surprises (deciles 7,8,9), mild surprises (deciles 3,4,5,6) and negative surprises (deciles 0,1,2) separately. Hirshleifer et al (2002) also ask this question, but they do not look at the interaction between surprise and trading behavior. While their method gives interesting new results, it is also important to control for the interaction with the surprise and to look as well at large-trade behavior. If we found a trade imbalance of 0 and an earnings surprise of 0, the underreaction and correction theories would predict no drift. With an initial trade imbalance of 0 and an extremely positive surprise, the underreaction and correction theories would predict positive drift. Similarly, if there were a trade imbalance of 0 and an extremely negative earnings surprise, we would expect negative drift. Hirshleifer et al (2002) essentially combine these three cases into one. Our method will look at each case separately[4]. One can see from this simple example that small-trade buying should be a negative predictor of returns for a given stock and surprise. If small traders sell after a positive earnings surprise, they are underreacting severely and we would expect higher future returns. If they bought, on the other hand, they would already have reacted to some of the new information,

[4] Hirshleifer et al (2002) find that individual trading is a weak negative predictor of 6 month and 9 month returns. We also attempt our regressions without interacting the trading variables with surprise type, and find that our small trader imbalance does not significantly predict returns for any of those horizons, although the coefficients are negative for the 4-6 month and 7-9 month horizons. We do find significant negative predictive power for the 2nd and 3rd months, though. We use CARs whereas Hirshleifer et al use buy-and-hold returns. Since buy-and-hold returns would cause the effect of the 2-3 month return on the 0-9 month return to be higher, this could be a contributing factor to the higher significance Hirshleifer et al find.

resulting in a smaller amount of positive drift, that is, lower future returns. Assuming that trade imbalance has a similar affect on stock prices across firms, and that the earnings surprise level is a proxy for the "correct" return reaction, we would expect small-trade buying to be a negative predictor of returns when we aggregate across stocks and earnings surprises in a similar category.

We estimate the regression,

$$CAR_{(t_1,t_2),e} = \alpha^{Pos} + \alpha^{Mild} + \alpha^{Neg} + \beta S^{Pos} * S_e * \mathrm{I}\left(SurpDec_e \in \{7,8,9\}\right) +$$

$$\beta S^{Mild} * S_e * \mathrm{I}\left(SurpDec_e \in \{3,4,5,6\}\right) + \beta S^{Neg} * S_e * \mathrm{I}\left(SurpDec_e \in \{0,1,2\}\right) +$$
$$\beta L^{Pos} * L_e * \mathrm{I}\left(SurpDec_e \in \{7,8,9\}\right) + \beta L^{Mild} * L_e * \mathrm{I}\left(SurpDec_e \in \{3,4,5,6\}\right) +$$
$$\beta L^{Neg} * L_e * \mathrm{I}\left(SurpDec_e \in \{0,1,2\}\right) + \varepsilon_e,$$

(9)

where S_e is the event-time small trade imbalance for event *e* and L_e is the event-time large trade imbalance for event *e*, with event-time measured over days –1, 0 and 1. If small-trade behavior is driving post-earnings-announcement drift, then we should find that $\beta S < 0$ for returns measured after the event period, that is $t_1 > 1$. Table 5 displays the results. Most noticeable is that large-trade imbalance around the earnings announcement seems to be a strongly negative predictor of future returns. This suggests that while small traders may be underreacting relative to large traders, large traders are underreacting themselves. Small trade imbalance during the event period is a strong positive predictor of returns throughout the first week, and a weak positive predictor of returns for the remainder of the first month. During the first month, the securities which small trades buy most enthusiastically do the best, while the prediction of the traditional underreaction-correction theory is that these securities would do the worst. There does appear to be some negative predictive ability beyond the first month, but only for three of the time-period surprise-group combinations. Including size and book-to-market ratio deciles as control variables does not change the significant negative relationship between large-trade imbalance and future returns or the significant positive relationship between small-trade imbalance and returns in the first month after the announcement.

While small-trade behavior could be a factor in post-earnings-announcement drift beyond the first month, it is not clearly driving early drift. One simple explanation resolving the evidence is that small trades simply take some time to correct their mistake, and that large traders take advantage of them to some extent during this intervening period – so that prices drift despite a failure of small traders to correct their behavior. As we saw when looking at lagged trading behavior, small traders did continue to underreact relative to large traders during the first month after the surprise. Overall, these return results seem to indicate that underreaction by both small and large traders is playing a role in driving post-earnings-announcement drift during the first six months, but event-time underreaction is clearly not the only cause of the post-earnings-announcement drift.

VII. Conclusion

The literature offers many explanations of post-earnings-announcement drift. Explanations differ as to whether investors underreact or overreact initially, and as to whether there is a delayed correction or an overreaction. We have found evidence suggesting that small traders react less strongly, initially, to the earnings announcement than do large traders, at least if that earnings surprise differs from the previous earnings surprise. Small traders reacted more strongly to surprises based on a random-walk expectations model if those surprises were late in a series of same-type surprise. But if the surprise was the first of it's type, there is some weak evidence of an underreaction. Small traders clearly react more weakly to analyst forecast based surprises than large traders, regardless of the past series.

We have seen evidence that large traders capitalize on post-earnings-announcement drift during the first month following an earnings surprise, while small traders overreact in the long run relative to a benchmark of zero and relative to large traders. Small trader abnormal trade-initiation depends significantly on the earnings surprise even nine months after the information has been released, while large-trader behavior is largely independent of the surprise after the first month.

Looking at whether event-time trading predicts returns, we find that small trader abnormal imbalance is a positive predictor of returns in the first month after the surprise, but a weakly negative predictor thereafter. Large-trade abnormal imbalance is a consistently negative predictor of returns. These results suggest that small traders do underreact relative to large traders, but that large traders themselves are initially underreacting to earnings announcements.

The most traditional explanation of post-earnings-announcement drift states that drift is caused by the correction of initial investor underreaction. Our return results indicate that initial underreaction, by both small and large traders, is a major factor in driving drift. But we also find strong evidence of eventual overreaction in small-trader behavior, suggesting that investor underreaction and correction is not the full story.

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Table 1: Event-Time Trade Reaction – Full Sample

Results from regressions of the form:

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

where the dependent variable is abnormal trade imbalance. α represents the abnormal trade imbalance for a decile 0 surprise. β represents the dependence of trade imbalance on surprise decile. Small trades are trades of less than $5,000 and large trades are those of at least $50,000. "t-stat for equality" tests the significance of the difference between the coefficients for small and large traders. "Day, t" represents the day of the dependent variable relative to the earnings announcement, in event-time trading days. Panel A presents results based on an earnings surprise calculated from a random walk with drift model while Panel B presents results based on an earnings surprise calculated from the analyst forecasts taken from the I/B/E/S summary file. Standard Errors are in parentheses.

Panel A. Standardized Unexpected Earnings

Day, t	α^L	α^S	t-stat for equality	β^L	β^S	t-stat for equality
-3	0.0013	0.0364	3.03	0.0015	-0.0035	-2.24
	(0.0079)	(0.0085)		(0.0015)	(0.0016)	
-2	-0.0016	0.0308	2.81	0.0034	-0.0031	-2.96
	(0.0079)	(0.0084)		(0.0015)	(0.0016)	
-1	-0.0085	0.0283	3.24	0.0068	0.0021	-2.18
	(0.0077)	(0.0083)		(0.0015)	(0.0016)	
0	-0.0040	0.0153	1.74	0.0068	0.0134	3.09
	(0.0076)	(0.0081)		(0.0014)	(0.0015)	
1	-0.0061	0.0274	3.00	0.0044	0.0142	4.64
	(0.0077)	(0.0081)		(0.0014)	(0.0015)	
2	-0.0004	0.0425	3.78	0.0013	0.0050	1.69
	(0.0078)	(0.0082)		(0.0015)	(0.0016)	
3	-0.0089	0.0237	2.88	0.0014	0.0048	1.56
	(0.0078)	(0.0083)		(0.0015)	(0.0016)	
4	-0.0046	0.0340	3.39	0.0012	0.0031	0.87
	(0.0078)	(0.0083)		(0.0015)	(0.0016)	
5	0.0023	0.0214	1.66	0.0006	0.0039	1.54
	(0.0079)	(0.0083)		(0.0015)	(0.0016)	

Panel B. Analyst-based Earnings Surprise

Day, t	α^L	α^S	t-stat for equality	β^L	β^S	t-stat for equality
-3	-0.0164	0.0305	2.69	0.0064	-0.0053	-3.63
	(0.0118)	(0.0129)		(0.0022)	(0.0024)	
-2	-0.0012	0.0459	2.72	0.0053	-0.0046	-3.11
	(0.0117)	(0.0128)		(0.0022)	(0.0023)	
-1	-0.0201	0.0418	3.66	0.0110	-0.0013	-3.96
	(0.0113)	(0.0125)		(0.0021)	(0.0023)	
0	-0.0123	0.0330	2.80	0.0102	0.0098	-0.13
	(0.0105)	(0.0123)		(0.0019)	(0.0022)	
1	-0.0281	0.0628	5.58	0.0098	0.0088	-0.34
	(0.0107)	(0.0123)		(0.0020)	(0.0023)	
2	-0.0065	0.0793	5.14	0.0041	-0.0021	-2.00
	(0.0111)	(0.0125)		(0.0021)	(0.0023)	
3	-0.0190	0.0754	5.60	0.0043	-0.0049	-2.97
	(0.0113)	(0.0125)		(0.0021)	(0.0023)	
4	-0.0158	0.0840	5.91	0.0027	-0.0068	-3.07
	(0.0113)	(0.0125)		(0.0021)	(0.0023)	
5	-0.0146	0.0640	4.63	0.0039	-0.0034	-2.34
	(0.0114)	(0.0126)		(0.0021)	(0.0023)	

Table 2: Event-Time Trade Reaction – N $\in$ {0,1} Subsample

This table presents results for earnings announcements which occur early in their given earnings surprise sequence, ie. Earnings surprises with N $\in \{0,1\}$
Results from regressions of the form,

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

where the dependent variable is abnormal trade imbalance. α represents the abnormal trade imbalance for a decile 0 surprise. β represents the dependence of trade imbalance on surprise decile. Small trades are trades of less than $5,000 and large trades are those of at least $50,000. "t-stat for equality" tests the significance of the difference between the coefficients for small and large traders. "Day, t" represents the day of the dependent variable relative to the earnings announcement, in event-time trading days. Panel A presents results based on an earnings surprise calculated from a random walk with drift model while Panel B presents results based on an earnings surprise calculated from the analyst forecasts taken from the I/B/E/S summary file. Standard Errors are in parentheses.

Panel A. Standardized Unexpected Earnings

Day, t	α^L	α^S	t-stat for equality	β^L	β^S	t-stat for equality
-3	0.0106	0.0399	1.84	-0.0006	-0.0044	-1.23
	(0.0108)	(0.0117)		(0.0021)	(0.0023)	
-2	0.0101	0.0348	1.56	0.0012	-0.0037	-1.55
	(0.0108)	(0.0116)		(0.0021)	(0.0023)	
-1	-0.0106	0.0435	3.46	0.0079	-0.0009	-2.88
	(0.0106)	(0.0115)		(0.0021)	(0.0023)	
0	-0.0097	0.0279	2.45	0.0084	0.0108	0.80
	(0.0105)	(0.0112)		(0.0021)	(0.0022)	
1	-0.0190	0.0625	5.30	0.0071	0.0067	-0.15
	(0.0106)	(0.0112)		(0.0021)	(0.0022)	
2	0.0006	0.0588	3.73	0.0015	0.0016	0.06
	(0.0107)	(0.0114)		(0.0021)	(0.0022)	
3	-0.0359	0.0408	4.91	0.0065	0.0017	-1.55
	(0.0107)	(0.0114)		(0.0021)	(0.0023)	
4	-0.0182	0.0448	4.02	0.0037	0.0011	-0.85
	(0.0107)	(0.0114)		(0.0021)	(0.0023)	
5	-0.0147	0.0408	3.51	0.0043	-0.0005	-1.55
	(0.0108)	(0.0115)		(0.0021)	(0.0023)	

Panel B. Analyst-based Earnings Surprise

Day, t	α^L	α^S	t-stat for equality	β^L	β^S	t-stat for equality
-3	-0.0099	0.0230	1.49	0.0040	-0.0031	-1.70
	(0.0148)	(0.0163)		(0.0029)	(0.0031)	
-2	0.0103	0.0549	2.05	0.0034	-0.0053	-2.09
	(0.0147)	(0.0161)		(0.0028)	(0.0031)	
-1	-0.0155	0.0396	2.59	0.0107	0.0001	-2.61
	(0.0142)	(0.0158)		(0.0027)	(0.0030)	
0	-0.0300	0.0439	3.64	0.0144	0.0081	-1.62
	(0.0132)	(0.0154)		(0.0025)	(0.0029)	
1	-0.0339	0.0870	5.88	0.0121	0.0043	-1.99
	(0.0135)	(0.0155)		(0.0026)	(0.0030)	
2	-0.0280	0.1096	6.54	0.0077	-0.0071	-3.66
	(0.0140)	(0.0157)		(0.0027)	(0.0030)	
3	-0.0352	0.0967	6.22	0.0058	-0.0086	-3.54
	(0.0141)	(0.0158)		(0.0027)	(0.0030)	
4	-0.0321	0.1110	6.73	0.0056	-0.0111	-4.11
	(0.0143)	(0.0158)		(0.0028)	(0.0030)	
5	-0.0149	0.0896	4.89	0.0049	-0.0076	-3.06
	(0.0143)	(0.0159)		(0.0028)	(0.0030)	

Table 3: Lagged Trade Reaction

This table presents regression coefficients from estimation of the equation

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

The dependant variable is abnormal trade imbalance. For the period (*x, y*), abnormal trade imbalance is summed over the trading days that are least *x* and at most *y* trading days after the earnings announcement. The sample is limited to earnings announcements with $N \in \{0,1\}$. "t-stat for equality" tests the significance of the difference between the coefficients for small and large traders. Standard errors are in parentheses.

	α^L	α^S	t-stat for equality	β^L	β^S	t-stat for equality
(0, 20)	-0.1307	0.6177	7.60	0.0667	-0.0104	-3.98
	(0.0629)	(0.0757)		(0.0124)	(0.0149)	
(21, 41)	-0.1119	-0.1011	0.11	0.0052	0.0008	-0.23
	(0.0613)	(0.0745)		(0.0120)	(0.0146)	
(42, 62)	0.0016	0.2778	2.83	0.0213	-0.0025	-1.24
	(0.0624)	(0.0752)		(0.0122)	(0.0148)	
(63, 83)	0.2121	0.2266	0.15	-0.0088	0.0518	3.17
	(0.0622)	(0.0749)		(0.0122)	(0.0147)	
(84, 104)	-0.1029	-0.4080	-3.16	0.0113	0.0630	2.73
	(0.0612)	(0.0745)		(0.0120)	(0.0146)	
(105, 125)	0.0844	-0.0120	-0.99	-0.0014	0.0450	2.43
	(0.0622)	(0.0746)		(0.0122)	(0.0147)	
(126, 146)	0.2737	0.2121	-0.63	-0.0128	0.0546	3.52
	(0.0624)	(0.0748)		(0.0123)	(0.0147)	
(147, 167)	-0.0095	-0.2758	-2.75	-0.0177	0.0315	2.58
	(0.0615)	(0.0749)		(0.0121)	(0.0147)	
(168, 188)	0.0185	-0.0042	-0.23	0.0123	0.0393	1.40
	(0.0622)	(0.0754)		(0.0122)	(0.0148)	
(189, 209)	0.0995	0.2843	1.88	0.0119	0.0237	0.61
	(0.0627)	(0.0756)		(0.0123)	(0.0149)	
(210, 230)	-0.1409	-0.4744	-3.43	0.0156	0.0759	3.15
	(0.0619)	(0.0752)		(0.0122)	(0.0148)	
(231, 251)	-0.0231	0.0620	0.86	0.0083	0.0345	1.35
	(0.0632)	(0.0759)		(0.0124)	(0.0149)	

Table 4: Lagged Trade Reaction Differences – Robustness Checks

This table presents differences between small and large trade regression coefficients, from estimation of the equation

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

The dependant variable is abnormal trade imbalance. For the period (*x, y*), abnormal trade imbalance is summed over the trading days that are least *x* and at most *y* trading days after the earnings announcement. The sample is limited to earnings announcements with $N \in \{0,1\}$. Standard errors are in parentheses.

Column Headings:

SUE: No Drift – presents results using a version of the SUE surprise measure calculated assuming drift equals 0.

Analyst-Based – presents results using earnings surprises based on monthly analyst forecast consensus.

Return Controls – presents results using the standard SUE with drift measure of surprise, and abnormal trade imbalance which has been adjusted for prior returns, that is the adjusted abnormal trade imbalance measure is taken as the residual of an OLS regression of abnormal trade imbalance on cumulative abnormal returns for the periods: [-1], [-5, -2], [-20, -6], [-60, -21] in event time trading days.

Alternate Imb. – presents results using the alternate abnormal trade imbalance measure, which is adjusted for calendar-time effects and prior values of trade imbalance and returns.

	SUE: No Drift		Analyst-Based		Return Control		Alternate Imb.	
	$\alpha^S - \alpha^L$	$\beta^S - \beta^L$	$\alpha^S - \alpha^L$	$\beta^S - \beta^L$	$\alpha^S - \alpha^L$	$\beta^S - \beta^L$	$\alpha^S - \alpha^L$	$\beta^S - \beta^L$
(0, 20)	0.6333	-0.0550	1.3907	-0.2335	0.4351	-0.0252	0.2551	-0.0313
	(0.0992)	(0.0196)	(0.1332)	(0.0258)	(0.0957)	(0.0188)	(0.0567)	(0.0111)
(21, 41)	-0.1782	0.0319	0.6283	-0.1202	-0.2083	0.0260	0.1577	-0.0229
	(0.0978)	(0.0194)	(0.1309)	(0.0254)	(0.0943)	(0.0185)	(0.0561)	(0.0110)
(42, 62)	0.2075	-0.0103	0.4827	-0.0867	0.0457	0.0053	0.0165	-0.0063
	(0.0987)	(0.0196)	(0.1334)	(0.0259)	(0.0954)	(0.0187)	(0.0550)	(0.0108)
(63, 83)	-0.0504	0.0745	-0.0132	0.0255	-0.1051	0.0647	-0.0481	0.0170
	(0.0986)	(0.0195)	(0.1335)	(0.0259)	(0.0949)	(0.0186)	(0.0559)	(0.0110)
(84, 104)	-0.4711	0.0884	-0.3017	0.0597	-0.4079	0.0542	-0.0134	0.0039
	(0.0978)	(0.0194)	(0.1328)	(0.0258)	(0.0942)	(0.0185)	(0.0562)	(0.0110)
(105, 125)	-0.0780	0.0462	-0.2338	0.0607	-0.2105	0.0441	-0.0897	0.0157
	(0.0988)	(0.0196)	(0.1342)	(0.0260)	(0.0947)	(0.0186)	(0.0548)	(0.0108)
(126, 146)	-0.0915	0.0655	-0.1837	0.0658	-0.1559	0.0697	-0.0795	0.0240
	(0.0998)	(0.0198)	(0.1357)	(0.0263)	(0.0950)	(0.0187)	(0.0557)	(0.0110)
(147, 167)	-0.3607	0.0736	-0.4159	0.0913	-0.3589	0.0508	-0.0938	0.0220
	(0.0994)	(0.0197)	(0.1360)	(0.0264)	(0.0949)	(0.0186)	(0.0564)	(0.0111)
(168, 188)	-0.1023	0.0371	-0.1805	0.0479	-0.1326	0.0274	-0.1312	0.0247
	(0.1008)	(0.0200)	(0.1371)	(0.0265)	(0.0953)	(0.0187)	(0.0551)	(0.0108)
(189, 209)	0.0932	0.0218	-0.0849	0.0206	0.0753	0.0157	-0.0217	0.0098
	(0.1021)	(0.0202)	(0.1409)	(0.0273)	(0.0958)	(0.0188)	(0.0561)	(0.0110)
(210, 230)	-0.3883	0.0541	-0.2368	0.0322	-0.4140	0.0609	-0.1817	0.0366
	(0.1021)	(0.0202)	(0.1389)	(0.0269)	(0.0953)	(0.0188)	(0.0566)	(0.0112)
(231, 251)	0.1144	0.0044	0.0652	-0.0015	-0.0362	0.0266	-0.0534	0.0068
	(0.1039)	(0.0206)	(0.1417)	(0.0275)	(0.0964)	(0.0190)	(0.0556)	(0.0110)

Table 5: Relationship Between Small and Large Trades and Future Returns

Results for βS from regressions of the form:

$$CAR_{(t_1,t_2),e} = \alpha^{Pos} + \alpha^{Mild} + \alpha^{Neg} + \beta S^{Pos} * S_e * \mathrm{I}(SurpDec_e \in \{7,8,9\}) + \beta S^{Mild} * S_e * \mathrm{I}(SurpDec_e \in \{3,4,5,6\}) + \beta S^{Neg} * S_e * \mathrm{I}(SurpDec_e \in \{0,1,2\}) + \beta L^{Pos} * L_e * \mathrm{I}(SurpDec_e \in \{7,8,9\}) + \beta L^{Mild} * L_e * \mathrm{I}(SurpDec_e \in \{3,4,5,6\}) + \beta L^{Neg} * L_e * \mathrm{I}(SurpDec_e \in \{0,1,2\}) + \varepsilon_e$$

where S_e is the event-time small trade imbalance for event e and L_e is the event-time large trade imbalance for event e, event-time measured over days –1, 0 and 1. A small trade is one of value less than $5,000 and a large trade has a value of at least $50,000. Standard errors in parentheses. The sample contains the full set of earnings surprises for NYSE common stocks with all required data available.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level, using 1-tailed tests

	Small trades			Large trades		
(t_1,t_2)	positive surprise	mild surprise	negative surprise	positive surprise	mild surprise	negative surprise
(-1,1)	0.0016	0.0019	0.0025	0.0078	0.0074	0.0074
	(0.0003)***	(0.0003)***	(0.0003)***	(0.0003)***	(0.0003)***	(0.0003)***
(2,5)	0.0003	0.0003	0.0008	0.0000	-0.0002	-0.0009
	(0.0002)*	(0.0002)*	(0.0002)***	(0.0002)	(0.0002)	(0.0003)***
(6,20)	0.0004	0.0009	0.0006	-0.0011	-0.0001	-0.0009
	(0.0004)	(0.0004)**	(0.0004)*	(0.0004)***	(0.0004)	(0.0004)**
(21, 40)	-0.0010	-0.0006	-0.0005	-0.0013	0.0000	-0.0013
	(0.0005)**	(0.0005)	(0.0005)	(0.0005)***	(0.0005)	(0.0006)**
(41, 60)	-0.0010	-0.0005	-0.0006	-0.0013	-0.0006	0.0000
	(0.0005)**	(0.0005)	(0.0005)	(0.0005)***	(0.0005)	(0.0006)
(61, 120)	-0.0002	0.0003	-0.0020	-0.0025	-0.0023	-0.0016
	(0.0009)	(0.0008)	(0.0009)**	(0.0010)***	(0.0009)***	(0.0010)*
(121, 180)	-0.0003	-0.0004	-0.0011	-0.0015	-0.0008	0.0003
	(0.0009)	(0.0008)	(0.0010)	(0.0010)*	(0.0009)	(0.0010)

Figure 1: Trade Reaction to Earnings Surprises – Full Sample

Days –1, 0 and 1 in event-time are included in the event-period. Small trades are trades with a value of less than $5,000 and large trades are trades with a value of at least $50,000. Decile 0 earnings surprises are the most negative earnings surprises, and decile 9 are the most positive.

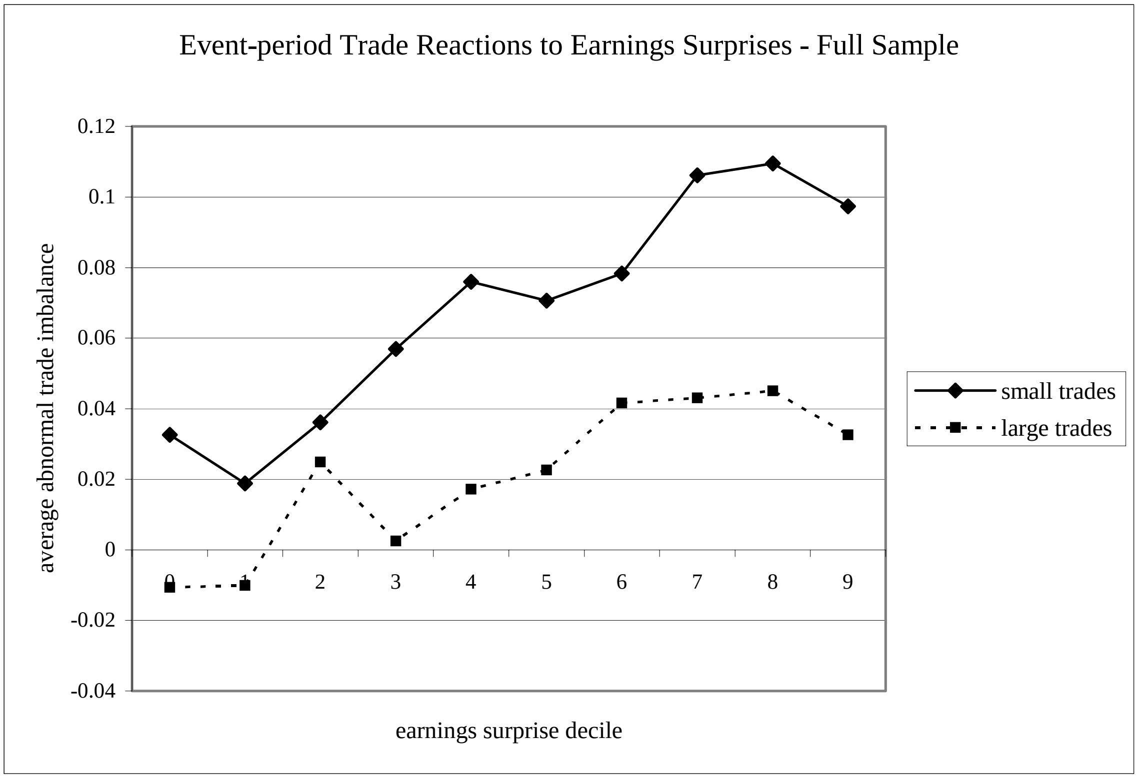


Figure 2: Trade Reaction to Earnings Surprises – N$\in${0,1} Subsample

Days –1, 0 and 1 in event-time are included in the event-period. Small trades are trades with a value of less than $5,000 and large trades are trades with a value of at least $50,000. Decile 0 earnings surprises are the most negative earnings surprises, and decile 9 are the most positive. The earnings surprise sample is constrained to include N=0 or N=1 surprises; earnings announcements that are either mild surprises (deciles 4, 5, 6, 7, N=0) or that are different from the type of preceding surprises (negative surprise following positive or mild, positive surprise following negative or mild).

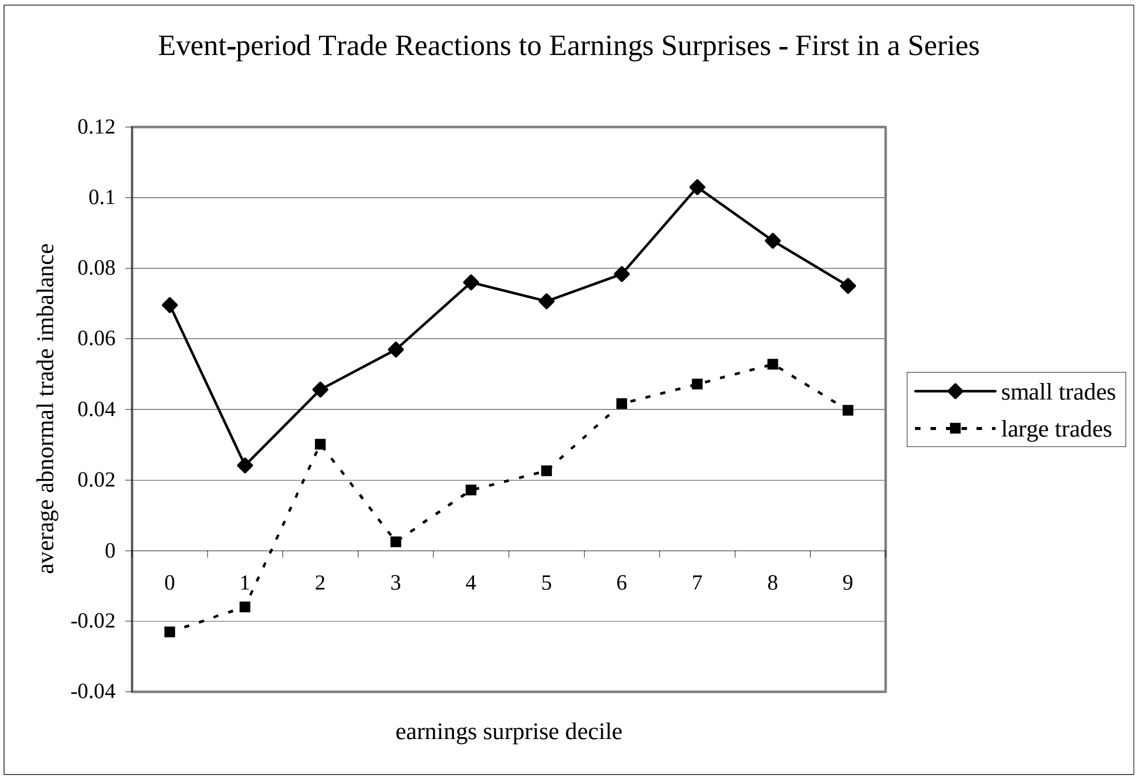


Figure 3: Lagged Trade Reaction – N $\in$ {0,1} Subsample

Results from regressions of abnormal trade imbalance on a constant and earnings surprise decile, interacted with trade size group, where small trades are trades of less than $5,000 and large trades are trades of at least $50,000. N=0 indicates that the earnings surprise is a mild surprise, N>0 indicates the placement of a positive or negative surprise in a series of similar surprises; N=1 indicates that it is the first, N=2 the second and so on. In this figure, the earnings samples is limited to earnings announcements with N $\in$ {0,1}. The figure displays the slope coefficient from the regressions, estimated for a five-day interval surrounding each trading day in event time, from day -10 through 500.

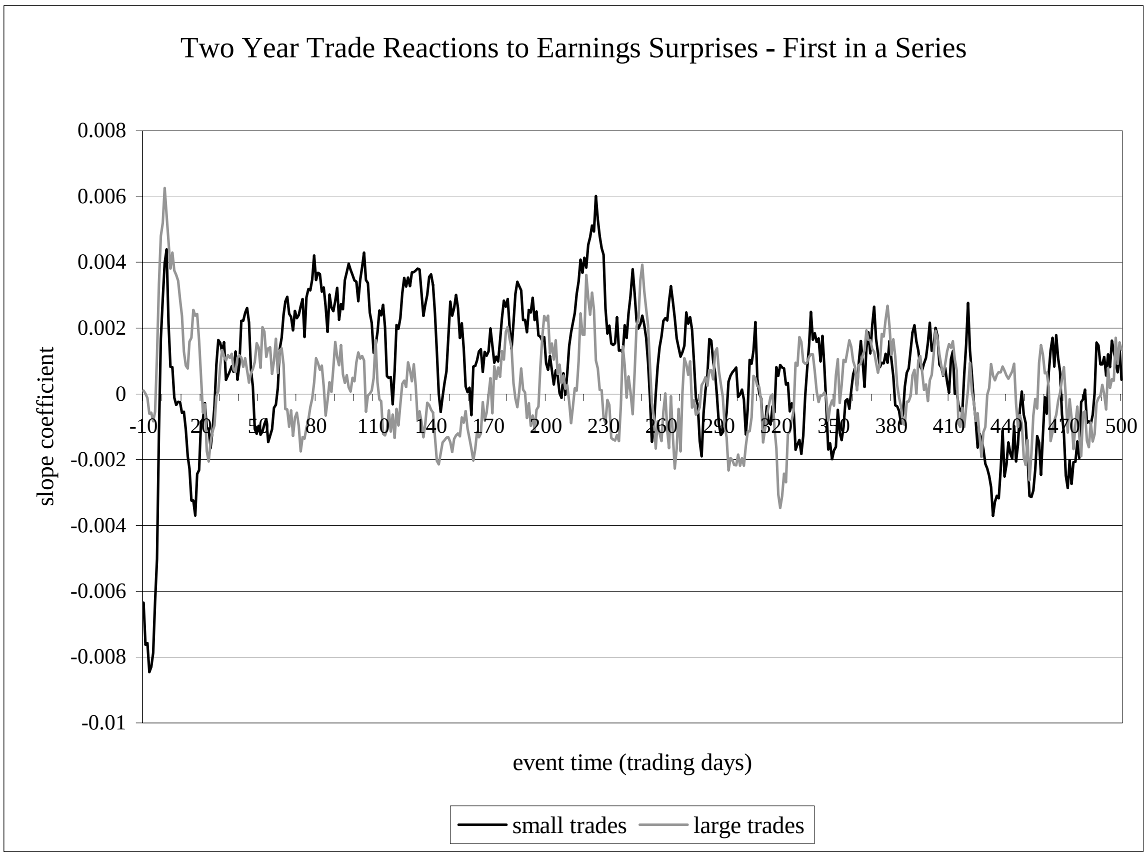
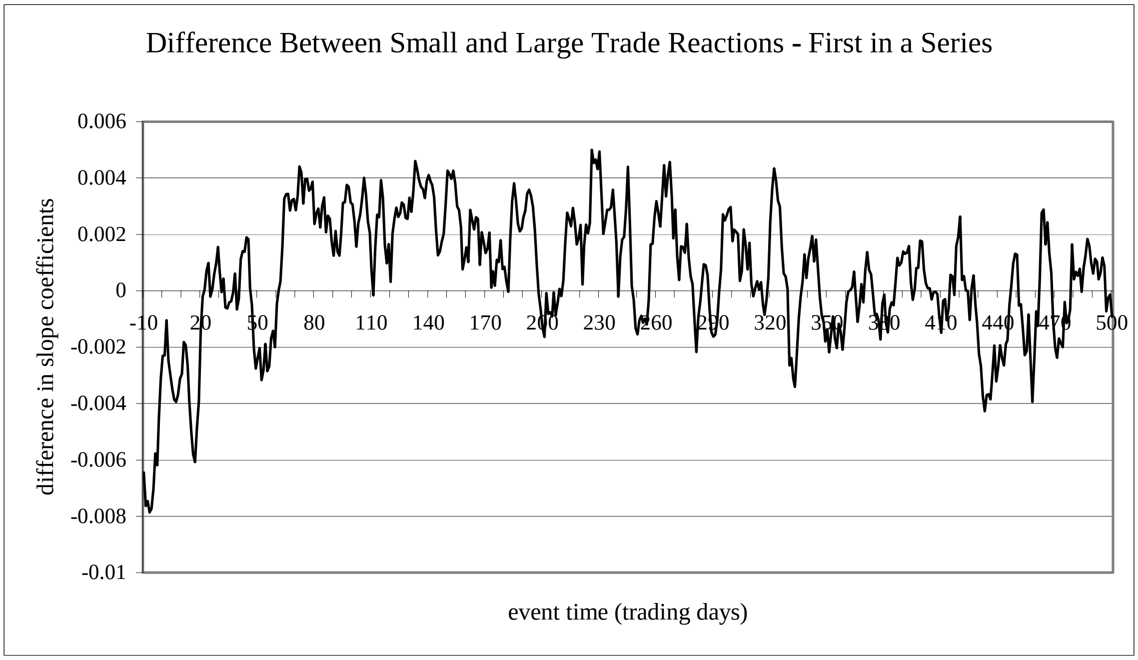


Figure 4: Lagged Trade Reaction Differences – N $\in$ {0,1} Subsample

Results from regressions of abnormal trade imbalance on a constant and earnings surprise decile, interacted with trade size group, where small trades are trades of less than $5,000 and large trades are trades of at least $50,000. N=0 indicates that the earnings surprise is a mild surprise, N>0 indicates the placement of a positive or negative surprise in a series of similar surprises; N=1 indicates that it is the first, N=2 the second and so on. In these figures, the earnings sample is limited to earnings announcements with N $\in$ {0,1}.

4A: Difference in Slope Coefficient: $\beta^S - \beta^L$



4B: Significance of Difference in Slope Coefficient: $\beta^S - \beta^L$