Consecutive Earnings Surprises: Small and Large Trader Reactions

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Abstract

Prior research demonstrates that investors respond differently to earnings surprises that occur as part of a string than to those that do not but is inconclusive about why the market ascribes such importance to these earnings patterns. To shed light on this question, I compare the trading responses of small traders, whom prior research has shown to be relatively naïve, and large traders, whom prior research has shown to be more sophisticated, to earnings surprises that occur during strings of either positive or negative surprises. I find that the intensity of small traders' buying (selling) activity in response to positive (negative) earnings surprise strings is positively related to the length of the string. That is, small traders initiate more purchases (sales) in response to positive (negative) earnings surprises that occur later in a string than to similar surprises that occur earlier in the string. In contrast, the intensity of large traders' buying and selling activity in response to earnings surprises that occur as part of a string is independent of the length of the string. Moreover, I find that announcement period returns are related to the behavior of small traders. These results suggest that less sophisticated investors' sensitivity to earnings patterns is a cause of previously documented pricing patterns for earnings surprise strings.

Keywords: earnings string, earnings momentum, trade imbalance, small and large trade

Data Availability: All data used in this study, with the exception of data obtained from an anonymous discount brokerage firm, are publicly available from the sources indicated in the text.

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I. INTRODUCTION

Prior research demonstrates that investors respond differently to earnings surprises that occur as part of a string than to those that do not, but is inconclusive about why the market ascribes such importance to these earnings patterns. In particular, Barth, Elliott and Finn (1999) find that firms with patterns of increasing earnings have higher return reactions to the earnings surprises and higher price-earnings multiples as the pattern progresses relative to other firms. To shed light on the cause, I compare the trading responses of investors who make large trades (large traders), whom prior research has shown to be sophisticated, and investors who make small trades (small traders), whom prior research has shown to be relatively naïve, to earnings surprises that occur during strings of either positive or negative surprises. Since the two classes of investors differ systematically in sophistication but not in risk preferences, differences in their responses to earnings strings shed light on whether mispricing or risk-based explanations are more likely. To provide direct evidence on whether small investors drive the market response to earnings strings, I also examine whether small trading patterns are associated with the stock returns surrounding the announcement of earnings surprises that occur as part of a string.

I test for differences in small and large trader responses to patterns in earnings growth and earnings surprises (both based on random-walk models and analyst forecasts). To measure investor reactions, I use New York Stock Exchange Trades and Quotations (TAQ) data. Following prior literature, I split trades based on the dollar value of the trade, and calculate measures of trade-initiation using the Lee-Ready algorithm. This measure captures the direction (buy vs. sell) of the reaction.[1] I examine each trade group's level of reaction to "strings" of consecutive increases in seasonally-adjusted quarterly earnings. I find that small traders buy more intensely as a string of earnings increases lengthens while large traders' buying and selling activity does not depend on the length of the string. These inferences hold when I focus on sequences of "strong positive" and "strong negative" surprises (defined to be in the top 30% and bottom 30% of earnings surprises) and when I define strings based on analyst-based earnings surprises. Small traders buy (sell) more strongly as a sequence of positive (negative) surprises lengthens, while large traders do not.

I relate small trade imbalances to concurrent returns around the earnings announcement, to verify that small trade imbalances are associated with returns, and find a strongly significant

[1] Lee and Ready (1992) develops the method and Lee and Radhakrishna (2000) and Odders-White (2000) test the accuracy of the buy/sell classification and the separation of individual and institutional investors.

positive relation between small trades and the overall return response, even after controlling for large trades and the earnings surprise level. This positive association between the small trade response and concurrent returns remains significant throughout the earnings surprise series.

Together, these results suggest, first, that small traders have a preference for consistent performance, while large traders do not value consistency as highly. Second, the results suggest that "earnings momentum" trading is a cause of the return patterns documented in Barth, Elliott and Finn (1999), Kasznik and McNichols (2002), and Myers, Myers and Skinner (2007). These results contribute to our understanding of the market response to earnings patterns by providing evidence that small traders influence the market response to consistent patterns in earnings growth and earnings surprises.

This study contributes to the literature by providing evidence of whether it is less sophisticated small traders who react positively to earnings consistency or whether more sophisticated large traders value consistency as well. Bhattacharya (2001) and Battalio and Mendenhall (2005) increase our understanding of post-earnings-announcement drift by showing that it is small traders who respond most strongly to random-walk-based earnings surprises. This study increases our understanding of the market reactions to the time-series-pattern in earnings by building on the literature started by Bhattacharya (2001), extending the literature to examine small and large trade reactions to earnings time-series-patterns, and documenting significant trade response variations related to these patterns.

Prior work that examines market responses to earnings patterns has focused on returns-based tests (e.g. Barth, Elliott and Finn 1999; Kasznik and McNichols 2002; Myers, Myers and Skinner 2007). This study's direct examination of trading patterns of small and large investors has the advantage of using each firm as its own control, assessing how different investors respond to the same announcement rather than comparing one set of firms with an unavoidably imperfect control sample. This research design increases our understanding of the market response, suggesting that "earnings-momentum" trading of unsophisticated investors is an important cause, and complementing the prior studies. .

The paper proceeds as follows. Section II describes the hypothesis development and related literature. Section III explains the empirical methods and data used in this paper, including the data and methods used to measure earnings surprises and trade reactions. Section IV presents results and Section V presents robustness checks. Section VI concludes.

II. HYPOTHESIS DEVELOPMENT

Barth, Elliott and Finn (1999), Kasznik and McNichols (2002), Myers, Myers and Skinner (2007) and Lev, Ryan and Wu (2008) examine pricing multiples and stock returns related to patterns of consistent earnings increases or consistently positive earnings surprises, while Frieder (2008) investigates aggregate trade imbalances. All of these papers suggest that the market values consistent earnings patterns.

However it is not clear what drives the market premium for consistency. Barth, Elliott and Finn (1999) comment that they cannot identify the cause of the price/returns pattern and suggest several possible explanations, falling into two primary categories: (1) Earnings patterns may capture dimensions of growth or risk that the usual proxies for these variables do not capture, or (2) there may be an element of mispricing due to "earnings momentum" trading. Examination of the trading patterns of investors that differ in sophistication but not in risk preferences can potentially shed light on which explanation is more likely. Specifically, if sophisticated and naïve investors react similarly to earnings surprise strings then mispricing becomes a less likely explanation for systematic return responses to such strings. On the other hand, if the two classes of investors differ in their response then it is more likely that information processing biases of the less sophisticated subset of investors are driving the result. The mispricing explanation becomes even more likely if the response of the unsophisticated group is most consistent with observed return patterns.

In this study, I use trade size to proxy for investor sophistication, with small trades likely arising from naïve investors, such as individuals trading on their own accounts, and large trades arising from more sophisticated investors, such as professional money managers. A large body of work has empirically documented differences in small- and large-trader behavior. The evidence from this literature suggests that large traders make superior trading decisions relative to small traders. Large traders' better information sets and their greater skill are the primary explanations for their superior trades.

Investors making larger trades will invest more in information acquisition and information processing, as fixed information costs are employed to earn a larger dollar return. The reverse causality would also drive a positive association; an investor with better information is likely to make a larger trade to exploit that information. Easley and O'Hara (1987) develop a theoretical model predicting that larger trades will incorporate more information and Hasbrouck (1988, 1991) provides empirical evidence suggesting that larger trades contain more information.

Large trades are likely to be made by institutional investors and investors who receive advice from professional investment advisors. Professional investors' and advisors' training and resources allow them to make more sophisticated trading decisions. Experimental researchers have tested for differences between nonprofessional and professional judgments in several accounting and finance contexts, finding evidence suggesting that professionals are more successful in avoiding behavioral biases (Smith and Kida 1991; Frederickson and Miller 2004).

Finally, a growing body of empirical work finds that small traders consistently make less sophisticated trading decisions than large traders. Bhattacharya (2001), Battalio and Mendenhall (2005) and Lee (1992) examine small and large trades, while Hirshleifer, Myers, Myers and Teoh (2008) look at individual brokerage account trading. All of these papers find that small traders buy for earnings announcements, even if the earnings surprise is negative. Bhattacharya (2001) and Battalio and Mendenhall (2005) find that small traders rely more strongly on a seasonal random-walk model to form their earnings expectations than on analyst expectations, even though analyst expectations impound more information. Bhattacharya, Black, Christensen and Mergenthaler (2007) find differences between small and large trading surrounding pro-forma earnings announcements. Malmendier and Shanthikumar (2007a, 2007b), using the same trade data as this paper, and Mikhail, Walther and Willis (2007) find that small investors react more naively to analyst recommendations and earnings forecasts than large traders.

In all of these settings, the results are consistent with small traders displaying less sophistication and using less information in their trading decisions than large traders. If the previously documented return differences are an overreaction due to "earnings momentum" trading, I predict that less sophisticated small investors display the strongest preference for these patterns. Simply put, if the market is reacting incorrectly, it is most likely the small traders who are making the strongest mistake. In this case, small traders buy more strongly when a firm has announced several positive surprises in a row, than when a firm announces a single positive surprise, and more negatively when a firm has announced several negative surprises in a row. They react more strongly (buying or selling more) as a string progresses, relative to large traders.[2]

[2] It is important to note that the predictions for small and large traders are relative predictions. It may be the case that even large traders "prefer consistency." However I argue that if the preference for consistency

If the return differences are due to risk factors, I posit that small traders will not react more strongly as a string progresses, relative to large traders. The previous empirical and theoretical literature all point to small traders behaving more naively than large traders, however the literature has yet to discover systematic differences in risk preferences. As Lee (1992) discusses, prior literature shows that individual investor have larger holdings in certain high-risk stocks, such as small firms and over-the-counter stocks, however they also have larger holdings in certain extremely low-risk stocks such as utilities (Lee, Shleifer and Thaler 1991). Barsky, Juster, Kimball and Shapiro (1997) elicit risk preferences from over 11,000 respondents and find no systematic relationship between elicited risk preferences and respondents' wealth or education. More recently, Brunnermeier and Nagel (2006) find that the share of households' liquid assets in risky assets does not vary with changes in their wealth, suggesting that individuals' risk aversion remains steady as wealth changes. Finally, although prior literature has shown that mutual funds with incentive fees exhibit higher risk taking on average, it has shown that the effect depends on prior returns; incentive fees increase risk-taking by losers but decrease risk-taking by winners (Elton, Gruber and Blake 2003). And it is not clear how the risk aversion displayed by mutual fund managers (with or without incentive fees) compares to that of individuals.

To see why large traders will react at least as strongly as small traders if returns are due to changes in risk or growth, consider two possibilities for price-adjustment concurrent with changes in risk. First, consider the case where prices adjust immediately to the change in risk signaled by the earnings pattern. In this case, there is no reason for large traders to react any more weakly or strongly than small traders; both groups hold stocks that are priced correctly given their risk. Second, consider the case where there is some friction in price-adjustment and prices do not adjust immediately; for example after a positive string prices do not increase as much as they should to match the decrease in risk. The better informed and more sophisticated large traders will react more strongly to the later earnings surprise, as they better understand the changes in risk and expected growth of the firm. By buying the lower-risk stock at a discount, they can earn abnormal returns until prices reach equilibrium levels.

is based on behavioral factors, small traders will exhibit a *stronger* preference. Given that it is almost impossible to determine the correct trade response, I use large traders as the benchmark for testing small trade behavior.

I test these competing explanations by examining strings of quarters with increases (or decreases) in seasonally-adjusted earnings.[3] This provides preliminary evidence on small- and large-trader reactions to the time-series of earnings information. I state the hypothesis predicted by earnings-momentum trading:

> **H1a:** Small traders buy more strongly as a sequence of increases in seasonally-adjusted quarterly earnings progresses, and sell more strongly for a sequence of decreases, relative to large traders.

A focus on earnings increases or decreases has some limitations. An investor's preference for a string of positive earnings increases may be due either to that investor's preference for sequences of positive performance, or to the investor's failure to understand the nature of a "true surprise," i.e. investors reacting too strongly to small positive changes in earnings. For example, if I find that small traders react more strongly to a string than large traders, it could be that both groups prefer consistent performance, but small traders view a one cent earnings increase as a surprise and large traders do not.

In contrast, earnings surprises, relative to a measure of earnings expectations, are likely to be viewed as true earnings surprises by *both* investor groups. In particular, I examine reactions to a series of strongly positive (top 30% of surprises) or strongly negative (bottom 30%) earnings surprises, excluding the middle 40% as these are more likely to have mixed interpretations as surprising or not surprising. I use both a random-walk earnings expectations model and analyst-based expectations. This is consistent with the large literature on "meeting or beating earnings expectations," including Matsumoto (2002), Brown and Caylor (2005), and Graham, Harvey and Rajgopal (2005), among others.

In addition, examining earnings surprises naturally allows a focus on an earnings-response-coefficient measure, rather than focusing on "positive" and "negative" series separately. In particular, I focus on the "slope" of the trading reaction relative to the earnings surprise level – i.e. the strength of the trader reaction to the information content of the earnings surprise. This approach allows me to capture sensitivity to earnings information as a series continues, rather

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[3] This pattern is similar to the one examined in Barth, Elliott and Finn (1999), which focuses on consistent increases and decreases in annual earnings and Myers, Myers and Skinner (2007), which focuses on firms with 20 consecutive quarters of increasing seasonally-adjusted earnings. Ke, Huddart and Petroni (2003) and Ke and Petroni (2004) exploit breaks in these types of earnings strings to test the use and dissemination of insider information among insiders and active institutional investors prior to the break, but neither examine trading and returns during the formation of the string.

than simply a level reaction. This removes the possible confounding effects of variation in the extremity of earnings surprises as a series continues, and possible variation in the level of investor "attention effect" buying.[4]

Focusing on earnings surprise series, and an earnings-response-coefficient measure, the predictions are still similar: if the price premium on consistent earnings performers is due to investor overreaction, small traders will react more strongly as a series of surprises continues, as compared to large traders. If the premium is due to risk or growth differences, I should find either a similar reaction or a stronger increasing reaction pattern from large traders. This leads to a second hypothesis, predicted if there is earnings-momentum trading:

H1b: Small traders' buying and selling is more sensitive to earnings surprise information (they react more strongly) as a sequence of similar earnings surprises continues, relative to large traders.

The final test examines the impact of small trades on the market response to earnings announcements in a series. Recent research has found that trading by retail investors or small traders is correlated both across investors and across securities. Because of this, the trades of even very small investors can have a significant impact on the market. De Long, Shleifer, Summers and Waldmann (1990) develop a model of noise trading in which correlated noise trading affects market prices even with sophisticated investors in the market. Baker and Wurgler (2006) show the effect of investor sentiment on stock returns. Kumar and Lee (2006) show that retail investor trades explain return comovements across securities. Finally, Barber, Odean and Zhu (2006) show that the trading of small investors in individual stocks has predictive power for the future returns of those stocks. However, the affect of small investors will vary across firms and over time. Bhattacharya (2001) and Battalio and Mendenhall (2005) show that small traders react most strongly to seasonal-random-walk-based earnings surprises, however Hirshleifer, Myers, Myers and Teoh (2008) show that retail investors are not fully responsible for post earnings announcement drift, highlighting the importance of testing for a direct relationship between small trades and returns.

[4] See Barber and Odean (2008) for a more general study of attention effects. The purchasing behavior of small traders in response to negative surprises documented in Lee (1992), and the purchasing of individuals documented in Hirshleifer, Myers, Myers and Teoh (2008), is one possible example of an attention effect, and suggests that controlling for this effect is important when examining investor reactions to earnings announcements.

Given the prior work establishing higher market valuations for earnings surprises as a series progresses, a natural question is whether there is a direct link between small trading and the higher market valuations for these later surprises. Thus, the third hypothesis is:

> **H2a:** There is a positive relation between small trades and the concurrent market return reaction to earnings announcements.

We may further expect that, since small traders exhibit a stronger sensitivity to earnings series patterns than large traders, small trades may have a larger influence on price as a series progresses. Thus, I also test:

> **H2b:** The relation between small trades and concurrent market return reactions to earnings announcements is increasing in the length of a string of similar earnings surprises.

It is important to note, however, that a stronger trade-return relationship for earnings surprises later in a series is not necessary for small traders to have a significant impact on prices: As long as small traders have a positive impact on price, their increasingly strong reactions would help to drive the increasing market response documented in prior literature.

III. DATA AND RESEARCH DESIGN

The sample covers common stock securities trading on the New York Stock Exchange between January 1, 1993 and December 31, 2002. Certificates and depository receipts, foreign companies, Americus trust components, closed-end fund shares and Real Estate Investment Trusts are excluded, corresponding to including securities with a Center for Research in Security Prices (CRSP) share code of 10 or 11. The final sample includes 2,801 securities for 2,723 firms. I obtain returns data from CRSP, earnings announcements and firm characteristics from Compustat, and analyst earnings forecasts from the Institutional Brokers Estimates System (IBES). I calculate trading measures from the New York Stock Exchange Trades and Quotations (TAQ) database and use data on individual accounts with a large discount brokerage firm to evaluate the TAQ-based data.

Measuring earnings surprise events

I extract quarterly earnings announcement dates from Compustat. Hughes and Ricks (1987) report that, with their sample of 677 annual earnings announcements for the years 1979-1981, the Compustat date is accurate 75% of the time. They do not describe the errors for the other 25% of the cases. To ensure that the Compustat report date will give accurate event dates for our sample, I randomly select 125 stock-quarter combinations between 1993 and 2001. I compare the Compustat earnings announcement date with the first report date found in the Dow Jones News Service (DJNS) and Wall Street Journal (WSJ). In each case, the Dow Jones News Service reported before the Wall Street Journal. In the random sub-sample, eight earnings announcements do not appear in the DJNS Index or the WSJ. Four of these lack earnings announcement dates in Compustat. Six announcements lack dates in Compustat but are available in the DJNS Index. Among the remaining 117 announcements, the dates are the same in 79.5% of the cases. In the cases where the dates differ, the Compustat date is usually one day after the DJNS report date, corresponding with the Wall Street Journal report date. There are only 3 cases, 2.6% of the sample, in which the dates differ by more than 1 day, and only 1 case where they differ by more than 2 business days.

If an announcement is made on a holiday or weekend, I use the first trading day after the announcement date as the event date. I limit the sample to earnings announcements falling in the years 1993 through 2002, due to constraints related to the trade data. TAQ data is only available beginning in 1993, and the trade identification methods are likely to be problematic after 2002, as discussed in Malmendier and Shanthikumar (2007a), and as I describe in the subsection labeled "Measuring Small and Large Trading" below. The final sample contains 59,658 earnings announcements, for the main earnings surprise measure.

Prior literature typically uses measures of earnings surprise based on prior earnings, analyst forecasts of earnings, or stock returns around the announcement date. Alternatively, rather than using earnings "surprises," some prior work focuses on earnings increases and decreases. I use increases and decreases for initial trade reaction tests. However, the primary measure for this paper is the earnings surprise, defined using two alternate methods, as defined below. The main measure is standardized unexpected earnings, commonly used in the post-earnings-announcement drift literature. This measure allows for adjustment for market expectations without constraining the sample to those firms with active analyst coverage. This is particularly important when we consider that large trades might dominate the generally larger and higher institutional-ownership firms that have analyst coverage.

In order to calculate standardized unexpected earnings (SUE), I assume that earnings expectations are based on a seasonal random walk model, with drift.[5] I define expected earnings as

$$E\left(e_t^i\right) = e_{t-4}^i + \delta^i \ , \tag{1}$$

where δ^i is the earnings drift for firm *i*. For each stock, I estimate drift using up to twenty quarters of previous data, as

$$\hat{\delta}^i = \frac{1}{n}\sum_{j=1}^{n}\left(e_{t-j}^i - e_{t-j-4}^i\right) , \tag{2}$$

where n ≤ 16. I use less data if the full period is not available, although at least one year of data is required. This introduces a slight survivorship bias into the sample, but it eliminates only 5.34% percent of the earnings announcements and 2.97% of firms. I then standardize the unexpected earnings measure by dividing each firm surprise by the standard deviation of that firm's earnings, as measured by the available subset of the preceding 20 announcements.[6] The primary measure is as follows:

$$SUE_t^i = \frac{e_t^i - e_{t-4}^i - \hat{\delta}^i}{\sqrt{Var(e_t^i)}} \ , \tag{3}$$

where $Var(e_t)$ is estimated using the previous 20 announcements. Finally, I rank earnings announcements by SUE within each year, and place them into deciles 0-9, where the most negative surprises are in decile 0 and the most positive in decile 9.

I also use an alternate measure of earnings surprises based on analyst forecasts. The surprise is defined as the difference between announced earnings-per-share and the analyst forecast, normalized by stock price as of the forecast consensus date. The IBES analyst forecast database provides a sample size in the tens of thousands, but the limits on analyst coverage still reduce the sample size by almost one half. Thus the analyst-based surprise measure is used as a robustness check rather than as the primary measure. I use two measures of the consensus

[5] I also use a seasonal random walk without drift for robustness tests, and the results are robust with this variation.
[6] As a robustness check, I also normalize the unexpected earnings measure by the standard deviation of earnings changes rather than the standard deviation of earnings. Results are similar.

forecast. The first measure is based on the IBES 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 date from 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 tend to be very similar, with a correlation coefficient of 0.998. I construct a second measure of consensus using data from the IBES detail files. I define the alternate consensus measure to be the median of forecasts occurring at least one week before the earnings announcement and no more than two months before the announcement, when there are at least four earnings forecasts during that period. The sample contains 29,649 earnings announcements using the monthly consensus measure and 14,505 earnings announcements using the daily measure.

Prior literature suggests a third measure of earnings surprise is the stock return on the days surrounding the earnings announcement. Rather than measuring the difference between expected and realized earnings, this method measures the reaction to this difference, making it unsuitable for this study, as the returns will depend on the trade reactions.[7]

Defining the Earnings Surprise Series

I create a variable, labeled as S, to denote the position of a given surprise in an earnings surprise series. An earnings surprise is assigned a value of S=0 if it is a “mild surprise,” in deciles 3, 4, 5 or 6, as it is not a part of a “positive” or “negative” surprise series. A surprise is assigned a value of S=1 if it is a strongly negative surprise (deciles 0, 1 or 2) and the preceding surprise for that firm was not strongly negative, or if it is strongly positive (deciles 7,8 or 9) and the preceding surprise was not strongly positive, as it is the first surprise in a new series. The surprise has a value of S=2 if it is the second surprise of the same type, strongly negative or strongly positive, S=3 if it is the third and so on. Figure 1 provides an example for the definition of the S variable.

[7] Although the return-based measure is not ideal for the analysis in this paper, I repeat the primary tests using this surprise measure. I define the surprise to be the cumulative abnormal return over trading days –1 through 1 surrounding the earnings announcement date. This yields mixed results, with some evidence that small traders exhibit an increasing reaction, and some evidence that the trading reactions are virtually identical to the surprises regardless of prior surprise history. However, these results do not speak directly to the behavioral question at hand: How do investors react to the time-series of earnings information, and what is driving previously documented valuation patterns?

Table 1 reports sample statistics for the firms with complete data. The table displays firm size, book-to-market ratio, and standardized unexpected earnings statistics for the whole sample and subsamples based on earnings surprise S value. Table 1 indicates that only about one half of the S=1 surprises are followed by an S=2 surprise and similarly about one half of the S=2 surprises are followed by an S=3 surprise, so that each surprise in the series is in fact a surprise. The magnitudes of the standardized unexpected earnings variables do not seem to vary systematically as the series continues. One pattern that emerges from Table 1 is an apparent decrease in firm size with increasing S, but as the high standard deviation suggests, these decreases are not significant. Regression results show that the t-statistics on decreases in size are consistently less than 1. For example, while the magnitude of the firm-size decrease from S=1 to S=7 is $812 million, the standard error on that decrease is $1.16 billion.

Measuring Small and Large Trading

It is important to note that the sample is chosen specifically to ensure a robust separation of small and large trades. As in Malmendier and Shanthikumar (2007a), I restrict the sample to 1993-2002, common stock traded on the New York Stock Exchange (NYSE). Later in this section I present a validity test for my measures of small and large trade, using trading in discount retail brokerage accounts as a measure of small investor trade. Malmendier and Shanthikumar (2007a) also test these measures using institutional ownership as a measure of large investor trade and discuss some of the potential problems with these methods after 2002, including the increasing splitting of trades by institutions. A valid alternative approach would be to use NASDAQ data for 1993-1996, following Battalio and Mendenhall (2005), however the NASDAQ data would provide a smaller sample for this study. Moreover, as discussed below, the specific methods used in this paper have been tested using NYSE data, by Lee and Ready (1991), Odders-White (2000) and Lee and Radhakrishna (2000).

I collect the raw trading data 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 order to measure trading reactions, I first classify each NYSE trade as buyer or seller initiated. I use the modified Lee and Ready (1991) algorithm, recommended in Odders-White (2000), to determine which side initiated a given trade: the buy side or sell side. The algorithm involves matching a trade to the most recent quote preceding 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, it is classified based on the previous price using a "tick test"– if the trade occurs at a price that is higher (lower) than the price of the previous trade it is classified as buyer (seller) initiated. The original Lee-Ready algorithm also employs a "zero-tick" in the case that a trade is at the bid-ask midpoint and the same price as the previous trade, but this aspect of the algorithm is the most problematic. Odders-White (2000) reports that the "zero-tick" classifies only 60% of trades accurately, miss-classifying 40%, and recommends using a modified version of the Lee-Ready algorithm without the "zero-tick" test, leaving this 6% of trades unclassified. However using the original Lee-Ready algorithm for a large subsample of the data yields similar final results as the modified algorithm.

To separate small and large trades I use a set of four cutoffs: $5,000, $10,000, $20,000 and $50,000. I then aggregate the trade-by-trade data to find daily trading measures for each stock. The final dataset contains data from over 640 million trades over ten years, with each category containing a similar number of trades. 20.8% of the classified trades occur below $5,000, 16.4% between $5,000 and $10,000, 16.8% between $10,000 and $20,000, 20.4% between $20,000 and $50,000 and 25.6% above $50,000.

The analyses in the paper will focus on "small" trades of less than $5,000 or less than $20,000 and "large" trades of at least $50,000. The choice of primary cutoffs in this paper is strongly based on the evidence of Lee and Radhakrishna (2000), who analyze these sorts of methods. In particular, Lee and Radhakrishna (2000) show that dollar based cutoffs create less noise in separating individuals from institutions than share-based cutoffs. They also find that, for their three-month sample from 1990-1991, a very low cutoff such as $5,000 or less is most effective in separating out individuals. Similarly a high cutoff of $50,000, or even $100,000, is most effective in separating out institutions. There are also several other papers which use the NYSE TAQ data to judge reactions to information, with similar small/large cutoffs.[8] In more recent work, Griffin, Harris and Topaloglu (2003) find, with their more recent May 2000 through

[8] Other existing papers use the NYSE TAQ data to examine small and large trader behavior in a similar way, judging reactions to information. Lee (1992) uses a single cutoff of $10,000, with $5,000 and $20,000 as robustness checks. Hvidkjaer (2006), uses firm-size dependent cutoffs ranging from less than $5,000 to more than $30,000, maintaining a buffer zone between small and large trades. Bhattacharya (2001) uses dollar cutoffs of $5,000 and $50,000. The buy/sell classification is suited to determining reactions to information. One possible confounding effect is the desire to minimize the revelation of private information by using limit orders or splitting trades, but this should be less of a problem in the case of public information such as earnings announcements. In addition, the primary cutoff between medium and large trades is not extremely high, in this study or its predecessors, so that strategizing to minimize market impact should not be a major factor in trade-size category.

February 2001 sample of NASDAQ firms, that there is still an extremely strong relationship between trade size and trader identity. Malmendier and Shanthikumar (2007a) relate small and large trade initiation measures to quarterly changes in institutional ownership and find significant correlations in the expected directions: Small (large) trade buying is correlated with a reduction (an increase) in institutional ownership. Finally, as discussed in the following subsection, I relate the trade measures used in this paper to individual investor trading data on the trades made through retail brokerage accounts, to further validate the relationship between trade size and trader type. While this paper's aim is not specifically to discriminate between individuals and institutions, this interpretation is useful.

Calculating abnormal trading measures

The primary variable of interest used in this paper is a measure of abnormal 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*:

$$IMB_{i,x,t} = \frac{buys_{i,x,t} - sells_{i,x,t}}{buys_{i,x,t} + sells_{i,x,t}} \quad . \tag{4}$$

I then normalize this trade imbalance measure by subtracting off the non-event-time firm-year sample mean, and dividing by the non-event-time firm-year sample standard deviation, with

$$IMB_{i,x,t}^{abnormal} = \frac{IMB_{i,x,t} - E\left(IMB_{i,x,year(t)}\right)}{\sqrt{Var(IMB_{i,x,year(t)})}} . \tag{5}$$

This controls for non-event-time patterns in trading behavior. The event period that is excluded in calculating $E(IMB_{i,x,year(t)})$ 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. The exclusion is important to maintain differences in reactions to the earnings announcements as part of our abnormal imbalance measure. The normalization thus controls for systematic differences in trading behavior for different stocks, trading groups, and times, but does not correct for differences in trading reactions to the earnings surprises.[9]

Before moving to the empirical analysis, I conduct a comparison of the TAQ-based abnormal trade imbalance measure with trading from retail brokerage accounts, in order to corroborate the intuitive interpretation of the measures; namely that small trade imbalances correlate positively with individual "small investor" buying and selling. I obtain trading data from 50,000 individual accounts at a large discount brokerage firm, for the period of 1991-1996. These data describe the actual trades made by the brokerage account clients, including trades made through both market and limit orders, along with characteristics of these trades and the individuals owning the accounts. The overlapping period and firm sample reduces the brokerage firm trade data to 462,310 trades. Table 2 displays correlations between imbalance measures for these brokerage account trades and the TAQ-based abnormal trade imbalance, both aggregated to the monthly level. The correlations between small trade imbalance and individual trade imbalance are significantly positive, for number of trades, number of shares and dollar value traded, while the correlations between large trade imbalance and individual trade imbalance are significantly negative. These are the correlations I expect if small trades are more representative of individual trading and large trades are more representative of institutional trading. Similarly, Barber, Odean and Zhu (2008) find significant correlations in the proportion of trades which are "buy" trades in a large data-set of trade-initiation based on TAQ and the Institute for the Study of Securities Markets (ISSM) data, and two brokerage data sets.

IV. RESULTS

Small and Large Trade Reactions

In this section, I present results for the trading behavior of the different trade-size groups, testing H1a, reactions to earnings increase/decrease strings, and H1b, reactions to sequences of strong positive and strong negative surprises.

An earnings increase (decrease) occurs if earnings are higher (lower) than in the same quarter of the prior year. $INCREASE_1$ indicates an earnings value which is an increase in

[9] Additional variations on the abnormal trade imbalance measure are used for robustness checks and are discussed in Section V.

seasonally-adjusted earnings following a quarter with either a decrease or no change. $INCREASE_2$ indicates an increase following an $INCREASE_1$ increase, indicating that it is the second quarter in a row with an increase in seasonally-adjusted earnings. $INCREASE_3$ indicates an increase following an $INCREASE_2$ increase, and so on. $INCREASE_{\geq 7}$ indicates earnings increases which are the seventh, eighth, ninth or higher in a string of increases. $DECREASE_X$ is defined in the same way, for earnings decreases. To measure investor reactions I estimate the following regression:

$$\begin{aligned} IMB_{s,t}^{abnormal} &= \alpha_1^t INCREASE_1 + \alpha_2^t INCREASE_2 + \ldots + \alpha_6^t INCREASE_6 + \alpha_7^t INCREASE_{\geq 7} + \\ &\beta_1^t DECREASE_1 + \beta_2^t DECREASE_2 + \ldots + \beta_6^t DECREASE_6 + \beta_7^t DECREASE_{\geq 7} + \varepsilon_{s,t}, \end{aligned} \tag{9}$$

where t is the trading day in event-time and s is the specific earnings surprise. To control for potential differences in the timing of small and large trader reactions, I use the sum of abnormal trade imbalance over days -5 through 5 in event time as the dependant variable. This ensures that the trading measure will capture any pre-announcement anticipation in the week before the announcement, and any delayed response in the week after.[10]

Table 3 reports results from estimating Equation 9. Focusing first on strings of increasing earnings, the results show a significant increasing reaction on the part of small traders, that is, their reactions become more positive as this series of increases continues. The coefficients increase almost monotonically, with small traders reacting 25-50% more strongly for the fifth, sixth or seventh and higher increases in a series than for the first or second. The increase between the smallest trader reaction to the first positive surprise and the reaction to all surprises from the third on is statistically significant at the 1% level, as is the increase between the second surprise and the fifth, sixth and seventh on. In contrast, there is no consistent pattern in large traders' response to strings of earnings increases. The fourth column, labeled "Difference <5 vs. ≥50" displays results for the difference between small and large trade reaction estimates. The difference between the small trader reaction and the large trader benchmark increases monotonically from the first increase through the fifth. While small traders buy significantly less than large traders around the first earnings increase, they react weakly more positively than large traders to the second and third, and significantly more positively to the fourth and fifth.

[10] In untabulated regressions I estimate Equation 9 for a range of individual trading days surrounding the earnings announcement date, and find that results are similar using alternate event windows.

For a string of decreasing earnings, there is no obvious pattern for either group. Small traders react significantly more negatively to a *DECREASE*$_2$ or *DECREASE*$_3$ surprise than to a *DECREASE*$_1$ surprise, and significantly more negatively to a *DECREASE*$_4$ surprise than to a *DECREASE*$_1$, *DECREASE*$_2$ or *DECREASE*$_3$ surprise. Small traders also sell more strongly relative to large traders. But for decreases after the fourth, the small trader reaction becomes more positive. Of course, the sample sizes are far smaller for earnings decreases than for earnings increases, and the difference in sample sizes between positive and negative earnings change strings is larger later in the string.

Overall, these reactions seem consistent with the mispricing stories suggested by Barth, Elliott and Finn (1999) and Myers, Myers and Skinner (2007). In particular, small traders seem to value strings of earnings increases. In contrast, large traders do not appear to value these strings. If consistent earnings increases were a sign of a reduction in firm risk, I would expect both small and large traders to respond to the string pattern, with sophisticated large traders possibly reacting more strongly than small traders given their likely advantage in understanding and interpreting changes in risk. Instead, the results show small traders reacting more strongly, pointing to a behavioral preference for consistency, rather than a change in firm risk. Of course, as described in Section II, earnings strings do pose challenges to interpretation of the results. It could be that small traders explicitly prefer consistent growth, or it could be that small traders fail to adjust their earnings expectations for the previous pattern, while large traders make the appropriate adjustments to their expectations.

Hypothesis H1b focuses on series of positive earnings surprises and negative earnings surprises, controlling for likely market expectations of earnings. To test H1b I use earnings surprise measures, and estimate a model which captures the trading earnings-response-coefficient. Thus, I estimate the following regression:

$$\begin{aligned} IMB_{s,t}^{abnormal} &= \alpha_1^t \mathrm{I}(S_e = 1) + \alpha_2^t \mathrm{I}(S_e = 2) + \alpha_3^t \mathrm{I}(S_e = 3) + \alpha_4^t \mathrm{I}(S_e \geq 4) + \\ &\quad \beta_1^t \mathrm{I}(S_e = 1) * SurpDec_e + \beta_2^t \mathrm{I}(S_e = 2) * SurpDec_e + \beta_3^t \mathrm{I}(S_e = 3) * SurpDec_e \\ &\quad \beta_4^t \mathrm{I}(S_e \geq 4) * SurpDec_e + \varepsilon_{e,t}, \end{aligned} \tag{10}$$

where t is the trading day in event-time, e is the specific earnings surprise, $SurpDec_e$ is the surprise decile for earnings surprise e and $\mathrm{I}(S_e = X)$ is the indicator that the earnings surprise e

has position *X* in a series, as defined in Section III. I focus on the one-year earnings surprise sequence, rather than 7 quarters, as the sample sizes are much smaller for these sequences than for earnings increase/decrease strings. I again use the sum of abnormal trade imbalance over days -5 through 5 as the dependant variable, allowing for possible differences in the timing of small and large trades around the earnings announcement date. Results are similar using alternate event windows.

Recall that *SurpDec* is defined as ranging from 0 through 9. Thus, in Equation 10, the α coefficients measure the intercepts for a trade group's abnormal trade imbalance reaction to an earnings announcement (with a particular S value), which is their reaction to an extremely negative surprise (decile 0). β reflects the sensitivity of the trade group's abnormal trade imbalance to the earnings surprise decile, the measure of the information content of the surprise. Essentially, β measures the strength of the reaction, similarly to an earnings response coefficient. I also estimate a variant on the basic regression which is more similar to Equation 9, to examine behavior for positive surprises (deciles 7, 8, and 9) and negative surprises (deciles 0, 1, and 2) directly. Results using this alternate model are discussed below, in the paragraph headed "Reactions to Positive Surprise Series and Negative Surprise Series."

Table 4, Panel A, displays the coefficient estimates for trades less than \$5,000, between \$5,000 and \$10,000, between \$10,000 and \$20,000, between \$20,000 and \$50,000, and for trades of at least \$50,000, as well as statistics for the difference in coefficient estimates for trades less than \$5,000 and trades of at least \$50,000. Panel B displays differences in the β estimates across S groups. Figure 2 displays the results for β, the abnormal trade imbalance "earnings response coefficient," graphically. Focusing first on the smallest group of trades, those less than \$5,000, the slope is higher for S=2 than for S=1, with values of 0.0377 and -0.0079 respectively. The difference is statistically significant at the 1% level. The reaction to S=3 is significantly higher, again at the 1% level, with a slope coefficient of 0.0813. While the reaction to S≥4 surprises is similar to that for S=3, it is significantly higher than for both the S=1 and S=2 surprises. Figure 2 and the regression results in Table 4 indicate that the increasing reaction also appears, monotonically, in the \$5,000-\$10,000 trade group and the \$10,000-\$20,000 trade group, though the total magnitude of reaction increase is smaller for the \$10,000-\$20,000 trades than for the other two groups. As this suggests, the small trade increasing response is robust to using a \$5,000, \$10,000 or \$20,000 cutoff for small trades.

Large traders, in contrast to small traders, react similarly to earnings surprises at different stages in the sequence, with a reaction to S≥4 surprises which is almost identical to the reaction to S=1 surprises, 0.0326 and 0.0338 respectively. In the last column, Table 4 displays t-statistics for the difference between the smallest and largest groups of trade size. Small traders react significantly more weakly than large traders to an S=1 surprise, insignificantly more strongly for S=2 and significantly more strongly for S=3 and S≥4. This increase in small trade reaction relative to large trade reaction, as S increases, is statistically significant, as indicated in Panel B. The difference between small and large trader reaction patterns provides strong evidence that the previously documented market preference for consistent positive earnings surprises is attributable to less sophisticated investors' preference rather than a more sophisticated response to risk-related information.

Reactions to Positive Surprise Series and Negative Surprise Series. The increasing reaction phenomenon is not solely attributable to reactions to positive surprises. Evidence on the intercept term in Table 4, and additional untabulated results for reactions to positive and negative surprises separately, show that the small trade reaction becomes more extreme for both positive and negative surprise series, and the large trade reaction does not become more extreme for either. Generally, I focus on slope, i.e. the abnormal trade imbalance earnings-response-coefficient, rather than on absolute reactions to the two extremes, due to the potential confounding factor of attention effects (see Barber and Odean, 2008), but untabulated results for each extreme show that the small trade reaction to decile 0, the most negative decile, becomes monotonically lower, indicating stronger selling, as S increases. Similarly the reaction to decile 9, the most positive decile, becomes monotonically higher, indicating stronger buying, as S increases. The reactions to the intermediate deciles (1, 2, 7 and 8) follow a similar pattern, with some minor variations from the monotonic pattern for these less extreme surprises. For large traders, there is no clear increasing or decreasing reaction pattern to either positive or negative surprise series individually.

Reactions of Intermediate Trade-size Groups. While there is a significant difference between the reactions of the very smallest trades and the very largest trades, it is also interesting to examine the trading in the intermediate range. The results displayed in Table 4 and Figure 2 indicate that as trade size grows, the reaction to the first surprise increases in magnitude. While the earnings-response-coefficient measure for S=1 surprises, i.e. β_1, is negative in magnitude for trades below \$5,000 or in the \$5,000-\$10,000 range (-0.0079 and -0.0120 respectively), it is insignificantly positive for trades between \$10,000 and \$20,000 (0.0087), marginally significantly positive for trades between \$20,000 and \$50,000 (0.0158), and strongly significant for trades over

$50,000 (0.0338). Similarly, the reactions to the later surprises, such as S=3 and S≥4, drops as trade size grows. These results suggest that, not surprisingly, there is a gradual progression between the behavior of the very small traders and the very large traders. The preference for earnings surprise series, i.e. the stronger response to surprises later in the series, is clearly present for trades in the below $5,000 range, the $5,000 to $10,000 range and the $10,000 to $20,000 range. The significance of the increasing pattern for trades in the $10,000 to $20,000 range does vary with additional controls and method variations, but the pattern remains consistent, and the increasing reaction for the $5,000 to $10,000 range is robust. And while the reaction for S≥4 surprises is below that for S=3 surprises for trades in the $20,000-$50,000 range, these traders react more strongly to both S=3 and S≥4 surprises than to S=1 and S=2 surprises.

Considering the potential market impact of preferences for earnings growth consistency, note the robustness of the increasing response in larger trade-size groups. First, trades below $20,000 represent over 50% of the trades in our sample, and for many firms, particularly smaller firms or those with lower institutional ownership, trades below $20,000 will represent a much higher fraction of trading volume. Second, while the category of largest trades does not exhibit a significant preference for consistency on average, it may be the case that they occasionally exhibit this preference. The potential for investors to occasionally display this sensitivity to earnings patterns, or the tendency of a significant subset of investors to display this sensitivity, may be enough to influence manager behavior, even if the largest investors do not always exhibit it. This may also suffice to influence market returns, at least in certain situations, such as in smaller firms or firms with more individual investor ownership. I directly examine the relation between the return response to earnings surprises and small trading, at various stages in a series, in the next subsection.

The Market Impact of Small Trades

Prior research has indicated that the market values earnings growth consistency (Barth, Elliott and Finn 1999; Myers, Myers and Skinner 2007; Lev, Ryan and Wu 2008). The results in the previous subsection provide evidence that small traders react more strongly as a series of similar earnings surprise progresses, while large traders do not appear to react more strongly as a series progresses. These trading results suggest that the previously documented market valuation is more strongly attributable to investors' preferences for consistency, i.e. "earnings momentum trading," than by changes in firms' risk characteristics. Therefore, I directly test whether there is a positive relation between returns and small trading around earnings announcements, to better understand whether small traders have a significant influence on the overall market valuation.

To test hypotheses H2a and H2b, I directly relate raw returns around the earnings announcement dates (in the window of -5 through +5 trading days) to concurrent small trade abnormal imbalance over the same window.[11] Table 5 displays results. The four leftmost columns display the estimated relation between announcement-window returns and small trade imbalance for the full sample of earnings announcements. The first column shows the relationship with trades of less than $5,000. The results in the table indicates that trades of less than $5,000 exhibit a significant positive relation with concurrent returns. In particular, a one standard deviation change in the trade imbalance for trades less than $5,000 corresponds to returns of 0.05% over the same window, a change in returns of roughly 7%. The group of trades below $20,000 has an even larger impact, 0.07% returns in absolute magnitude, roughly 10% of the average announcement-period return. The third and fourth columns in the table include additional control variables. The third column tests whether the relation between small trade and returns remains significant after controlling for large trades. While the magnitude of the coefficient on small trades decreases, it remains positive and statistically significant (0.03%). Including the level of earnings surprise (i.e. earnings surprise decile) in the model further improves the ability to explain returns, but only marginally decreases the estimated relation between small trade and returns (to 0.029% from 0.031% in the model without earnings surprise decile). Thus, the results in Table 5 provide strong support for hypothesis H2a; small trades exhibit a significantly positive relation with concurrent returns around earnings announcements. This suggests that the increasing small trade reaction as a series progresses contributes to the increasing market valuation of these later surprises.

To test hypothesis H2b, I estimate the relation between small trade imbalance and concurrent returns for subsamples of earnings surprises occurring at different stages in series. The fifth through eighth columns in Table 7 display the results for each of four "S" groups: S=1, 2, 3 and S≥4. The estimated relation is similar for S=1 and S=2, at 0.084% and 0.086% respectively (both statistically significant). The relation is statistically significantly higher for S=3, at 0.129%, but is then lower for the S≥4 subsample, at 0.061%. Thus I find mixed evidence in testing hypothesis H2b. Of course, as long as there is a positive relation, the stronger small

[11] Results are similar if I measure returns and trade over a window of (-1, +1) around the earnings announcement.

trade response could contribute to a stronger market response – the relation itself does not have to be increasing over a series for small traders to have a significant market impact.

V. ROBUSTNESS CHECKS

Alternate Trade Imbalance Measures; Controls for Prior Returns, and Alternate Trade-Data Methods

In general, a firm that has had prior positive earnings surprises will also have had prior positive returns. It is possible that the difference in reactions between small and large traders or the differences among small trader reactions to surprises in a sequence could be attributable to a naïve reaction to past returns. In order to rule out this possibility, I further adjust abnormal trade imbalance by using the residual abnormal trade imbalance after removing the portion of abnormal trade imbalance attributable to prior returns.

In order to calculate a "return-adjusted" abnormal trade imbalance measure, I first regress abnormal trade imbalance on cumulative abnormal returns (CARs), which are the sums of daily CRSP beta-adjusted abnormal returns. I estimate the following equation for each trade-size-group:

$$IMB_{i,t}^{abnormal} = \alpha_0 + \alpha_1 AR_{t-1}^{i} + \alpha_2 CAR_{t-5,t-2}^{i} + \alpha_3 CAR_{t-20,t-6}^{i} + \alpha_4 CAR_{t-60,t-21}^{i} + \varepsilon_{i,t}\,, \tag{11}$$

where AR_{t-1}^{i} is the prior day abnormal return and $CAR_{t1,t2}^{i}$ are the cumulative abnormal returns over days *t1* through *t2* in event time. This equation essentially groups prior returns into the prior day (*t*-1), week (*t*-5 through *t*-2), month (*t*-20 through *t*-6) and quarter (*t*-60 through *t*-21). I then define return-adjusted abnormal trade imbalance as the residual from Equation 11, that is, the abnormal trade imbalance that is not accounted for by the investor's reaction to the previous day, week, month and quarter returns.

Table 6 presents results from estimating Equation 11. From the regression results in Table 6, large traders appear to be "momentum" traders – buying more strongly when prior returns have been higher – while small traders appear to be "contrarians". These results are consistent with evidence on mutual fund portfolios (Grinblatt, Titman and Wermers 1995) and evidence on individual investor trading (Kaniel, Saar and Titman 2008). Because of these different responses to prior returns, the results are stronger with the controls for prior returns.

Table 7 Panel A reports regression results from estimating Equation 10 using the return-adjusted measure of abnormal trade imbalance, i.e. the residuals from estimating Equation 11. Small traders exhibit a strongly increasing reaction to surprises later in a series, while large traders have about the same reaction to the consecutive surprises. The difference between the two groups is statistically significant, as is the increase in small trader response as a series progresses. The differences are similar in magnitude, or slightly larger, as for the main results without prior-return controls.

I use an additional, alternate, normalization procedure to control for prior returns. Chordia, Roll and Subrahmanyam (2002), find that net trades (i.e. buys minus sells for all investors), are serially correlated, are contrarian with respect to prior returns, and exhibit a calendar effect. Based on this evidence, I perform a normalization controlling for calendar-effects, serial correlation in the trade imbalance variable, and dependence of trade imbalance on prior returns. The method I use is similar to that used in Frieder (2008), with the key difference being that I normalize small and large trades separately, rather than pooling all trade sizes into a single category. 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 residual from these regressions is used in the final step. In order to ensure that the values are comparable across trade size groups, in the third step, the mean for that security and trade-size group is subtracted and the mean-adjusted imbalance is divided by the standard deviation for that security and trade-size group. This final step is similar to the primary normalization shown in Equation 5, removing the mean and standard deviation effects for each firm and trade-size group.[12]

The second column of Table 7 Panel A reports regression results using this alternate normalization procedure, which accounts for calendar-time effects, past returns for the fifteen

[12] Details of the procedure and insights for calendar-effects in returns are described in Shanthikumar (2004).

prior trading-days, and past trade imbalance for the fifteen prior trading-days. The results using this alternate measure are similar to the primary results, with increases in small trader reaction remaining significant.

Alternate Earnings Surprise Measures

One potential concern with the results is that I may not be properly capturing earnings expectations, due to the use of a fairly simple model. In untabulated regression results, I repeat tests using four variations of the SUE measure and find similar and significant results whether earnings surprises are calculated with or without accounting for earnings drift and whether the unexpected earnings measure is normalized by standard deviation of earnings or standard deviation of earnings changes.

A direct test for a potential failure to capture earnings expectations is to use analyst forecasts as a proxy for earnings expectations, as analyst forecasts present a more complete and sophisticated measure of expectations. Analysts should account for the history of earnings for the given firm as well as other financial variables, non-financial data, industry-wide data and economy-wide information. Using this measure, the increasing reaction pattern is slightly different, but is still consistent with the increasing reactions hypothesis. Table 7, Panel B, displays results for earnings surprises based on IBES summary data. Results are similar using IBES detail data to construct an earnings forecast consensus measure as described in Section III. Turning to the first column of Table 7 Panel B, small traders exhibit a slightly stronger reaction to the S=2 surprise than to the S=1 surprise, but the difference is smaller than using the SUE measures, 0.0255 rather than 0.0456 in Table 4, for trades below $5,000. However, the small trade reaction continues to increase, with their reaction to the third analyst-based surprise being higher than to the second, and their reaction to surprises with $S \geq 4$ higher still. The total increase from S=1 to $S \geq 4$ is 0.0988, comparable in magnitude to the 0.0909 increase reported in Table 4 using earnings surprises from the random walk model.

For large traders the reaction to the second surprise is actually lower than the reaction to the first, while the reactions to the third and fourth surprises are lower still, though by a statistically insignificant magnitude. If large traders are making less biased trading decisions, this strongly suggests that small traders are overreacting to “earnings momentum.” The difference between small and large traders is again statistically significant.

Fiscal-Year-Ends. There are two reasons to repeat the main analysis excluding fiscal-year-ends. First, annual earnings reports may affect the results. Second, there may be some element of increased investor involvement as a series continues, perhaps because press coverage increases as a string of similar earnings surprises progresses. Such an effect may be stronger at the fiscal-year-end, when press coverage and investor attention are high. In essence, we might view earnings surprises for a firm's fourth quarter as being substantively different from earnings surprises for the other three quarters. A simple and straightforward test of both of these is to discard all quarterly announcements that occur at the end of a firm's fiscal year. Table 7, Panel B, displays the results, which are extremely similar to the main results, and remain significant.

Fixed Effects

Trading behavior may vary over time or across firms. If firm characteristics are related to the likelihood of a firm exhibiting an earnings string, then results may reflect variation in firm characteristics. In order to ensure that the results are robust to potential variation in trade imbalance across firms, I repeat the key regressions including fixed-effects for each security, to remove any systematic effects driven by that security's characteristics. I also estimate Equation 10 including fixed effects for each of the 40 sample quarters to control for any time-driven effects. Table 7, Panel C, displays the results. The results in the table show that the increasing reaction among small traders, and the difference between small and large traders, remains significant in both fixed effect specifications.[13]

Additional Robustness Checks

Large traders may be more likely to predict which earnings series will continue and which will not. For example, they may watch the firms with more extreme earnings surprises more closely, thus reacting to new information in a timelier manner before the next earnings announcement. Alternatively they may simply learn of the coming earnings announcement values in advance. To test whether this affects the results, I include the trading results for the

[13] In addition to estimating a fixed effects model, I examine several subsamples of the data. In untabulated tests, I estimate Equation 10 for a set of thirty subsamples: each of the ten years from 1993 through 2002, each of the ten size deciles and each of the ten book-to-market ratio deciles. While the strength of the results varies from group to group, the general results remain, and there are no groups that exhibit contradictory results or that seem to be driving the full-sample results.

months prior to the earnings announcement. In particular, rather than measuring the reaction as the sum of daily abnormal trade imbalance from event-time trading-days -5 through 5, I repeat the regressions using periods such as -40 through 5, -50 through 5, and even -70 through 5, which would incorporate the reaction to the preceding surprise. With all of these variations, the primary results remain: Small traders display a significantly increasing reaction as the series progresses while large traders do not display any increase.

Finally, I perform additional method sensitivity checks on a large subsample of the data. These additional checks include using an alternate buy/sell classification method, a time-varying size cutoff to approximate a percentage cutoff, a firm-size dependent cutoff and normalizing the trade imbalance by mean only. As a final control for any market-wide reaction effects on a given day I include date fixed-effects. The untabulated results from these variations reinforce the main results. Small traders consistently display a significantly strengthening reaction to earnings surprises as a series of similar surprises progresses, while large traders do not.

VI. CONCLUSION

This paper documents investor reactions to the time-series of earnings surprises. The results document that smaller traders react more positively as a string of earnings increases progresses, while large traders exhibit no increase in their response. Focusing on series of strong positive and negative surprises, to eliminate the possible effect of small, possibly expected, changes in earnings, I find that small traders react more strongly to surprises later in a series, while the largest category of traders does not exhibit increasing reactions. These results are robust to many method variations, including alternate earnings surprise measures and alternate abnormal trading measures. In addition, results indicate that smaller traders tend to trade as contrarians and larger traders as momentum traders, independent of earning surprises. Because of this, results remain equally strong after controlling for prior returns. The paper also documents that the announcement-period market reaction to earnings surprises is significantly related to small traders' concurrent trading. Together, these results suggest that the price/returns patterns documented in Barth, Elliott and Finn (1999), Myers, Myers and Skinner (2007), and Lev, Ryan and Wu (2008) are more strongly attributable to non-standard investor preferences, i.e. overreactions to "earnings momentum," than to changes in firm risk communicated by the pattern.

The small and large investor reaction to earnings sequences documented here is also relevant to behavioral finance models which predict that investors will react more strongly as similar information is released (Barberis, Shleifer and Vishny 1998; Daniel, Hirshleifer and Subrahmanyam 1998). These models show that increasing investor reactions can explain both short-run momentum and long-run mean-reversal in returns. There is disagreement from the experimental finance literature regarding whether investors display a preference for consistency in laboratory settings (Bloomfield and Hales 2002; Asparouhova, Hertzel and Lemmon 2006). This paper documents that small traders display the preference through market trading data.

Finally, these results are relevant to understanding managers' desire to "meet or beat" earnings. While the literature has established how investors and the market respond to a one-time earnings announcement's "meet or beat" status, this study shows that the market reacts differentially to earnings depending on the time series pattern as well. It is an open question whether managers pay attention to the time-series pattern themselves, but certainly earnings press releases and financial articles are filled with phrases like "for the fifth quarter in a row."

The trading evidence provided in this paper shows that small traders are more sensitive to earnings information if a pattern of similar information is released, while large traders do not display such an increasing sensitivity. By stepping beyond aggregate market response measures such as price and returns and examining small and large traders separately, these results increase our understanding of the market's reaction to the time-series pattern of earnings information.

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Table 1
Earnings Surprise Sample Statistics

		All Surprises	Non-string Surprises (S = 0)	Surprises in a String S = 1	S = 2	S = 3	S = 4	S ≥ 4
Sample Size		58,945	25,797	15,923	7,012	4,065	2,795	6,148
Size	Mean	4574	4703	4658	4470	4280	4190	4127
	Median	867	901	890	836	787	796	761
	Std. Dev.	16359	16520	15613	16403	17040	17744	17042
B/M	Mean	0.511	0.455	0.481	0.623	0.622	0.624	0.627
	Median	0.490	0.468	0.509	0.513	0.505	0.508	0.492
	Std. Dev.	6.170	7.146	7.569	0.799	0.921	1.235	1.013
SUE	Mean	-0.271	0.050	-0.603	-0.336	-0.404	-0.468	-0.431
	Median	0.050	0.060	-0.190	-0.255	-0.320	-0.450	-0.260
	Std. Dev.	26.331	0.245	49.150	3.418	3.693	3.957	3.815
SUE - top 30%	Mean	1.595		1.561	1.597	1.669	1.966	1.632
	Median	1.090		1.000	1.130	1.230	1.490	1.210
	Std. Dev.	1.638		1.797	1.571	1.466	1.542	1.354
SUE - bottom 30%	Mean	-2.491		-2.726	-2.161	-2.282	-2.523	-2.412
	Median	-1.150		-1.020	-1.220	-1.320	-1.470	-1.340
	Std. Dev.	47.713		69.086	3.678	4.077	4.201	4.330

This table presents sample statistics for firm-quarters for NYSE common stock from 1993 through 2002, with matching TAQ trading data. Size is defined as market value (shares outstanding * price-per-share) and is reported in millions of dollars. Book-to-market ratio (B/M) is defined as the ratio of book value of equity to market value of equity (size). SUE is defined as the standardized unexpected earnings based on a random-walk with drift earnings expectations model. If a surprise is the first in a series of same-type (top or bottom 30%) surprises, it receives a value of S=1. If it is the second in a series, S=2 and so on. S=0 indicates a surprise which is not in a top/bottom 30% series, i.e. a surprise in the middle 40%.

Table 2
Correlations Between TAQ-based and Brokerage Account-based Trading Variables

	Brokerage Trade Imbalance		
	Number of Trades	Number of Shares	Dollar Value
Small Trades, less than $5,000	0.1976	0.1740	0.1738
	(0.0000)	(0.0000)	(0.0000)
Small Trades, less than $20,000	0.2069	0.1863	0.1861
	(0.0000)	(0.0000)	(0.0000)
Large Trades, at least $50,000	-0.0343	-0.0402	-0.0401
	(0.0000)	(0.0000)	(0.0000)

This table displays correlations between (1) a monthly measure of TAQ-based trade imbalance for each trade-size group, defined as the sum of the daily TAQ-based abnormal trade imbalance measure for all days in the given month, and (2) monthly trade imbalance measures derived from 50,000 retail brokerage accounts. The sample comprises all NYSE common stock from 1993 through 1996 with both TAQ and brokerage data available. P-values are reported in parentheses.

Table 3
Series of Earnings Increases and Decreases

	Trade Size Group			Difference	Sample Size:
	<\$5,000	<\$20,000	≥\$50,000	<5 vs. ≥50	N Inc/Dec
$INCREASE_1$	-0.0040	-0.0021	0.0209	-0.0249	11,525
	(0.46)	(0.25)	(3.16)	(2.34)	
$INCREASE_2$	0.0298	0.0331	0.0058	0.0222	8,236
	(2.63)	(2.88)	(0.66)	(1.60)	
$INCREASE_3$	0.0451	0.0376	0.0213	0.0224	6,655
	(3.34)	(2.78)	(2.06)	(1.36)	
$INCREASE_4$	0.0690	0.0750	0.0117	0.0619	6,030
	(4.33)	(4.67)	(0.97)	(3.19)	
$INCREASE_5$	0.0833	0.0785	0.0115	0.0691	5,062
	(4.23)	(4.00)	(0.75)	(2.78)	
$INCREASE_6$	0.0383	0.0183	0.0220	0.0081	4,429
	(1.54)	(0.77)	(1.09)	(0.25)	
$INCREASE_{7+}$	0.0603	0.0549	0.0395	0.0321	11,814
	(2.96)	(2.59)	(2.16)	(1.19)	
$DECREASE_1$	0.4920	0.5280	-0.0034	0.5220	8,956
	(8.92)	(9.69)	(0.08)	(7.66)	
$DECREASE_2$	0.2450	0.2200	0.0567	0.2010	4,767
	(3.42)	(2.96)	(0.95)	(2.22)	
$DECREASE_3$	0.2650	0.3100	0.0371	0.2210	3,035
	(2.94)	(3.36)	(0.51)	(1.99)	
$DECREASE_4$	0.0482	0.0526	0.0775	-0.0028	2,286
	(0.45)	(0.49)	(0.96)	(0.02)	
$DECREASE_5$	0.1030	0.1480	-0.0421	0.1430	1,231
	(0.71)	(1.00)	(0.37)	(0.78)	
$DECREASE_6$	0.4620	0.5490	-0.1080	0.6290	683
	(2.41)	(2.96)	(0.70)	(2.51)	
$DECREASE_{7+}$	0.1900	0.2610	-0.1350	0.2770	814
	(1.09)	(1.43)	(0.84)	(1.18)	
R^2	0.0132	0.0126	0.0014		
N	47,665	55,003	55,151		

This table presents coefficient estimates from a regression of abnormal trade imbalance, summed over trading days -5 through 5, surrounding the earnings announcement date, on a series of indicators for the earnings increase or decrease relative to the same quarter in the previous year, and the position of that increase or decrease in a string of the same sign of earnings change (i.e. a string of all earnings increases). If an announcement is the first increase (decrease) in a series of same-sign earnings changes, it is defined as an $INCREASE_1$ ($DECREASE_1$) surprise. If it is the second in a series, it is $INCREASE_2$ ($DECREASE_2$) and so on. The earnings announcement sample contains all non-zero earnings changes for NYSE sample firms from 1993 through 2002. <\$5,000, <\$20,000 and ≥\$50,000 indicate the trade size used to measure trade reaction. Difference <5 vs. ≥50 displays results for the difference between coefficient estimates for trades of <\$5,000 and trades of ≥\$50,000. For each column the sample is restricted to firm-days on which stock price is low enough so that the given trade size is possible with a round lot of 100 shares. T-statistics are in parentheses. Standard errors are robust to heteroskedasticity and arbitrary within-firm correlation.

Table 4
Abnormal Trade Reaction to Earnings Surprise by Trade-Size Category

Panel A. Coefficient Estimates

	Trade size category, in thousands of dollars					Difference
	<5	5-10	10-20	20-50	≥50	<5 vs. ≥50
S=1	0.5780	0.4450	0.2780	0.1520	-0.0221	0.6380
	(8.52)	(7.27)	(4.94)	(2.90)	(0.45)	(7.84)
S=2	0.3230	0.2930	0.1470	0.0384	0.1220	0.2140
	(3.38)	(3.40)	(1.76)	(0.50)	(1.64)	(1.79)
S=3	0.2470	0.2940	0.2280	0.0761	0.0885	0.1860
	(2.02)	(2.62)	(2.23)	(0.80)	(0.90)	(1.26)
S≥4	0.0235	0.0186	-0.0880	-0.0232	-0.1120	0.1300
	(0.24)	(0.21)	(1.02)	(0.30)	(1.39)	(1.04)
surpDec*(S=1)	-0.0079	-0.0120	0.0087	0.0158	0.0338	-0.0437
	(0.68)	(1.13)	(0.89)	(1.71)	(3.85)	(3.10)
surpDec*(S=2)	0.0377	0.0137	0.0329	0.0187	0.0065	0.0345
	(2.18)	(0.89)	(2.22)	(1.37)	(0.49)	(1.63)
surpDec*(S=3)	0.0813	0.0533	0.0500	0.0505	0.0220	0.0525
	(3.81)	(2.77)	(2.80)	(2.94)	(1.30)	(2.01)
surpDec*(S≥4)	0.0830	0.0830	0.0687	0.0371	0.0326	0.0564
	(4.72)	(5.43)	(4.41)	(2.66)	(2.33)	(2.55)
R^2	0.0129	0.0090	0.0065	0.0032	0.0018	
N	28,274	32,104	32,416	32,455	32,512	

Panel B. Coefficient Differences, for Interaction Terms Estimated Above

	Trade size category, in thousands of dollars					Difference
Coef. Differences Between:	<5	5-10	10-20	20-50	≥50	<5 vs. ≥50
surpDec*(S=2) and surpDec*(S=1)	0.0456	0.0257	0.0242	0.0029	-0.0273	0.0782
	(2.28)	(1.44)	(2.39)	(2.19)	(3.88)	(3.50)
surpDec*(S=3) and surpDec*(S=2)	0.0436	0.0396	0.0171	0.0318	0.0155	0.0180
	(4.39)	(2.91)	(3.57)	(3.24)	(1.39)	(2.59)
surpDec*(S≥4) and surpDec*(S=3)	0.0017	0.0297	0.0187	-0.0134	0.0106	0.0039
	(6.07)	(6.10)	(5.22)	(3.96)	(2.67)	(3.25)
surpDec*(S=3) and surpDec*(S=1)	0.0892	0.0653	0.0413	0.0347	-0.0118	0.0962
	(3.87)	(2.99)	(2.94)	(3.40)	(4.06)	(3.69)
surpDec*(S≥4) and surpDec*(S=2)	0.0453	0.0693	0.0358	0.0184	0.0261	0.0219
	(5.20)	(5.50)	(4.94)	(2.99)	(2.38)	(3.03)

Panel A presents coefficient estimates from regressions of abnormal trade imbalance, summed over trading days -5 through 5, on a constant and the earnings surprise decile (0-9), interacted with indicators for S value. If a surprise is the first in a series of same-type (top or bottom 30%) surprises, it receives a value of S=1. If it is the second, S=2 and so on. The earnings surprise sample contains all extreme (top or bottom 30%) earnings surprises for NYSE sample firms from 1993 through 2002. Difference <5 vs. ≥50 displays results for the difference between coefficient estimates for trades of <$5,000 and trades of ≥$50,000. For each column the sample is restricted to firm-days on which stock price is low enough so that the given trade size is possible with a round lot of 100 shares. Panel B displays differences between the interaction coefficient estimates in Panel A. T-statistics are in parentheses. Standard errors are robust to heteroskedasticity and arbitrary within-firm correlation.

Table 5
Relationship Between Small Trade Imbalance and Concurrent Returns Around Earnings Announcement Dates

	Full Sample				Subsamples			
					S=1	S=2	S=3	S≥4
Trade Imbalance, <\$5,000	0.047%							
	(5.39)							
Trade Imbalance, <\$20,000		0.065%	0.031%	0.029%	0.084%	0.086%	0.129%	0.061%
		(7.83)	(3.71)	(3.48)	(5.82)	(4.11)	(5.15)	(2.77)
Trade Imbalance, ≥ \$50,000			0.347%	0.344%				
			(35.10)	(34.90)				
Earnings Surprise Decile				0.244%				
				(18.50)				
Constant	0.656%	0.650%	0.631%	-0.456%	0.701%	0.720%	0.546%	0.465%
	(17.00)	(17.50)	(17.30)	(6.56)	(10.40)	(7.30)	(4.18)	(4.37)
R^2	0.0007	0.0018	0.0325	0.0407	0.0028	0.0031	0.0061	0.0015
N	49,640	52,130	52,130	52,130	14,880	6,575	3,784	5,717

This table presents coefficient estimates from regressions of cumulative raw returns, summed over trading days -5 through 5 around earnings announcement dates, on abnormal trade imbalance, summed over the same window, and a constant, for the full sample of earnings surprises, and for sub-samples determined by the position of a surprise in a series (S value). Earnings surprise decile is also included as a control variable. If a surprise is the first in a series of same-type (top or bottom 30%) surprises, it receives a value of S=1. If it is the second in a series, S=2 and so on. The earnings surprise sample contains all earnings surprises for NYSE sample firms from 1993 through 2002. T-statistics are in parentheses. Standard errors are robust to heteroskedasticity and arbitrary within-firm correlation.

Table 6
Relationship Between Abnormal Trade Imbalance and Prior Returns

	Trade Size Category		
	Less Than $5,000	Less Than $20,000	At Least $50,000
AR_{t-1}	0.1460	-0.0866	0.9991
	(8.18)	(2.52)	(34.78)
$CAR_{t-5,\ t-2}$	-0.1896	-0.4551	0.3831
	(20.45)	(24.05)	(28.73)
$CAR_{t-20,\ t-6}$	-0.2232	-0.3872	0.1115
	(43.79)	(30.98)	(16.84)
$CAR_{t-60,\ t-21}$	-0.1526	-0.2051	-0.0001
	(46.41)	(27.00)	(0.02)
constant	0.0058	0.0072	0.0022
	(10.54)	(17.37)	(7.81)
R^2	0.0013	0.0031	0.0013
N	3,261,828	3,768,623	3,768,623

This table presents coefficient estimates from regressions of abnormal trade imbalance on prior cumulative abnormal returns. Cumulative abnormal returns are CRSP beta-adjusted daily returns, summed over the respective period. The sample includes all NYSE common stock with the necessary TAQ and CRSP data, for the period 1993 through 2002. T-statistics are in parentheses. Standard errors are robust to heteroskedasticity and arbitrary within-firm correlation.

Table 7

Robustness Checks: Alternate Trade Imbalance, Alternate Earnings Surprise, and Fixed Effects

Panel A. Alternate Trade Imbalance Measures

	a			b		
	<$5,000	≥$50,000	Difference	<$5,000	≥$50,000	Difference
S=1	0.4490	0.0214	0.4590	0.0658	-0.0625	0.1300
	(6.37)	(0.43)	(5.51)	(1.72)	(2.15)	(2.78)
S=2	0.1500	0.1170	0.0438	-0.0951	-0.0386	-0.0467
	(1.52)	(1.55)	(0.36)	(1.70)	(0.89)	(0.66)
S=3	0.0395	0.0867	-0.0210	-0.1410	0.0014	-0.1430
	(0.31)	(0.86)	(0.14)	(2.01)	(0.02)	(1.69)
S≥4	-0.1230	-0.0841	-0.0582	-0.2930	-0.0429	-0.2810
	(1.22)	(1.02)	(0.46)	(4.80)	(0.95)	(3.95)
surpDec*(S=1)	0.0027	0.0202	-0.0185	0.0171	0.0134	0.0056
	(0.22)	(2.26)	(1.28)	(2.51)	(2.57)	(0.70)
surpDec*(S=2)	0.0564	-0.0038	0.0643	0.0521	0.0048	0.0500
	(3.13)	(0.28)	(2.92)	(5.16)	(0.61)	(4.03)
surpDec*(S=3)	0.1060	0.0104	0.0885	0.0658	0.0078	0.0601
	(4.69)	(0.60)	(3.24)	(5.07)	(0.80)	(3.80)
surpDec*(S≥4)	0.0912	0.0203	0.0785	0.1030	0.0016	0.1120
	(4.99)	(1.43)	(3.45)	(9.75)	(0.20)	(8.72)
R^2	0.0098	0.0009		0.0079	0.0003	
N	26,196	30,354		28,274	32,512	

Panel B. Alternate Earnings Surprise

	Analyst Surprise			Mid-Fiscal-Year		
	<$5,000	≥$50,000	Difference	<$5,000	≥$50,000	Difference
S=1	0.7520	-0.1750	0.9680	0.5700	-0.0316	0.6250
	(8.68)	(2.56)	(9.21)	(6.80)	(0.52)	(6.10)
S=2	0.5530	-0.0617	0.5760	0.0816	0.0982	-0.0246
	(3.43)	(0.59)	(3.05)	(0.72)	(1.12)	(0.18)
S=3	0.1220	0.0583	0.1290	0.1770	0.1010	0.1230
	(0.56)	(0.33)	(0.49)	(1.27)	(0.87)	(0.72)
S≥4	0.2930	-0.1500	0.5090	0.0519	-0.0879	0.1380
	(1.30)	(0.93)	(1.79)	(0.45)	(0.88)	(0.92)
surpDec*(S=1)	-0.0500	0.0736	-0.1300	0.0020	0.0300	-0.0273
	(3.27)	(6.32)	(7.06)	(0.14)	(2.71)	(1.54)
surpDec*(S=2)	-0.0245	0.0626	-0.0780	0.0775	0.0194	0.0620
	(0.93)	(3.50)	(2.51)	(3.79)	(1.23)	(2.48)
surpDec*(S=3)	0.0022	0.0244	-0.0283	0.0928	0.0172	0.0645
	(0.06)	(0.84)	(0.64)	(3.67)	(0.86)	(2.08)
surpDec*(S≥4)	0.0488	0.0431	0.0037	0.0889	0.0290	0.0634
	(1.42)	(1.75)	(0.09)	(4.18)	(1.70)	(2.43)
R^2	0.0105	0.0055		0.0084	0.0009	
N	13,579	15,747		34,840	40,278	

Panel C. Fixed Effects

	Security Fixed Effects			Quarter Fixed Effects		
	<\$5,000	≥\$50,000	Difference	<\$5,000	≥\$50,000	Difference
S=1	0.1050	-0.1140	0.2340	0.0817	-0.1220	0.2210
	(1.30)	(1.95)	(2.42)	(1.05)	(2.20)	(2.40)
S=2	-0.1730	0.0218	-0.2000	-0.1930	0.0048	-0.2060
	(1.59)	(0.26)	(1.48)	(1.89)	(0.06)	(1.62)
S=3	-0.3010	-0.0045	-0.2880	-0.2420	-0.0104	-0.2240
	(2.23)	(0.04)	(1.78)	(1.91)	(0.10)	(1.46)
S≥4	-0.5730	-0.1990	-0.3990	-0.4750	-0.2140	-0.2890
	(4.96)	(2.13)	(2.69)	(4.66)	(2.52)	(2.19)
surpDec*(S=1)	-0.0089	0.0326	-0.0431	-0.0066	0.0341	-0.0438
	(0.72)	(3.55)	(2.93)	(0.56)	(3.85)	(3.08)
surpDec*(S=2)	0.0421	0.0055	0.0398	0.0468	0.0140	0.0360
	(2.33)	(0.40)	(1.79)	(2.71)	(1.06)	(1.70)
surpDec*(S=3)	0.0918	0.0146	0.0702	0.0831	0.0221	0.0531
	(4.09)	(0.84)	(2.56)	(3.91)	(1.32)	(2.04)
surpDec*(S≥4)	0.1060	0.0234	0.0863	0.0858	0.0337	0.0584
	(5.45)	(1.53)	(3.55)	(4.89)	(2.41)	(2.64)
const	0.4910	0.1070		0.4920	0.0990	
	(16.50)	(4.84)		(14.00)	(3.77)	
R^2	0.0536	0.0496		0.0168	0.0082	
N	47,157	54,644		46,963	54,305	

This table presents regression results for several robustness checks and variations on the primary regression. The dependant variable is abnormal trade imbalance, summed over days -5 through 5. For each specification, the table displays results for trade imbalance based on trades of <\$5,000 and trades of ≥\$50,000, and statistics for the difference between coefficient estimates for trades of <\$5,000 and trades of ≥\$50,000. For each column the sample is restricted to firm-days on which stock price is low enough so that the given trade size is possible with a round lot of 100 shares. If a surprise is the first in a series of same-type (top or bottom 30%) surprises, it receives a value of S=1. If it is the second in a series, S=2 and so on. The earnings surprise sample contains all extreme (top or bottom 30%) earnings surprises for NYSE sample firms from 1993 through 2002, except where described. T-statistics are in parentheses. Standard errors are robust to heteroskedasticity and arbitrary within-firm correlation. The specific variations are described below.

Panel A present results for alternate trade imbalance measures, in which the dependent variable is abnormal trade imbalance with additional adjustments. Column “a” presents results where the dependent variable is abnormal trade imbalance with additional adjustments for response to prior day, week, month and quarter returns. Column “b” presents results where the dependent variable is abnormal trade imbalance with adjustments for calendar-time effects, prior returns and prior trade-imbalances.

Panel B presents results for two alternate earnings surprise samples. The column “Analyst Surprise” presents results where the earnings surprise and corresponding surprises series (i.e. S=1, S=2, etc.) are determined based on analyst-forecast expectations, using the IBES summary file monthly consensus forecasts, using the median forecast, with at least four forecasts outstanding. The column “Mid-Fiscal-Year” presents results for the main standardized unexpected earnings measure, for the subset of earnings surprises excluding earnings announcements pertaining to the last quarter in the firm’s fiscal year.

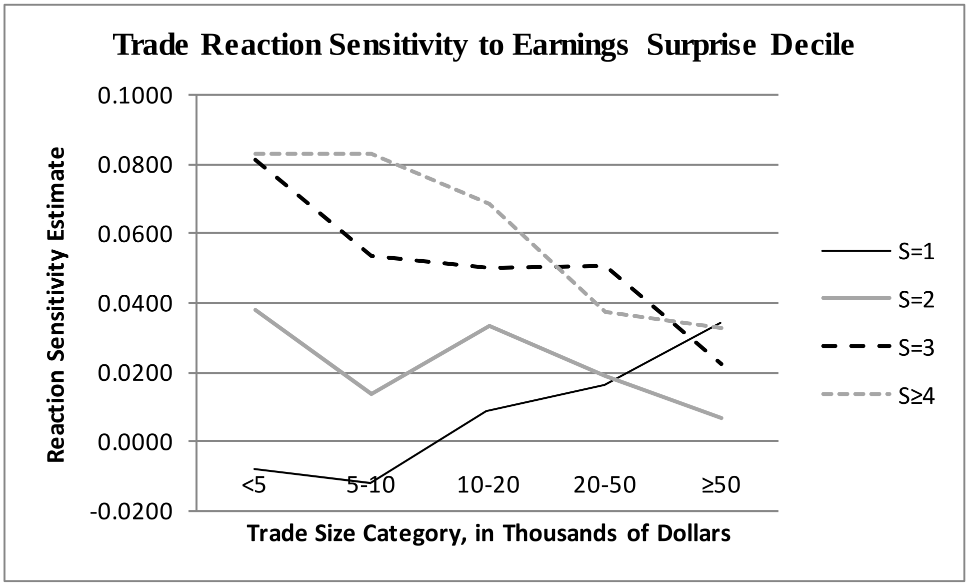
Panel C presents results for fixed effect regressions for the primary sample including S=0 surprises, i.e. the middle 4 deciles of earnings surprises. “Security” includes fixed effect for each unique security, as identified by 8-digit CUSIP. “Quarter” includes fixed effect for each of the 40 quarters in the sample.

Figure 1
Defining Earnings Surprise Series

Period:	Q1, 1993	Q2, 1993	Q3, 1993	Q4, 1993	Q1, 1994	Q2, 1994	Q3, 1994	Q4, 1994	Q1, 1995	Q2, 1995	Q3, 1995	Q4, 1995	Q1, 1996	Q2, 1996
Earnings Surprise Decile:	1	7	5	8	9	7	0	4	2	0	5	6	5	8
Extreme +/-:	-	+		+	+	+	-		-	-				+
S Value Assigned:	1	1	0	1	2	3	1	0	1	2	0	0	0	1

The figure presents an example for the assignment of “S” values, where S marks how far into a series a given surprise falls. Earnings surprises are assigned to deciles (0-9) in each quarter, where a decile of 0, 1 or 2 indicates an earnings surprise in the most negative 30% while a decile of 7, 8 or 9 indicates a surprise in the most positive 30%. If a surprise is the first in a series of same-type extreme surprise (deciles 0, 1 or 2 or deciles 7, 8 or 9), it receives a value of S=1. If it is second in a series, S=2 and so on. “Mild” surprises, in deciles 3-6, are assigned S=0.

Figure 2
Trade Reaction to a Sequence of Similar Earnings Surprises



The figure presents results from a regressions of abnormal trade imbalance, summed over trading days -5 through 5, on a constant and the earnings surprise decile (0-9), for subsamples based on S value. The figure plots β, the slope coefficient trade reaction to each earnings announcement. If a surprise is the first in a series of same-type extreme surprise, it receives a value of S=1. If it is second in a series, S=2 and so on. The x axis displays five trade-size categories, <\$5,000, \$5,000-\$10,000, \$10,000-\$20,000, \$20,000-\$50,000 and ≥\$50,000, in increasing order. The y-axis displays the reaction coefficient. Thus each point represents the sensitivity of the given trade-size-group's trade imbalance to earnings surprises with position S in a series.