

The effect of earnings announcements on trading outcomes for different investor classes

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October, 2010

This paper is based on my dissertation at Penn State University. I thank my committee, Orié Barron (chair), Paul Fischer, Karl Muller, and Laura Field for excellent advice in pursuing this paper. I also received helpful comments from Linda Bamber, Donal Byard, James Sinclair, Marco Rossi, and seminar participants at Penn State University, the University of Georgia, Baruch College, the University of Minnesota, Boston College, the University of Florida, the University of Pittsburgh, and the University of Utah.

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Abstract

Theory suggests that earnings announcements can either increase or decrease the level of information asymmetry between investors. I investigate this by testing the effect of earnings announcements on the relative ability of small and large investors to trade advantageously. On average, I find that large traders' returns increase following earnings announcements at the expense of small traders, indicating an increase in information asymmetry following earnings disclosures, at least in the short term. I also find that several proxies for the availability of private information are associated with the advantage of large traders following announcements. Finally, I test the hypothesis of Chae (2005) that volume patterns around earnings announcement are partially the result of less informed traders delaying their trades until after the announcement to achieve a more level informational playing field. Results are inconsistent with this hypothesis.

1. Introduction

The theoretical literature has modeled the effect of earnings disclosures on information asymmetry between investors in several different ways.¹ On one hand, disclosures have been seen as reducing or eliminating uncertainty about some future event, causing the better informed to lose some or all of their advantage over the uninformed (e.g. Kyle, 1986; Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988). On the other hand, disclosures can spur the generation of *new* private information about a firm's future state (Kim and Verrecchia, 1994, 1997). These two ideas are not mutually exclusive; disclosures can simultaneously resolve uncertainty about some aspect of a firm's future earning power while also giving better informed investors additional inputs from which they can refine their beliefs about future payouts. The purpose of this paper is to examine how earnings announcements change the relative advantage of the informed versus the uninformed, and which firm and market attributes serve to change this dynamic.

Prior studies have examined the effect of earnings announcements on information asymmetry using bid-ask spreads (Yohn, 1998; Libby, Mathieu and Robb, 2002), the adverse selection component of spreads (Krinsky and Lee, 1996), the price impact of trades (Brooks, 1996), and the probability of informed trade (Brown, Hillegeist and Lo, 2008). This paper differs from this prior work in that, rather than measuring a proxy for the presence of information asymmetry, I measure a likely *outcome* of that asymmetry. To examine the effect of information asymmetry on investors, I examine all trades made in the stock of each firm in my sample, and calculate the three day returns that could be earned by the initiator of each trade. I then classify the trade size as small, medium, and large, with the small group proxying for uninformed

¹ In this study, I consider information asymmetry between investors, which is distinct from the information asymmetry between the firm and outsiders. See Agarwal and O'Hara (2007) for a discussion of the differences between these two forms of information asymmetry.

investors and the large group proxying for better informed investors.² I then compute the overall imputed returns for each group for each trading day. Finally, I compare the relationship between small and large returns overall with the small and large returns shortly following earnings announcements, to see how these disclosures affect the relative returns earned by the two groups.

Results show that overall, there is an increase in large traders' profits relative to small traders' profits in the period immediately following an earnings announcement. I also run my tests using control variables for the direction and magnitude of earnings surprises, to mitigate concerns that results may be related to PEAD trading strategies. Results remain the same even with the inclusion of these earnings surprise control variables. I also examine some firm and announcement level characteristics that may be related to the production of private information. I find that large traders are at a greater advantage when trading in the shares of firms with large analyst following, suggesting that large traders are better able to produce private information following earnings announcements when incentives to produce such information is higher. Furthermore, reduction of private information, as measured by the change in analysts' consensus, is associated with a reduced advantage for large traders following announcements. However, a similar interaction using firm size, which has been used as a proxy for the incentive to generate private information in prior literature, does not produce significant results.

I also use this data to test the discretionary liquidity trader hypothesis in Chae (2005) concerning patterns of trading around earnings announcements. This hypothesis posits that the patterns of trading observed around earnings announcements (decrease in volume in the period immediately prior to the announcement followed by a large increase in volume immediately following the announcement) are due, at least in part, to uninformed traders who wish to time

² Following prior research, I do not use the medium group, as it is more difficult to make inferences about the composition of this group.

their trades advantageously. According to this hypothesis, uninformed traders with some discretion in the timing of their exogenously determined liquidity trades will wish to delay trade until after the earnings announcement, to reduce the adverse selection problem of trading against informed investors. This implies that uninformed traders who trade immediately following the announcement should enjoy better returns, relative to informed traders, than uninformed traders who trade immediately prior to the earnings announcement. I test this proposition directly by examining the difference in relative trade performance both prior to and following earnings announcements. While I find that large traders do better than small traders following earnings announcements, I find no difference in their relative trading performance immediately prior to the announcement. This evidence suggests that discretionary liquidity trade timing is unlikely to explain earnings announcement trading patterns.

The remainder of this paper proceeds as follows. In section 2, I briefly discuss some of the background literature and the rationale for the tests being performed. I then discuss the construction of the variables and the research design I use to test the hypotheses in section 3. In section 4, I discuss the data and results, and I conclude with section 5.

2. Related Literature and Hypothesis Development

2.1 Literature Related to Information Asymmetry Following Earnings Announcements

Theoretically, there are two distinct approaches to modeling the effect of information disclosure on information asymmetry between investors. In models such as Kim and Verrecchia (1991) and Foster and Viswanathan (1990), some investors have private signals concerning an upcoming announcement. The announcement supplants the private information, making their private signals no longer useful, and information asymmetry is alleviated. In contrast, in other models

(Kim and Verrecchia 1994; Kim and Verrecchia 1997) information disclosures can spur the generation of new, private information, which increases asymmetry. Although different models emphasize different features of information announcements, these two effects are not mutually exclusive, and in fact, complex disclosures such as earnings announcements are likely to substitute for some privately held information while simultaneously stimulating new private information among some investors, as in Kim and Verrecchia (1997). These two countervailing effects make it difficult to predict ex-ante the effect of accounting earnings announcements on information asymmetry between investors.

Researchers have used a number of proxies for information asymmetry in studying its relationship with earnings disclosures, with bid-ask spreads, or a spread-based construct being the most common. Other proxies include analyst consensus, probability of informed trade (PIN), and the price impact of block trades. No general consensus has emerged in this literature as to how the announcements affect asymmetry.

One of the first papers to study the issue of information asymmetry around earnings announcements is Morse and Ushman (1983). This study examines bid-ask spreads around quarterly earnings announcements, looking at each day from ten days prior to the announcement to ten days following the announcement. These days are individually compared to days that are further from the announcement date. No significant differences are found for any date in this window, although this non-result may be an artifact of the sample: 378 quarterly announcements for 25 firms over four years. It's also questionable how applicable this sample would be to the present day, as trading volume has increased dramatically, and spreads fallen greatly in the years since their sample ends in 1976.

Lee, Mucklow, and Ready (1994) provide a more modern and thorough examination of the behavior of spreads (and market depth) around earnings announcements. They show that liquidity decreases prior to earnings announcements (and prior to large surprises especially) and remains low in the wake of the announcement for a full day (i.e. spreads are higher than normal and quoted depth is lower than normal.) This effect is greatly mitigated, however, when volume is controlled for, in this case being limited to a liquidity decrease for only the first half hour following the announcement. The authors note, however, that the effect of controlling for volume is not perfectly clear theoretically.

Brooks (1996) approaches the question using the Hasbrouck (1991) decomposition of price variance. Price movements are decomposed by vector autoregression into a random walk component and a stationary component, and a measure of the proportion of private to public information is created. The author shows that this measure is significantly lower on earnings announcement days, although it oddly seems to be lower on the two previous days as well. Overall, Brooks (1996) interprets his results as being consistent with earnings announcements having an information leveling effect on asymmetry.

Krinsky and Lee (1996) examine the issue by using a decomposition of bid-ask spreads into its component parts. They note that prior literature examining spreads around announcements is difficult to interpret as components of the spread other than adverse selection may be changing in announcement periods as well. Upon decomposition, they find that different spread components tend to move in different directions simultaneously, and they attribute the previously mixed results in the literature to this fact. They find that while the adverse selection component of the spread increases following (and prior to) an announcement, while the inventory holding cost and order processing cost components decrease. They interpret their

results as being consistent with information asymmetry between investors increasing following earnings announcements. While this is an interesting result which addresses some of the difficulties of prior research with spreads, there have recently been a number of papers critical of the many various methods used to decompose elements of the spread. Van Ness, Van Ness and Warr (2001) examine five different measures of adverse selection, and find that they are uncorrelated with other measures of information asymmetry such as analyst forecast error and market to book. The measures are also only weakly correlated with each other and with measures of the presence of informed trade such as analyst following and institutional ownership. Neal and Wheatley (1998) document the puzzling result that different estimations of adverse selection components of the spread show consistently high values of adverse selection in closed-end mutual funds, which by their nature have little to no information asymmetry problems. These studies suggest that interpretations of decomposition based research remain difficult.

Barclay and Dunbar (1996) use yet another proxy for information asymmetry, the price impact of block trades, in addition to examining effective spreads (and a spread decomposition) around announcements. While they expect that prices will be more sensitive to block trades at times of higher asymmetry, they find no evidence that any window around the announcement has a different sensitivity than their baseline period. Similarly, they show no significant difference between their measure of spreads prior to and following the announcement. They conclude that they find “no evidence to support the hypothesis that the uninformed can trade on more favorable terms by varying the timing of their trades in relation to a quarterly earnings announcement.”

Yohn (1998) reaches a different conclusion. Testing a sample of 1,989 quarterly announcements between 1988 and 1990, she finds that spreads remain higher than normal for both the day of the announcement and the day following the announcement. She further

documents a positive relationship between this reaction and the size of the price reaction to the earnings announcement. She also notes that the size of the spread increase prior to the announcement is increasing in both firm size and analyst following.

Analyst forecast information is used by Barron, Byard and Kim (2002) to examine the issue from a different angle. Using the Barron et. al. (1998) estimation of the ratio of analysts' private information to analysts' common information, they show that, on average, earnings announcements tend to increase the proportion of idiosyncratic, private information in analysts' forecasts about future earnings. This suggests that earnings announcements can be used by sophisticated investors to increase their private information about future firm performance.

While the studies mentioned above have focused on U.S. equity markets, Libby, Mathieu, and Robb (2002) examine earnings announcements on the Toronto Stock Exchange. They examine spreads and quoted depth simultaneously, noting that both are methods used by market makers to provide or withdraw liquidity. They find that liquidity seems to increase following the announcements in their sample, although the window being tested is large (thirty days prior to and following the announcement.) As a result, it is difficult to make inferences about the short term effect of earnings announcements as a result of this study.

Prior research relating to information asymmetry following earnings announcements has also been used to make inferences about trading volume patterns at announcement time. In traditional models of trading in the presence of information asymmetry, such as Kyle (1985) and Glosten and Milgrom (1985), uninformed traders have exogenous liquidity needs, and are unable to choose the timing of their trades. Other models examine the effect of timing on trading outcomes for relatively uninformed investors. In Admati and Pfleiderer (1988), some uninformed liquidity traders can exercise discretion over the timing of their trades. This leads to trade

clustering, as the uninformed benefit from the lower sensitivity of price to trading when volume is high. The informed traders likewise benefit from the presence of the uninformed liquidity traders, which drives volume even higher. Chae (2005) hypothesizes that discretionary liquidity trading may explain some of the patterns that are observed around earnings announcements: slightly lower volume immediately prior to the announcement and very high volume immediately following it. Examining the differences between scheduled and unscheduled (e.g. merger) announcements, Chae (2005) notes that scheduled announcements have greater volume reductions prior to the announcement and larger increases in volume following the announcement than unscheduled announcements do. They conclude that this is consistent with uninformed traders delaying their trades until after the announcement, leading to pent-up demand that is released after the announcement. Additionally, Chae (2005) finds stronger results when some proxies for information asymmetry are high, implying that less informed investors are more likely to delay their trades until after the announcement, when asymmetry attenuates. If, however, information asymmetry tends to *increase* following earnings announcements, this calls into question the discretionary liquidity trader hypothesis.

2.2 Behavior of Small and Large Traders

In operationalizing my tests of information asymmetry, I divide investors between small and large traders, a proxy for the less informed and better informed investor classes. Two streams of literature examine the behavior of smaller, less sophisticated investors versus larger, more sophisticated ones. The first looks directly at the long term performance of trades made by different investor classes or of stocks that are heavily purchased or sold by individuals. The second uses the inferred net buying or selling activities of investors to see how large and small

traders react differently to various events. Among the first stream, Barber and Odean (2000) use data from a discount brokerage to examine the performance of individual investors and find that they underperform the market as a whole, and that frequent traders incur large transaction costs without any appreciable increase in performance. Hvidkjaer (2008) finds that shares favored by small investors experience declines in both the near and long term. Barber et. al. (2008) show that individuals trading in the Taiwan market lose systematically to institutions and foreign players, and that their losses stem largely from active trading (i.e., buy or sell orders rather than limit orders). In contrast, Kaniel, Saar, and Titman (2008) use NYSE data to examine the performance of stocks that are heavily bought or sold by individual investors, and finds that stocks that are heavily purchased by individuals have higher future returns. Kaniel et. al. (2009) do a similar analysis around earnings announcements and find that stocks that are heavily purchased by individuals prior to an announcement experience better returns in the coming days and months. They attribute this to both individuals' provision of liquidity to institutions, and superior private information possessed by individuals.

The second stream of literature uses the imbalance in trade orders to make inferences about the differing behavior of small and large investors. Lee (1992) found that whereas large traders tend to buy on good surprises around earnings announcements and sell on downside surprises, small traders buy on either good or bad news. Bhattacharya (2001) shows that small traders' abnormal trading activity is associated with a random walk model of earnings expectation, while the same does not hold true for large traders. Battalio and Mendenhall (2005) extend Bhattacharya (2001) by using the inferred sign of the trade to establish a net buying/selling position for small and large investors. They find similar results: small traders seem to respond to earnings announcements based on a random walk model, while large traders

respond based on analyst expectations. Other papers have looked at the role of small investors in causing PEAD (Hirshleifer et. al. 2008; Ayers, Li, Yeung 2009) and their interpretation of analyst recommendations (Malmendier and Shanthikumar, 2007). While these studies document interesting regularities in the behavior of different types of investors, they do not speak directly to the relative trading performance of these investors following earnings announcements.

Asthana, Balsam and Sankaraguruswamy (2004) examine the issue of relative trade profitability of small and large traders around 10-K filing dates. They find that small traders' trades tend to be less profitable in the period around 10-K filings, relative to other times, and that large traders' trades tend to be more profitable around these filings, though this effect is mitigated when firms file on EDGAR. Asthana, Balsam and Sankaraguruswamy (2004) is the only other paper of which I am aware that makes inferences based on the imputed profitability of small trades and large trades. My paper is the first which examines this profitability following earnings announcements, and the first which uses individual trading data rather than averages based on net buying activity (there is a more detailed discussion of the research method in section 3).

The discussion above shows that small and large investors tend to demonstrate systematically different trading behaviors. And while there are several different notions about the way that disclosures of important financial information affects information asymmetry, we know very little about how earnings announcements translate into trading outcomes for different investor classes. This paper is an attempt to understand how earnings announcements affect the actual trading performance of different sized investors. Do smaller investors benefit, on average, from the revelation of formerly private information that takes place at earnings announcements? Or does the advantage that accrues to larger, more sophisticated investors who are able to

generate private event-period information in the run-up to earnings announcements overwhelm any leveling effect that the announcement might have? As it is possible that either effect may predominate, I do not form a directional hypothesis. Instead, I proceed by first testing the sample as a whole to identify any general tendency in one particular direction.

As theory demonstrates, private information production following earnings announcement is likely to be due to private information gathered prior to the announcement in anticipation of it. I therefore also gather a number of firm and announcement characteristics that are likely related to private information production, and interact these variables with my measure of information asymmetry. I follow Yohn (1998) in examining the effect of both firm size and analyst following on my main variable of interest. The first variable I examine is firm size. Atiase (1985) proposes that market participants will generate more private information before earnings announcements when firm size is large, suggesting that large investors will benefit more from earnings announcements of larger firms. By conditioning on size, I test the extent to which the earnings announcement effect is greater or smaller for large versus small firms.

I also test the effect of analyst coverage on the relative performance of small versus large investors. Prior literature has seen analysts as either exacerbating (Brennan and Subrahmanyam, 1995) or alleviating (Roulstone, 2003) information asymmetry problems. I examine the effect of analyst coverage on my variables of interest, as the information that analysts generate may affect the ability of different investor groups to interpret earnings disclosures.

Finally, change in analysts' consensus (as defined in Barron et. al. 1998) has been shown in several studies to be associated with private information production (Barron, Byard and Kim, 2002; Botosan, Plumlee and Xie, 2004; Barron Harris and Stanford, 2005). The consensus variable measures the ratio of common to private information available to analysts in making

earnings forecasts. If consensus about future earnings decreases around an earnings announcement, this suggests that the announcement has stimulated the production of new private information.

3. Variables and Research Design

To investigate my research question, I use a measure of imputed short term profitability of trade, PROF. For each actual trade made for firms in my sample, I compare the actual transaction price with closing price three days later.³ This serves as a proxy for the ability of the investor initiating the trade to anticipate short term price movement. This is similar to the method Asthana, Balsam and Sankaragurswamy (2004) use to establish the potential short term profitability of trades. In their paper, they assess the potential profitability of buying or selling a specific security, and multiply this return by the net-buying or net-selling of the small investor group. This method assigns small investors, as a whole, a certain short-term potential profitability, with the intention of comparing their investment performance across disclosure regimes. In this paper, I construct a relative measure of profitability between the large and small groups by comparing *each* signed order (inferred using the Lee and Ready (1991) algorithm⁴) to the closing price three trading days later. I then value-weight the trades within the group to construct a return, and compare the returns that could potentially be earned by large versus small traders, and how that relationship changes in the wake of earnings announcements. This process is illustrated in a simplified example in Figure 1.

My measure of trade profitability has several advantages. Like the measure in Asthana, Balsam and Sankaragurswamy (2004), it gives a sense of the ability of the different groups of investors to assess the impact of earnings news in the short-term. But it also adds an additional

³ I use the midpoint of closing bid and ask quotes as closing price, to avoid the “bid-ask bounce” problem.

⁴ I use a one second rule to alleviate the concerns raised by Henker and Wang (2006).

<i>Trader Category</i>	<i>Trade Type</i>	<i>Execution Price</i>	<i>Number of Shares</i>	<i>3-Day Forward Price</i>	<i>Imputed Return</i>
Small	Buy	11.51	100	11.45	-0.0052
Large	Buy	11.53	5,800	11.45	-0.0070
Small	Sell	11.53	200	11.45	0.0070
Large	Sell	11.50	8,000	11.45	0.0044
PROF for small investors for firm-day:				0.0029	
PROF for large investors for firm-day:				-0.0004	

Figure 1: Simplified example of construction of PROF for a single firm-day. Each actual trade execution price is compared to the closing price 3 days forward to construct an imputed return for that trade. Then, the trades are value-weighted within the trader category to arrive at a PROF for each category for the day.

layer of precision by examining each trade individually.⁵ By comparing the short-term price benchmark to actual trading prices, PROF also measures the ability of investors to buy and sell at advantageous prices.

In order to partition trades into informed and uninformed, I use a trade size cutoff. Although many different cutoff points (and methods) have been used in the literature, I follow Bhattacharya (2001) in using a \$5,000 cutoff for small trades and a \$50,000 cutoff for large trades. I use these cutoffs because the rather conservative dollar values provide the best assurance that trades in each category truly represent trades from informed or uninformed investors. All trades between \$5,000 and \$50,000 are eliminated as ambiguous. If a stock's price, however, is above \$50, then single lot trades are still considered to be small trades, since trades of under \$5,000 would not be possible without trading odd lots. Stocks priced above \$100, however, are thrown out of my sample, as it no longer becomes possible to transact in those stocks at prices that unambiguously represent uninformed investors. I also perform a sensitivity test, described in section 4.4, to address concerns about changes in small and large trade patterns over time.

⁵ This allows the measure to capture not only the effect of intraday variation in prices, which can be large around earnings announcements, but also some of the transactions costs incurred by traders (via the bid-ask spread and price concessions.)

My main question of interest is in the effect of earnings announcements on the relative ability of small and large investors to trade advantageously. Prior research has shown that abnormal returns occur around earnings announcements; this effect has been attributed to both behavioral bias (DeBondt and Thaler, 1985) and risk shifting (Ball and Kothari, 1991). Due to the known patterns of abnormal returns around earnings announcements, my tests do not focus on the effect of the earnings announcement on each investor class, but rather on the *relative* impact of earnings announcements on the two groups. In other words, there are many reasons why the short term returns following an earnings announcement might vary, but the differential impact on small versus large traders should best capture the effect of the announcement on the change in informedness between the two groups. To investigate the effects of the difference between the two investor groups, I use a stacked regression with one observation for each imputed three day return for each investor type. I estimate the following equation for my main test:

$$PROF_{ij} = \alpha_0 + \alpha_1 EADay_i + \alpha_2 LG_j + \alpha_3 EADay_i * LG_j + CONTROLS + \varepsilon_{ij} \quad (1)$$

Where:

$PROF_{ij}$ = The imputed 3 day return on firm-day i of trades initiated by trader category j , expressed in percentage terms.

$EADay_i$ = An indicator variable equal to 1 if firm-day i is the day of or the day following an earnings announcement, and 0 otherwise.

LG_j = An indicator variable equal to 1 if trader category j is large, 0 otherwise.

This specification allows me to directly compare the differential effect of earnings announcements on the trading of large versus small investors. A positive estimation of α_3 would indicate that large traders improve their trading performance during the $EADay$ period relative to small traders. This result would be consistent with earnings announcements, on average, causing an increase in information asymmetry between investors. If α_3 is negative, on the other hand, this

would be indicative of an improvement in the performance of small traders relative to large, consistent with earnings announcements serving primarily to reduce information asymmetry between investors.

I include a number of controls for other features of the trading environment which may cause differences in returns around earnings announcements. $RET3_i$ measures the decile ranked magnitude of the three day return after the observation day (firm day i to firm day $i+3$). Since absolute returns following earnings announcements are larger, on average, than returns on non-announcement days, this control picks up the portion of variation in PROF that is simply a result of the magnitude of the price movement. Without the inclusion of this control, any results could be attributable to changes in return magnitudes, rather than in the underlying abilities of different investor classes.

$NB3_{ij}$ is the net-buying activity for investor class j in the three days prior to the observation (firm day $i-3$ to firm day i). This controls for the possibility that trading outcomes may be partially the result of short term reversals of prior trading positions. Kaniel et al. (2009) examine the behavior of individual investors using a proprietary data set that identifies trade initiators and conclude that some individuals tend to unwind their positions following the announcement. This control will help to alleviate concerns that patterns in the data may be the result of prior trading rather than earnings announcement information.

Other controls include $Q4_i$, a dummy which equals 1 if the earnings announcement is a fourth quarter and zero otherwise, and $BA\%_i$, a measure of the daily bid-ask spread, scaled by closing price. I also include a number of controls designed to describe the mix of traders, which could potentially affect the performance of the two different groups. $LPROP_i$ and $SPROP_i$ describe the proportion of total trades on firm-day i made by large and small investors,

respectively. $LVOLPROP_i$ and $SVOLPROP_i$ measure the proportion of trades by the two groups, and $LAVG_i$ and $SAVG_i$ is the average number of shares traded by each group on firm-day i . These variables control for changes in investor mix and trading activity around earnings announcements.⁶

One potentially confounding effect is post earnings announcement drift. If different investor types are differentially using PEAD-related trading strategies, their returns following earnings announcements may not reflect the degree to which they are using the announcement to generate private information. This presents a difficulty because the research question of this paper centers on the level of private information about a firm that different investor groups possess. If some traders are better able to understand and exploit PEAD, then results may pick up this difference rather than differences due to information based trading. As there is some evidence that institutional investors exploit PEAD (Ke and Ramalingegowda 2005) I control for the magnitude of the earnings surprise. But since earnings surprise is also information that informed investors can use to make investment decisions in conjunction with their private information, I estimate model (1) both with and without the surprise controls.

I use four different controls for earnings surprise. Given that small and large traders have been shown to respond differently to surprises calculated using the random walk or analyst forecast method (Bhattacharya, 2001), I include both as controls. I also partition the variables into negative and positive surprises, as the effect of PEAD can be different for negative versus positive surprises. $SURP_RW_POS_i$ represents the positive random walk earnings surprise of the earnings announcement closest to firm-day i , with $SURP_RW_NEG$ representing negative random walk earnings surprises. $SURP_AN_POS$ and $SURP_AN_NEG$ represent the corresponding variables for earnings surprises calculated using analyst forecasts.

⁶ Results are similar whether these variables are included or not.

I also examine the effect of two firm-level characteristics on the relationship explored in formula (1), firm size and analyst following. I do this by interacting these variables with my main variables of interest:

$$PROF_{ij} = \alpha_0 + \alpha_1 EAday_i + \alpha_2 LG_j + \alpha_3 EAday_i * LG_j + \alpha_4 PI_i + \alpha_5 PI_i * EAday_i + \alpha_6 PI_i * LG_j + \alpha_7 PI_i * EAday_i * LG_j + CONTROLS + \varepsilon_{ij} \quad (2)$$

Where PI is one of three variables designed to proxy for the amount of private information held by investors. MVE_RANK is the decile rank of firm size, measured as market value of equity. NUMAN is the number of analysts following the firm prior to the earnings announcement. And C_CONS is the change in analyst consensus, as defined in Barron et. al. (1998). Appendix A provides detailed variable definitions.

Finally, I test the discretionary liquidity trader hypothesis of Chae (2005). While the results of model (1) have some implications for this hypothesis, (1) by construction compares the post-earnings announcement period to all other periods. It is possible, however, that the period immediately prior to the announcement may also be fundamentally different from other periods. If large investors had a greater advantage in the pre-announcement period than in the post-announcement period, it would still be advantageous for uninformed investors with a short discretionary window to delay their trade until after an earnings announcement. I test the pre announcement period with the following model:

$$PROF_{ij} = \alpha_0 + \alpha_1 EAPre_i + \alpha_2 LG_j + \alpha_3 EAPre_i * LG_j + CONTROLS + \varepsilon_{ij} \quad (3)$$

This is identical to model (1), except for the substitution of EAPre for EAday. EAPre_i is an indicator variable which is equal to 1 if firm-day i is one of the two days prior to the earnings announcement (days -1 or -2). A positive coefficient estimate for α_3 would indicate that the pre

announcement period is more advantageous to large traders than other periods. A negative coefficient would indicate that this period is more advantageous for small traders.

4. Data and Results

4.1 Data Procedures

My sample includes all ordinary equity securities for domestic, non-ADR firms (CRSP shrcd 10 or 11) for the years 1994 to 2007 inclusive. I further restrict my sample to only firms listed on the NYSE to avoid difficulties in comparing microstructure techniques such as the Lee-Ready algorithm across different exchanges.⁷ For each security in my sample, I use the TAQ database to infer the direction of trade initiation. I eliminate all trades that are not routed through the NYSE (i.e. regional exchanges) as variations in the timing of quotes from these exchanges can make comparison with NYSE quotes and trades problematic. Trades with a negative price or a price more than \$5 different from the previous price are eliminated.⁸ I further eliminate quotes where the bid is equal to or greater than the ask price, where the spread is greater than \$5, where depth is negative, or where changes in the bid or ask are more than \$5 from the previous bid or ask. I then match the trades with the quotes, using the Lee-Ready (1991) algorithm (with the one second delay suggested by Henker and Wang (2006)) and infer the direction of the trade initiator by comparing executed price with the prevailing quote.

I then compute the short term imputed profit for each trade in my sample by comparing the actual execution price to the midpoint of the closing bid and ask quotes three days hence. Trade direction is used to determine the sign of the imputed return. Investors are also classified as small, medium, or large at this point based on the dollar value of the trade. All medium-sized

⁷ Additionally, as noted by Atkins and Dyl (1997) and Anderson and Dyl (2005), double counting of trades makes work with NASDAQ at the transaction level difficult. And Ellis, Michaely, and O'Hara (2000) point out issues related to using the Lee-Ready algorithm with NASDAQ.

⁸ These observations are likely errors in the database.

trades are discarded. For the small and large traders, $PROF_{ij}$ is computed by taking the value-weighted average of imputed three-day return for that day within that investor class.

The resulting dataset is then merged with Compustat to obtain earnings announcement dates and some firm variables. Firms without a minimum of five earnings announcement dates are dropped from the sample. To prevent serial correlation due to overlapping return periods, I drop two thirds of my observations. To maximize the number of earnings announcement observations, I anchor on earnings announcement days, using the following procedure. For each observation with two earnings announcement days (i.e. day 0 and day +1), I randomly choose one day to begin the process of culling overlapping return periods.⁹ After this, I begin dropping observations around the anchor date. For example, if day +1 relative to the earnings announcement is my anchor date, I would delete days +2 and +3, as well as days 0 and -1. I then continue through the days that have the relevant earnings announcement date as the nearest earnings announcement date, keeping days +4 and -2 in this example, and deleting days +5 and +6, -3 and -4, and so forth. This ensures that there are no overlaps between the many different calculated return periods in my sample.

4.2 Descriptive Statistics

A total of 2,883 unique firms representing 1,594,692 non-overlapping trading days are in the sample. 156,239 sample days are in the post-earnings announcement period, i.e. they are days 0 or 1 relative to the earnings announcement. Almost all of these days have some small trader activity, and 87% of days have some larger trade activity as well. Both mean and median PROF is negative for both large and small traders, although the mean is somewhat lower for small traders. Negative PROF is intuitive, as most of the three-day windows involve little price movement, but the entry or exit price of the security includes the cost of the spread.

⁹ In the case where only one of these two days is available, I use that day as the anchor.

Table 2 shows a correlation matrix consisting of the main variables used in the tests. $PROF_{ij}$ is positively correlated with $EAday_i$, $NB3_i$, MV_RANK_i and $NUMANAL_i$. As expected, $PROF_{ij}$ is significantly negatively correlated with $BA\%$, indicating that higher spreads reduce short term returns.

4.3 Main Results

Results of estimating (1) are shown in Table 3. The coefficients for both LG_j and $EAday_i*LG_j$ are positive and significant at conventional levels. This indicates that large traders enjoy an advantage in their short term returns compared to small traders in both the period following earnings announcements and at other times as well. The 0.022 coefficient for $EAday_i*LG_j$ indicates that earnings announcements cause large traders' advantage over small traders to more than double from the 0.014 percent advantage implied by the coefficient for LG_j . An increase of 0.022% over a three day window is an economically significant excess return for such a small period of time. Assuming 252 trading days in a year, excess return of 0.022% in each 3 day period would lead to an annual excess return of 1.87%. These results are consistent with earnings announcements on average causing an increase in short-term information asymmetry that benefits better-informed investors. If we set all control variables to their median values, the difference between small and large profitability following earnings announcements is 0.034% over three days, equivalent to a 2.90% annual return.

The second column of Table 3 shows results with the inclusion of controls for the magnitude and direction of the earnings surprise (each variable is included individually, as well as interacted with $EAday_i$ and LG_j individually, although only the three way interaction term is shown for brevity.) Interestingly, while none of the surprise interaction terms are statistically

significant, their inclusion increases the magnitude of the coefficient for $EADay_i * LG_j$ and decreases its standard error. Thus, to the extent that investors do trade strictly on PEAD following an earnings announcement, such trading the short term returns of investors, as expected. Higher levels of price movement are associated with higher individual trading returns, and this relationship becomes stronger on earnings announcement days. Prior net-buying seems to also affect individual short term returns, indicating that unwinding of prior positions does seem to affect the profitability of trade, although it is interesting to note that this relationship does not change in the period following earnings announcements. As expected, bid ask spreads have a negative impact on short-term returns.

Results for the incremental effect of information variables are shown in Table 4. The first column of panel A shows the results of inclusion of a firm size interaction with the main variables of interest. The coefficient for MV_RANK is positive and significant, indicating that trading profits are higher overall for large firms, although the negative does not appear to substantially explain the relative improvement in trading performance that large traders experience following an earnings announcement.

Regarding the control variables, the magnitude of the price change seems to affect coefficient for $MV_RANK * LG$ indicates that increases in size tend to benefit smaller traders. The coefficient for the three way interaction term $MV_RANK * LG * EADay$ is not statistically significant, nor is the coefficient for $MV_RANK * EADay$, indicating, contrary to expectations, that firm size does not seem to affect the difference between small and large traders' profits following earnings announcements.

Column 2 of Panel A shows the results of interactions with the number of analysts following a firm prior to the earnings announcement. Here results show that more analyst

following does affect trading around earnings announcements, with large traders benefiting from an increase in analyst coverage, relative to small traders. Interestingly, however, the opposite effect obtains in non-earnings announcement periods, although the magnitude of the effect is smaller. This indicates that, while heavily followed stocks are, *ceteris paribus*, a worse trading environment for large traders, these stocks are nonetheless more advantageous for large traders following earnings announcements.

Finally, in Panel B, we see the results of interactions with C_CONS , or change in analyst consensus. If analyst consensus decreases following an earnings announcement, this implies that the ratio of private information to common information has increased, which would tend to benefit sophisticated investors who can generate private information. Results are consistent with this notion, as the coefficient on $C_CONS*EAday*LG$ is negative. This indicates that if an earnings announcement produces information that increases the amount of private, idiosyncratic information in analysts' forecasts about future earnings (a decrease in consensus), large investors' advantage over small investors following the announcement is greater. This is consistent with the proposition of this paper that the relative profitability of trade between large and small traders following earnings announcements is driven by differential levels of private information.

Next, I turn to the discretionary liquidity trader hypothesis of Chae (2005). This argues that patterns in trading volume around earnings announcements can be explained by the "pent up demand" of liquidity traders who wish to delay their trade until after the earnings announcement, as that will reduce their chances of trading against informed traders and cause them to experience lower average returns. While the evidence presented in table 3 would seem to be inconsistent with this notion, it is possible that the conditions for small traders are even worse immediately

prior to an earnings announcement than immediately following the announcement. If this is the case, it still may be rational for uninformed traders who have exogenous liquidity needs to delay their trade until the announcement has been made. I test this proposition by running an estimation comparing small and large trade performance in the period immediately *prior* to the earnings announcement. Results of this test are presented in table 5.

If conditions for small traders are poor in this period, we would expect that the coefficient for $EAPre*LG$ would be positive and significant. Instead, the coefficient is not statistically significant, nor is the coefficient for $EAPre$ alone, indicating that there is no evidence to support the notion that the period prior to the announcement is a worse trading environment for small traders. Combined with the results in table 3, these results are consistent with the view that uninformed investors would put themselves at a *disadvantage* by waiting for the post-announcement period to execute their trades, the opposite of the discretionary liquidity trader hypothesis.¹⁰

4.4 Sensitivity Analyses

While the use of small and large trade size to proxy for less and more sophisticated investors is well established in the literature, it has also been noted that the proxy may be becoming less reliable over time, as electronic trading innovations make order splitting by institutions easier and less costly (Kaniel, Saar, Titman, 2008). While order splitting has been a potential strategy for masking informed trade for many years (Barclay and Warner, 1993) there is some evidence that its use has increased over time. Puckett and Yan (2008), using a large database of actual trades from 840 different institutions show a steady decline in median trade

¹⁰ This test is necessarily a joint test of investors' motivations and their ability to understand the trading environment. I cannot rule out the possibility that investors are motivated to delay their trades until the period following an earnings announcement due to an incorrect belief that they will be at less of a disadvantage.

size from 60,030 in 1999 to 14,232 in 2005. And Campbell et. al. (2009) show that very small trades are correlated with changes in institutional holdings, suggesting that some institutions are splitting their trades into very small portions. Finally, Hvidkaajer (2008) finds that in his sample, correlation between small trading direction and institutional holdings is negative until 2002, at which point it turns slightly positive.

I do two additional analyses to address these concerns. First, I partition my sample into an early and a late period. The early period (1994 – 2001) should have fewer concerns about proxy noise due to excessive institutional order splitting, compared to the later period (2002 – 2007). I rerun my tests on both periods in order to examine any differences. Abbreviated results of estimating (1) for these two time periods are shown in Panel A of Table 6. For the early period, results are consistent with the entire sample results reported in Table 3. The coefficients for LG and LG*EAday are both positive and significant, and both are larger in magnitude than the combined results. For the latter period, however, the coefficient on LG becomes negative and significant, with the coefficient for EAday*LG remaining positive but only at a marginal level of significance. These results are consistent with a change in trading patterns of informed and uninformed investors over time, although I cannot rule out the possibility of other influencing trends over time.

To better understand the changing nature of trade over time, I present trends in order size for my sample in Panel B. In examining the proportion of large and small trades both by number and by trading volume, a clear trend emerges away from large trades and towards small ones. While there are likely other causes for this trend besides order splitting (such as the emergence of online brokerages and day trading) the magnitude of the change points towards wide-spread changes in institutional trading

habits. This is consistent with the data presented in Chordia, Roll and Subrahmanyam (2008) who find a similar trend, and conclude that institutional order splitting is the most likely cause.

Secondly, I adopt a different technique for categorizing large and small traders based on evidence presented in Campbell et. al. (2009). This paper examines the correlation between different trade sizes and changes in reported institutional shareholdings. While large trades tend to be positively associated with institutional ownership, and most small trades negatively associated with institutional ownership, very small trades (below \$2,000) show a positive association, suggesting that many of these trades represent institutional order splitting. I therefore re-run my main analyses using negatively associated with institutional ownership, respectively. I classify trades between \$2,000 and \$10,000 as small¹¹, and trades greater than or equal to \$40,000 as large. Untabulated results from this alternate specification are nearly identical to the previously reported results. This suggests that the reported results are robust to alternate specifications designed to reduce the amount of investor type misclassification.

Additionally, I test my data for the presence of multicollinearity. Computing variance inflation factors for all the variables used in my main tests shows that none have a VIF of over 10. Several, however, are relatively high, with SPROP, LPROP, SVOLPROP, and LVOLPROP all being greater than seven. This is intuitive, as the proportion of small traders is highly negatively correlated with the proportion of large traders. As these are control variables, the relatively high VIF's are not a concern, but in any case removing them from the tests does not change inferences. All other variables have VIF scores under 3.5.

¹¹ Since the great majority of trades take place in round lots of 100 shares, eliminating trades under \$2,000 will only eliminate trades for shares with a price of \$20 or less. To address the possibility that very small order splitting takes place for shares with a price above \$20, I eliminate all single lot trades from this analysis.

5. Conclusion

In this paper I test the effect of earnings announcements on the relative ability of small and large investors to trade advantageously. While many studies have examined the issue of the effect of earnings announcements on information asymmetry, using various proxies for asymmetry, a clear consensus has yet to emerge. I measure information asymmetry between large and small investors (a proxy for informed and uninformed investors) by examining how well those investors' actual trades predict short-term price movement. Results show that, on average, large traders tend to improve their trading performance following an earnings announcement more than small traders. This effect is strongest for firms which are very large and have large analyst followings, and for earnings announcements which produce more private information about future earnings. There is some evidence that large traders improve their relative performance when earnings surprises (as measured by analysts' forecasts) are high. Other attributes of earnings surprises, however, fail to yield significant results. Similarly, examination of attributes of institutional ownership fails to find evidence that certain types of institutions are more likely to increase the advantage of large trading on post earnings announcement days.

This paper contributes to two different streams of literature. The first is the broad category of research on the effect of earnings announcements on information asymmetry. This paper differs from prior work in that it examines the *consequences* of information asymmetry, rather than relying on estimations of the probability of informed trade. Regulatory concern relating to accounting disclosures is focused on the consequences of accounting disclosures on the trading behavior of investors. This paper examines this issue directly by analyzing the short-term returns of actual trades.

Secondly, this paper contributes to the literature on volume patterns around earnings announcements. Prior literature has suggested that one possible explanation for the large amount of trading volume following earnings announcements is the “pent up demand” of uninformed traders who were waiting for an information-leveling event before executing their trades. Results in this paper suggest, however, that informed traders increase their advantage following earnings announcements, while no such advantage can be demonstrated in the period immediately preceding the announcement. Collectively, these results are inconsistent with the idea that earnings announcement trading volume patterns are caused by the type of trade-shifting described in Chae (2005).

Appendix – Variable Definitions

PROF _{ij}	The three day imputed profit earned by investor group j on firm-day i. For group j (large or small), PROF is the value weighted average of returns earned by buying or selling at each actual transaction price, and reversing this position three days later (the midpoint of daily close bid-ask three trading days forward.) PROF is then multiplied by 100 to express it in percentage terms, and winsorized at the 1% and 99% levels.
RET3 _i	The decile ranked absolute value of the security's return over the three trading day period from i to i+3
NB3 _{ij}	The net-buying activity of investor group j in the three days prior to day i. Net buying is computed as the number of shares bought by group j on firm-day i less the number of shares sold, divided by the total number of shares transacted by group j on firm-day i.
BA% _i	Bid-ask spread for firm-day i, expressed in percentage terms. Computed as the closing ask less the closing bid, divided by closing price on firm-day i.
LG _{ij}	An indicator variable equaling 1 if investor group j is the large investor group on firm-day i, and 0 otherwise.
EAday _i	An indicator variable equaling 1 if firm-day i is in the post earnings announcement period (days 0 or 1 relative to the earnings announcement.)
EAPre _i	An indicator variable equaling 1 if firm-day i is in the pre earnings announcement period (days -1 or -2 relative to the earnings announcement.)
SURP_RW_POS _i	Positive seasonal random walk earnings surprise. Seasonal random walk is computed as the difference between earnings per share in the earnings announcement closest to firm-day i less earnings per share four quarters prior (adjusted for stock transactions). If the surprise is positive, SURP_RW_POS takes its value. Otherwise, it takes a zero value.
SURP_RW_NEG _i	Negative seasonal random walk earnings surprise. The random walk earnings surprise is calculated as above, if it is negative, then SURP_RW_NEG _i takes its value. Otherwise, it takes a zero value.
SURP_AN_POS _i	Positive analyst expectation earnings surprise. Surprise is defined as the difference between actual EPS (as defined by IBES) and the most recent forecast or forecast update prior to the earnings announcement closest to day i. If an announcement has no forecasts or updates within the 30 days prior to the announcement, it is not assigned a value. If the surprise is positive, SURP_AN_POS takes its value. Otherwise, it takes a zero value.
SURP_AN_NEG _i	Negative analyst expectation earnings surprise. The analyst expectation earnings surprise is calculated as above, if it is negative, then SURP_AN_NEG _i takes its value. Otherwise, it takes a zero value.

MV_RANK _i	Decile rank of market value (defined as market price at the end of the prior quarter multiplied by shares outstanding, as defined by CRSP).
NUMAN _i	Number of analysts following a firm. Defined as the number of unique analyst codes in IBES (excluding 0000) identified as making earnings forecasts for the announcement closest to firm-day i.
Q4 _i	An indicator variable that takes the value 1 if the earnings announcement closest to firm-day i is for the firm's fourth fiscal quarter, and 0 otherwise.
C_CONS _i	Decile ranked change in analyst consensus for one quarter ahead earnings. Consensus is defined as in Barron, Harris and Stanford (2005) where Consensus = 1 – D/V. D is defined as analyst forecast dispersion, and V is defined as the squared differences in analysts' forecasts: $V = \sum_{i=1}^n (FC_i - EPS)^2 / n$ Where FC _i is analyst i's earnings forecast, EPS is actual earnings per share, and n is the number of forecasting analysts. The measure represents the ratio of commonly held information to private information. An increase (positive C_CONS) represents a decrease in the proportion of private information due to information released in the earnings announcement closest to day i.
LPROP _i	The proportion of trades made by large traders to total trades on firm-day i.
SPROP _i	The proportion of trades made by small traders to total trades on firm-day i.
LVOLPROP _i	The proportion of trading volume generated by large traders to total trading volume on firm-day i.
SVOLPROP _i	The proportion of trading volume generated by small traders to total trading volume on firm-day i.
LAVG _i	The average number of shares traded per large trader transaction on firm-day i.
SAVG _i	The average number of shares traded per small trader transaction on firm-day i.

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TABLE 1**Descriptive Statistics for a Sample of NYSE firm trading days for calendar years 1994 - 2007**

PROF is defined as the value weighted imputed 3-day return for each investor class for the firm-day. LPROP and SPROP are the proportion of the total number of large trades and small trades, respectively, to the total number of trades in the day. LVOLPROP and SVOLPROP are the proportion of the total volume composed of large trades and small trades in a day, respectively. LAVG and SAVG are the average number of shares per large trade and per small trade, respectively. SURP is the absolute value of the earnings surprise, defined as the difference between the analyst consensus (defined as the average of forecasts initiated or reiterated in the 45 days prior to the announcement) and IBES actuals. If this number is unavailable, I use the difference between reported earnings and the seasonal random walk. EADay is an indicator variable equal to 1 if the day is an earnings announcement day (or the day following an announcement) and zero otherwise. LG is an indicator variable equal to 1 if the investor group is large, and zero otherwise.

Panel A:

Sample Description

Total Number of Firms in Sample:	2,883
Total Number of Earnings Announcement Firm-Days	156,239
Total Number of Firm-Days	1,594,692
Firm-Days with Calculable Large Trader Profit	1,388,730
Firm-Days with Calculable Small Trader Profit	1,578,662

Panel B:

Variable Descriptives

Variable Name	N	Mean	Median	Std	25 th	75 th
PROF (LG=1)	1,388,730	-0.0365	-0.0565	1.652	-0.5734	0.4630
PROF (LG=0)	1,578,662	-0.0818	-0.0517	1.388	-0.4564	0.2865
RET3	1,577,698	0.0336	0.0203	1.024	0.0087	0.0400
NB3	1,570,341	0.0611	0.0857	0.276	-0.0667	0.2174
SURP_RW_POS	1,546,347	0.0098	0.0012	0.033	0	0.0057
SURP_RW_NEG	1,547,578	-0.0093	0	0.036	-0.0051	0
SURP_AN_POS	1,225,012	0.0013	0.0002	0.003	0	0.0012
SURP_AN_NEG	1,225,021	-0.0017	0	0.009	-0.0002	0
LPROP	1,355,122	0.2494	0.1786	0.229	0.0426	0.4219
SPROP	1,355,122	0.3632	0.3262	0.202	0.1964	0.5000
LVOLPROP	1,355,122	0.6054	0.6636	0.304	0.3377	0.8948
SVOLPROP	1,355,122	0.0927	0.0456	0.112	0.0146	0.1304
LAVG	1,388,730	5,391	3,566	9,452	2,201	5,942
SAVG	1,372,700	145	100	113.5	100	150

TABLE 2**Correlation Matrix of Selected Variables**

Variables are defined in Appendix A. Pearson correlations are on the top right, Spearman correlation on the bottom left. P-values are displayed below correlations.

	PROF	EADay	LG	RET3	NB3	BA%	SURP_AN POS	SURP_AN NEG	MV_RANK	NUMAN	C_CONS
PROF	-	0.0102 0.000	0.0149 0.000	0.0012 0.038	0.0228 0.000	-0.0619 0.000	-0.0099 0.000	0.0266 0.000	0.0456 0.000	0.0092 0.000	0.0021 0.013
EADay	0.0104 0.000	-	0.0048 0.000	0.0019 0.001	0.0011 0.071	0.0081 0.000	0.0101 0.000	-0.0053 0.000	-0.0087 0.000	-0.0029 0.001	0.0000 0.972
LG	-0.0078 0.000	0.0023 0.009	-	-0.0023 0.000	0.0313 0.000	-0.0468 0.000	-0.0238 0.000	0.0565 0.000	0.0899 0.000	0.0116 0.000	0.0002 0.826
RET3	-0.0012 0.1923	0.0484 0.000	-0.0023 0.009	-	-0.0048 0.000	0.0257 0.000	0.0035 0.000	-0.0155 0.000	-0.0127 0.000	0.189 0.000	-0.0153 0.000
NB3	0.0161 0.000	0.0018 0.038	0.0638 0.000	-0.0174 0.000	-	-0.1818 0.000	-0.0585 0.000	0.0883 0.000	0.2157 0.000	0.0902 0.000	0.0036 0.000
BA%	-0.0624 0.000	0.0113 0.000	-0.0039 0.000	0.1678 0.000	-0.1139 0.000	-	0.0999 0.000	-0.2655 0.000	-0.4797 0.000	-0.1593 0.000	-0.0195 0.000
SURP_AN_POS	0.0057 0.000	0.0168 0.000	-0.0063 0.000	0.0163 0.000	-0.0169 0.000	-0.0498 0.000	-	0.0811 0.000	-0.1667 0.000	-0.0742 0.000	0.0007 0.000
SURP_AN_NEG	0.0099 0.000	-0.0000 0.964	0.0035 0.000	0.0025 0.0042	0.0477 0.000	-0.0223 0.000	0.5775 0.000	-	0.2604 0.000	0.0503 0.000	0.0197 0.000
MV_RANK	0.0409 0.000	-0.0057 0.000	0.0207 0.000	-0.1240 0.000	0.1625 0.000	-0.3822 0.000	-0.0602 0.000	0.0760 0.000	-	0.5256 0.000	0.0028 0.001
NUMAN	0.0208 0.000	-0.0053 0.000	0.0126 0.000	0.0169 0.000	0.0873 0.000	-0.1936 0.000	-0.0486 0.000	0.0674 0.000	0.5323 0.000	-	0.028 0.000
C_CONS	0.0034 0.000	0.0004 0.635	0.0003 0.6895	-0.0113 0.000	0.0025 0.004	-0.0204 0.000	0.0119 0.000	0.0359 0.000	0.0036 0.000	0.0333 0.000	-

TABLE 3**Results of Regressions of Short Term Trader Profitability on Trader Characteristics and Information Variables**

Variables are defined in Appendix A. Stacked regression consists of one observation per trader type (small or large) per trading day (only one out of each three potential trading days is used, to avoid overlapping return periods.) Some interactions are omitted for brevity (all earnings surprise variables are also interacted with EAday and LG individually). Firm fixed effects are included. All standard errors are clustered by date using the Rogers (1993) method. Coefficients in *italics* are statistically significant at the 5% level. All tests are two-tailed

Variable Name	Estimate	T-Stat	Estimate	T-Stat
Intercept	<i>0.00941</i>	<i>0.96</i>	<i>0.01605</i>	<i>1.57</i>
EAday	-0.01217	-1.65	-0.02208	-2.78
LG	<i>0.01436</i>	<i>4.94</i>	<i>0.00396</i>	<i>3.22</i>
EAday*LG	<i>0.02184</i>	<i>2.38</i>	<i>0.03425</i>	<i>3.22</i>
RET3	<i>0.00744</i>	<i>7.53</i>	<i>0.00677</i>	<i>6.61</i>
RET3*LG	0.00098	1.08	<i>0.00084</i>	<i>0.91</i>
RET3*EAday	<i>0.00990</i>	<i>4.82</i>	<i>0.01068</i>	<i>5.00</i>
RET3*EAday*LG	0.00038	0.16	-0.00144	-0.58
NB3	<i>0.02302</i>	<i>3.82</i>	<i>0.02071</i>	<i>3.22</i>
NB3*EAday	0.00501	0.20	0.02131	0.82
NB3*EAday*LG	-0.04209	-1.44	-0.04430	-1.43
Q4*EAday	-0.00724	-0.74	-0.00893	-0.87
BA%	<i>-2.22494</i>	<i>-13.05</i>	<i>-2.15328</i>	<i>-12.02</i>
SURP_RW_POS*EAday*LG			-0.67895	-1.89
SURP_RW_NEG*EAday*LG			0.30154	0.96
SURP_AN_POS*EAday*LG			1.32583	0.48
SURP_AN_NEG*EAday*LG			-0.85744	-0.63
LPROP	<i>0.06914</i>	<i>3.22</i>	<i>0.07499</i>	<i>3.35</i>
SPROP	-0.04726	-2.45	-0.02859	-1.42
LVOLPROP	-0.07251	-5.19	-0.07436	-5.11
SVOLPROP	-0.03219	-0.87	-0.04992	-1.32
LAVG	0.00000	-0.05	0.00000	-0.06
SAVG	<i>-0.00022</i>	<i>-6.51</i>	<i>-0.00024</i>	<i>-6.35</i>
Number of observations:	2,558,530		2,277,370	

TABLE 4

**Effect of Firm-Level Variables on the Relative Advantage of Large Traders
Following Earnings Announcements**

Variables are defined in Appendix A. Stacked regression consists of one observation per trader type (small or large) per trading day (only one out of each three potential trading days is used, to avoid overlapping return periods.) Some interactions are omitted for brevity (all earnings surprise variables are also interacted with EAday and LG individually). All standard errors are clustered by date using the Rogers (1993) method. Coefficients in italics are statistically significant at the 5% level. All tests are two-tailed.

Panel A:

Incremental effect of firm size and analyst following

Variable Name	PI = MV_RANK		PI = NUMAN	
	Estimate	T-Stat	Estimate	T-Stat
Intercept	<i>0.1477</i>	<i>1.42</i>	<i>0.0248</i>	<i>1.67</i>
EAday	-0.0203	-2.45	-0.0212	-1.41
LG	<i>0.0057</i>	<i>1.78</i>	<i>0.0170</i>	<i>3.56</i>
EAday*LG	0.0334	3.10	<i>0.0097</i>	<i>0.57</i>
PI	<i>0.0000</i>	<i>1.05</i>	<i>-0.0002</i>	<i>-0.33</i>
PI*LG	<i>-0.0000</i>	<i>-5.00</i>	<i>-0.0011</i>	<i>-2.81</i>
PI*EAday	-0.0000	-1.24	-0.0009	-0.76
PI*EAday*LG	0.0000	0.67	<i>0.0027</i>	<i>2.09</i>
RET3	<i>0.0068</i>	<i>6.64</i>	<i>0.0058</i>	<i>4.45</i>
RET3*LG	0.0008	0.86	-0.0004	-0.40
RET3*EAday	<i>0.0106</i>	<i>4.85</i>	<i>0.0123</i>	<i>4.53</i>
RET3*EAday*LG	-0.0014	-0.57	<i>-0.0015</i>	<i>-0.51</i>
NB3	<i>0.0207</i>	<i>3.23</i>	<i>0.0152</i>	<i>1.64</i>
NB3*EAday	0.0217	0.84	0.0661	1.56
NB3*EAday*LG	-0.0439	-1.42	-0.0501	-1.00
Q4*EAday	-0.0092	-0.89	-0.0054	-0.43
BA%	<i>-2.1529</i>	<i>-12.01</i>	<i>-1.4961</i>	<i>-6.00</i>
SURP_RW_POS*EAday*LG	-0.6768	-1.88	-0.3407	-0.64
SURP_RW_NEG*EAday*LG	0.2999	0.96	0.0091	0.02
SURP_AN_POS*EAday*LG	1.3578	0.49	-1.7486	-0.42
SURP_AN_NEG*EAday*LG	-0.8674	-0.63	-0.7284	-0.30
LPROP	<i>0.0753</i>	<i>3.28</i>	<i>0.0789</i>	<i>2.76</i>
SPROP	-0.0284	-1.40	0.0057	0.20
LVOLPROP	<i>-0.0744</i>	<i>-5.08</i>	<i>-0.0857</i>	<i>-4.43</i>
SVOLPROP	<i>-0.0499</i>	<i>-1.32</i>	<i>-0.0821</i>	<i>-1.55</i>
LAVG	-0.0000	-0.05	0.0000	1.19
SAVG	<i>-0.0002</i>	<i>-6.35</i>	<i>-0.0003</i>	<i>-4.63</i>
Number of observations:	2,277,746		1,300,341	

Panel B:
Incremental effect of change in analyst consensus

PI = C_CONS

Variable Name	Estimate	T-Stat
Intercept	0.0202	1.45
EAday	-0.0485	-3.67
LG	0.0087	1.80
EAday*LG	0.0584	3.37
PI	0.0003	0.83
PI*LG	-0.0003	0.83
PI*EAday	0.0042	2.45
PI*EAday*LG	-0.0059	-2.48
RET3	0.0057	4.45
RET3*LG	-0.0005	-0.47
RET3*EAday	0.0124	4.55
RET3*EAday*LG	-0.0015	-0.52
NB3	0.0147	1.59
NB3*EAday	0.0659	1.54
NB3*EAday*LG	-0.0475	-0.95
Q4*EAday	-0.0053	-0.43
BA%	-1.4881	-5.97
SURP_RW_POS*EAday*LG	-0.3585	-0.67
SURP_RW_NEG*EAday*LG	0.0129	0.03
SURP_AN_POS*EAday*LG	-2.1094	-0.51
SURP_AN_NEG*EAday*LG	-0.5253	-0.22
LPROP	0.0816	2.88
SPROP	0.0073	0.25
LVOLPROP	-0.0859	-4.45
SVOLPROP	-0.0825	-1.56
LAVG	0.0000	-4.63
SAVG	-0.0071	-0.07

Number of observations: 1,300,461

TABLE 5**Relative Performance of Small and Large Traders Prior to the Earnings Announcement**

Variables are defined in Appendix A. Stacked regression consists of one observation per trader type (small or large) per trading day (only one out of each three potential trading days is used, to avoid overlapping return periods.) Some interactions are omitted for brevity (all earnings surprise variables are also interacted with EAday and LG individually). All standard errors are clustered by date using the Rogers (1993) method. Coefficients in italics are statistically significant at the 5% level. All tests are two-tailed.

Variable Name	Estimate	T-Stat
Intercept	0.0277	2.51
E _{Apre}	0.0078	0.71
LG	0.0133	4.60
E _{Apre} *LG	0.0117	0.81
RET3	0.2738	3.21
RET3*LG	-0.1258	-1.73
RET3*E _{Apre}	0.0775	0.31
RET3*E _{Apre} *LG	-0.0370	-0.12
NB3	0.0199	2.88
NB3*E _{Apre}	0.1253	3.33
NB3*E _{Apre} *LG	-0.0792	-1.76
Q4*E _{Apre}	-0.0283	-1.92
BA%	-2.0311	-10.79
LPROP	0.0798	3.31
SPROP	0.0166	0.76
LVOLPROP	-0.0654	-4.25
SVOLPROP	-0.0898	-2.30
LAVG	-0.0000	-0.14
SAVG	-0.0003	-7.10
Number of observations:	2,014,305	

TABLE 6**Sensitivity Test and Trends in Small/Large Trading Patterns**

Variables are defined in Appendix A. Selected estimates from estimation of equation (1) for different sample periods.

Panel A:

Variable Name	1994-2001		2002-2007	
	Estimate	T-Stat	Estimate	T-Stat
EADay	-0.0184	-1.43	-0.0048	-0.46
LG	<i>0.0393</i>	<i>10.64</i>	-0.0261	-8.13
EADay*LG	<i>0.0508</i>	<i>2.91</i>	0.0280	1.89

Panel B:

Average values by year of selected variables

Year	LPROP	SPROP	LVOLPROP	SVOLPROP
1994	0.390	0.270	0.808	0.040
1995	0.400	0.264	0.811	0.039
1996	0.414	0.252	0.816	0.036
1997	0.426	0.238	0.812	0.035
1998	0.415	0.244	0.800	0.038
1999	0.365	0.292	0.779	0.047
2000	0.359	0.307	0.771	0.052
2001	0.133	0.362	0.553	0.066
2002	0.086	0.450	0.553	0.108
2003	0.058	0.500	0.379	0.148
2004	0.056	0.482	0.348	0.152
2005	0.053	0.483	0.317	0.163
2006	0.042	0.517	0.269	0.194
2007	0.022	0.646	0.156	0.317