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Earnings Expectations and Investor Clienteles

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Abstract: Prior research suggests that the earnings expectations of some investors are systematically biased toward seasonal random walk (SRW) predictions. We provide clear and direct evidence that the net buying activity of small (large) traders around earnings announcements is significantly positively associated with SRW (analyst) forecast errors. Further, the interpretations of earnings news by the smallest and largest investors appear to be completely unrelated. Finally, small trades at the time of earnings announcements run counter to stock-price movements suggesting that small traders may impede stock prices from reflecting earnings-related information and may, therefore, play a role in post-earnings-announcement drift.

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Earnings Expectations and Investor Clienteles

Abstract: Prior research suggests that the earnings expectations of some investors are systematically biased toward seasonal random walk (SRW) predictions. We provide clear and direct evidence that the net buying activity of small (large) traders around earnings announcements is significantly positively associated with SRW (analyst) forecast errors. Further, the interpretations of earnings news by the smallest and largest investors appear to be completely unrelated. Finally, small trades at the time of earnings announcements run counter to stock-price movements suggesting that small traders may impede stock prices from reflecting earnings-related information and may, therefore, play a role in post-earnings-announcement drift.

I. Introduction

This paper investigates whether different types of investors (i.e., those making large versus small trades) base their buy and sell decisions on different information sets and whether some investor types hold beliefs that are biased in a systematically predictable way. Prior researchers speculate that post-earnings-announcement drift, the tendency for cumulative abnormal returns following earnings announcements to drift in the direction of the earnings surprise, may be caused by investors who hold naive earnings expectations. Specifically, some researchers believe that earnings expectations reflected in stock prices systematically fail to reflect the true time-series properties of earnings, but rather mirror seasonal random walk (SRW) forecasts. This paper presents clear and direct evidence on whether certain types of investors hold earnings expectations that are systematically biased in an ex ante predictable way.

Over the last several decades researchers have documented what appears to be a slow response to the information in earnings announcements. (See, e.g., Ball and Brown 1968, Rendleman, Jones, and Latané 1982, Foster, Olsen, and Shevlin 1984, and Bernard and Thomas 1989.) The manifestation of this apparent underreaction is significant post-announcement abnormal returns in the direction of the earnings surprise. In other words, when actual earnings exceed (fall short of) a proxy for the market's expectation of earnings, researchers observe positive (negative) abnormal returns for many weeks following the earnings announcement. After numerous attempts in the literature to resolve the drift anomaly by examining possible methodological shortcomings and various forms of risk correction, post-earnings-announcement drift remains the "granddaddy of all underreaction events" (Fama 1998, p.286).

After attempting to exhaust efficient-market explanations for the drift (Bernard and Thomas 1989), Bernard and Thomas (1990) propose a specific inefficient-market explanation. They hypothesize that stock prices do not reflect the true time-series properties of earnings, but rather they reflect naive expectations that resemble SRW forecasts. Under the SRW model, the earnings prediction for this quarter is simply earnings for the same fiscal quarter of the prior year. One motivation for their hypothesis is that the news media almost always compare announced earnings to earnings for the same quarter of the preceding year (the SRW forecast) and in many cases seem to assign special significance to this comparison.

The SRW model seems obviously naive because its errors exhibit a strong autocorrelation pattern (Foster 1977). Bernard and Thomas hypothesize that if investors anchor on the SRW prediction, then stock returns around earnings announcements will exhibit an autocorrelation pattern that mirrors that of the model's errors: positive and declining first, second, and third order and negative fourth order autocorrelation. They present evidence that seems to strongly support their hypothesis.

Some papers have tried to address the issue of naive versus sophisticated earnings expectations without directly examining the drift. Walther (1997) stratifies firms by variables she hypothesizes are correlated with the probability that the marginal investor is sophisticated. Her "results are consistent with market participants placing more weight on the analyst forecast relative to the SRW forecast as institutional ownership and analysts following increase" (p.178).

Bhattacharya (2001) takes the examination of this issue from the daily to the transaction level. He cites prior research suggesting that trade size increases in investor wealth (e.g., Cready 1988) and informedness (e.g., Easley and O'Hara 1987) to form hypotheses regarding the trading activity of those initiating small and large trades. He documents a positive correlation between the number of small trades that take place around earnings announcements and the absolute value of SRW errors, even after controlling for analysts' forecast errors. However, he also finds the puzzling result that the number of large trades in this window is *negatively* correlated with the absolute value of analyst forecast errors. While Bhattacharya interprets his evidence as suggesting that small traders' earnings expectations resemble SRW forecasts, he does not show that small traders tend to buy (sell) when the errors are positive (negative), only that they are more active when the absolute magnitude of the error is large. Indeed, Hirshleifer et. al. (2002) present evidence suggesting that individual investors may exhibit more abnormal net buying after bad news announcements than after good news announcements. We construct a different experiment and use recent tools from the market microstructure literature to better understand the relationship between forecast errors and investor behavior.

Specifically, we extend prior research by showing that small traders' net buying activity is significantly positively associated with signed SRW forecast errors. When the SRW forecast error is positive (negative), we observe an abnormally large (small) number of buy orders relative to sell orders for those who initiate small trades. Further we show that large trader's buying activity is positively associated with signed analysts' forecast errors. That is, the behavior that we document for small traders, with respect to the errors of a naive time-series model, we document for large traders for analysts' forecasts. Our results clearly show that investors categorized by trade size base their buying and selling actions on different sets of information. In fact, the correlation between net buying activity around earnings announcements of the smallest and largest trade-size categories is not significantly different than zero. These results clearly show that, on average, investors who initiate small trades hold earnings expectations that resemble an inefficient and inferior model of earnings while those who initiate large trades do not. Finally, we show that small transactions move against the direction of stock-price movements around earnings announcements. This suggests that the trading of unsophisticated investors may be an impediment to price movements at the time of earnings announcements and may be related to post-earnings-announcement drift.

The rest of this paper is organized as follows. In the next section we motivate and state specific testable hypotheses. In the following section we lay out the data, sample, and research methods. In the next-to-last section presents the empirical results and the final section concludes.

II. Hypotheses

As stated in the introduction, prior literature suggests that different types of investors may base their buy and sell decisions on different information sets. Smaller investors who are less wealthy and less well informed may rely on less sophisticated signals than larger investors. We investigate this issue for a particular case. Specifically, we examine investors' net buying activity around earnings surprise signals generated by two models. One model is the seasonal random walk (SRW) whose prediction is simply last year's earnings for the same fiscal quarter. The SRW model is clearly inefficient in that its consecutive errors are significantly correlated. Further it is significantly less accurate than the other model–analysts' forecasts. It is not surprising that analysts' forecasts are more accurate than time series models since analysts have at their disposal all such time-series models as well as other information. Further analysts can update their forecasts any time prior to the earnings announcement. The information in the SRW forecast is one year old.

Since investors initiating small trades are believed to be less wealthy and less well informed than those initiating larger trades, following other researchers we hypothesize that their earnings expectations will more closely resemble SRW predictions than analysts' forecasts. We choose to test this by examining the *net buying activity* of these investors in response to the two earnings signals. Net buying activity is defined formally in the next section, but generally it is a measure of the buy-sell imbalance around an earnings announcement for a particular order-size category (e.g., less than 500 shares). If small traders' earnings expectations resemble SRW forecasts, then it should be SRW forecast errors rather than analyst forecast errors that trigger trading among this group. Specifically, positive (negative) SRW forecast errors should stimulate these investors to initiate buy (sell) orders. The first hypothesis therefore is:

H_{1A}: The net buying activity of small traders at the time of an earnings announcement is more highly associated with the SRW forecast error than with the analyst forecast error.

Similarly, investors who place large orders are believed to be wealthier and better informed. We therefore hypothesize that their expectations should more closely resemble the predictions of the most accurate model available, analysts' forecasts, rather than those of a naive time-series model such as the SRW.

By the same logic as above, positive (negative) analyst forecast errors should trigger buy (sell) orders on the part of large traders. The second hypothesis is:

H_{2A}: The net buying activity of large traders at the time of an earnings announcement is more highly associated with the analyst forecast error than with the SRW forecast error.

We summarize the predictions of the first two hypotheses in the figure below:

Figure 1. Empirical predictions of the first two hypotheses

	Positive Analyst Forecast Error	Negative Analyst Forecast Error
Positive Seasonal Random Walk Forecast Error	Large Traders Buy Small Traders Buy	Large Traders Sell Small Traders Buy
Negative Seasonal Random Walk Forecast Error	Large Traders Buy Small Traders Sell	Large Traders Sell Small Traders Sell

If we find that small traders use a naive signal, the next logical question is whether their trades run opposite to stock-price movements. Bernard and Thomas (1990) suggest that it may be investors whose earnings expectations resemble SRW forecasts who give rise to post-earnings-announcement drift. If this is true, the trades of these investors must move counter to stock price movements at the time of earnings announcements. That is, the trades of these investors must impede stock prices from moving to where they would be absent these investors. We therefore examine whether the trades of these investors move with or counter to prevailing stock price movements. The third hypothesis is:

H_{3A}: Transactions of small traders run counter to price movements that occur at the time of earnings announcements.

III. Description of the Variables and Sample

Our sample begins with all earnings announcements in Nasdaq stocks between April 1, 1993 and December 31, 1996 available in Compustat. We compute analysts' forecast error (AFE) as the difference between actual earnings and the mean of analysts' earnings forecasts immediately prior to the earnings announcement, deflated by share price. Thus, if the earnings announcement date, the actual reported earnings figure, the associated stock price, or at least one analyst forecast (not more than 90 days old) is not available from IBES, we eliminate the earnings announcement from our sample. We calculate the seasonal random walk forecast error (SRWFE) as the difference between actual earnings and the actual earnings of the same fiscal quarter of the prior year, deflated by share price. So, if the earnings announcement date, the actual reported earnings figure, the actual reported earnings of the same fiscal quarter in the prior year, or the associated stock price is not available from Compustat, we eliminate the earnings announcement from our sample. Since we use the Compustat earnings announcement date as the event date in our analysis, we eliminate earnings announcements from our sample if the IBES and Compustat announcement dates are not within two days of each other.[1]

To investigate the relationship between trading by different investor clienteles and returns around earnings announcements, we require daily return data from CRSP. We investigate two return variables. The first, ANCAR, is the three-day cumulated stock return minus the equally-weighted return for the same period for the Nasdaq market-capitalization decile assigned by CRSP. The second, POSTCUM, is the security's compound return beginning the second day following the earnings announcement through the day of the subsequent earnings announcement minus the compound return of the equally-weighted return for the same

[1]Both the Compustat and IBES data sets adjust for stock splits over time. To be absolutely sure that earnings, forecasts, and stock prices are properly aligned in time, we take each item from the same data set. That is, when forming SRW (analyst) forecast error, we take actual earnings, forecasted earnings, and the stock price from Compustat (IBES). To be sure that the SRW and analyst forecast errors are aligned with each other (and with the transactions and returns data), we require that the earnings announcement dates from the two sources to be within two days of each other.

period of the firm's Nasdaq market-capitalization decile assigned by CRSP. Earnings announcements for which the data needed to compute ANCAR or POSTCUM are not available are eliminated from our sample.

We examine earnings announcements for Nasdaq-listed stocks rather than NYSE-listed stocks prior to 1997 for two reasons. First, the NYSE uses a single price call auction that transforms multiple trades into a single reported transaction to open and close trading. Nasdaq market participants, on the other hand, simply begin executing and reporting trades when the market opens and stop when it closes. Since researchers cannot decompose the results of the NYSE call auction into its component trades, the opening and closing auctions on the NYSE cannot be used. Madhavan and Panchapagesan (2000) document the importance of the opening auction using the NYSE's TORQ database, which contains detailed order data (including a buy/sell indicator) for 144 NYSE-listed securities for the three months November 1990 through January 1991. They find an average of 5.4% (25.8%) of the average daily dollar trading volume is executed at the open for their sample stocks in the lowest (highest) market capitalization decile. Given the correlation between the size of the opening call auction and a stock's market capitalization as well as potential for strategic trading at the open (see Brooks and Su (1997)), the exclusion of trades participating in the NYSE's opening and closing call auctions may lead to biased inferences.

The second feature of Nasdaq that makes it conducive for our experiment is Nasdaq's Small Order Execution System (SOES), a computerized system for routing orders from retail investors (via brokerage firms) to Nasdaq market makers for automatic execution. After the market crash of 1987, Nasdaq officials made market maker participation in SOES mandatory. Prior to the implementation of the Securities and Exchange mandated Order Handling Rules in January of 1997, Nasdaq market makers were required to post and honor bid and ask prices for a preset number of shares (typically 1000).[2,3] These rule changes made it difficult for market makers to back away from their quotes and they guaranteed investors the chance to automatically execute their orders (via their brokers) at posted prices. Harris and Schultz (1997) note that these features made SOES a popular trading mechanism for investors with information.[4]

In this environment, why would a wealthy investor who has or thinks he has value relevant information ever, say, buy 900 shares and earn 900(E[v|information] - ask) when he could earn 1000(E[v|information] - ask)? Conversely, since Nasdaq market makers are not obligated to transact at quoted prices for orders larger than the SOES minimum, why would our wealthy investor buy 1100 shares at a price that is unknown, but presumably higher than the quoted ask, and earn 1100(E[v|information] - $\tilde{p}$) when he could place an order to buy 1000 shares and earn 1000(E[v|information]-ask)? Obviously, as suggested by Easley and O'Hara (1987) and others, there will be instances in which wealthy investors have information that justifies bearing the execution price risk associated with acquiring positions well in excess of 1000 shares. Alternatively, it is hard to imagine circumstances in which these investors would place orders for less than 500 shares. Using this logic, we examine the six groups of trades based on size: 100 to 400 shares, 500 shares, 600 to 900, 1000 shares, 1100 to 4900 shares, and 5000 and more shares. We reason that the smallest trades correspond to the trading interests of naive, unsophisticated investors with little information and the largest trades correspond to the trading interests of wealthy, sophisticated investors with access to superior information.

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[2]For stocks averaging three or more transactions per day, market makers were required to honor their quoted prices for up to 1000 shares between January 1, 1993 and January 31, 1994, 500 shares between February 1, 1994 and March 27, 1995, and 1000 shares from March 28, 1995 through the passage of the Order Handling Rules, which were phased in throughout 1997. See Harris and Schultz (1997, 1998) and Battalio, Hatch and Jennings (1997) for more information on SOES and its affect on trading in the Nasdaq market.

[3]For more information on the Order Handling Rules, see Barclay, Christie, Harris, and Kandel (1999).

[4]Although SOES was intended for 'non-professional' use, NASD (1993) estimates that 84% of SOES trades in the early nineties were from professionals attempting to identify price trends and trade with market makers who were slow to revise their quotes.

In contrast to Nasdaq, investors trading on the NYSE in the 1990's could expect their orders to be executed at the posted price as long as the order did not exceed the current depth at that quote (which may have changed while the order was in transit). Since NYSE specialists are not required to offer more than a 100 shares at their quotes, there are no natural trade size bins that isolate the trading interest of sophisticated and naive investors. For this reason, the NYSE's trading environment provides a less powerful test of our hypotheses.[5]

We obtain the microstructure data for this study from the New York Stock Exchange's Trade and Quote (TAQ) database, which contains intraday trades and quotes for all securities listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the Nasdaq National Market System and SmallCap issues. Each quote record indicates the underlying stock, the trading venue from which the quote emanates, the date and time of the quote, the bid and ask prices and quantities, and a quote condition code. Each trade record indicates the underlying stock, the date and time the trade was reported, the venue reporting the trade, the transaction size and price, and codes indicating whether the trade is subsequently cancelled or is made with other 'special' conditions.[6] Because the TAQ database is unavailable prior to January 1, 1993, the use of trading activity several days prior to sample earnings announcements requires us to start our sample after February 1, 1993. We start our sample on April 1, 1993 because there are very few earnings announcements in February and March of 1993. We end our sample on December 31, 1996 to avoid complications associated with the commencement of the Order Handling Rules on January 20, 1997.

Our analysis uses trades typed as buys or sells. Since the trade data provided by TAQ do not identify transactions as buys or sells, we use the Lee and Ready (1991) algorithm to infer whether a trade was a buy

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[5]In April of 2001, the NYSE began offering immediate executions at the NBBO in all of its securities via NYSE Direct+.

[6]See the NYSE's TAQ2 User's Guide for an in-depth description of the TAQ database.

or a sell.[7] The Lee and Ready (LR) algorithm first attempts to classify a trade as a buy or a sell by comparing the trade's execution price to the prevailing quotes. Trades with execution prices above (below) the midpoint of the execution-time bid and offer are classified as buys (sells). To classify trades executed at the midpoint of the execution-time quotes, the LR algorithm looks to prior trades. If the execution price of the prior trade is lower (higher) than the current trade's execution price, the current trade is classified as a buy (sell). If the prior trade has the same execution price as the current trade, the LR algorithm moves backwards in time until it finds a prior trade with a different price and follows similar logic. Thus, the LR algorithm cannot classify opening trades executed at the midpoint of the execution-time National Best Bid or Offer (NBBO) nor can it classify the trades that follow these opening trades until the NBBO changes or a trade is executed at a different price.

To implement the LR algorithm, we must first create a NBBO for each stock in our sample and find benchmark execution-time NBBOs for each trade in our sample. At each moment in the trading day, a stock's NBBO is created by taking the highest bid and the lowest offer (i.e., the best prices) quoted by venues on which the stock is traded. Following Ellis, Michaely, and O'Hara (2000), we then use the execution-time NBBO with no lag as our benchmark quotes.[8]

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[7]Lee and Radhakrishna (1996), Odders-White (2000), and Finucane (2000) use the NYSE's TORQ database to test the Lee and Ready algorithm and document a success rate in excess of 85%. Ellis, Michaely, and O'Hara (2000) use a proprietary sample of trades that include a buy/sell indicator in 313 Nasdaq stocks traded between September 27, 1996 and September 29, 1997 to test the Lee and Ready algorithm and find a success rate of 81%. They find that the algorithm's success rate is 'somewhat lower' after the implementation of the Order Handling Rules, which incorporated the quotes and trades of ECNs (Electronic Communication Networks) into the trade and quote broadcasts for Nasdaq stocks in staggered waves throughout 1997. Ellis, Michaely, and O'Hara propose a modified trade typing algorithm to handle the different market structure on Nasdaq. Since this algorithm only improves the trade typing success rate by 0.9% in their sample and since our sample ends before the initiation of the Order Handling Rules, we use the more standard Lee and Ready algorithm to type trades.

[8]Since most trades on the NYSE are reported manually, the times at which trades in NYSE-listed securities actually occur precede the times reported on the TAQ database. For this reason, Lee and Ready (1991), Blume and Goldstein (1997), and others suggest lagging the execution times reported in TAQ by five to fifteen seconds before matching trades and quotes. However, Ellis, Michaely, and O'Hara (2000) note that most trades in Nasdaq stocks are reported electronically and find there is no need to use a lag when matching trades and quotes for Nasdaq stocks.

The typing of buys and sells necessitates the elimination of trades reported late or out of sequence since they cannot reliably be matched with execution-time NBBOs.[9] We also eliminate any trade with a transaction price more than \$5.00 away from the previous price on that day and trades with no reported quantities as 'obvious' data errors.[10] We eliminate trades for which the benchmark NBBO is invalid (i.e., the trade is reported during a trading halt) and trades that cannot be classified by the Lee and Ready algorithm from our analysis. Finally, we only consider trades executed between 9:30:00 and 16:00:00 since the time-stamps for trades (needed for the LR algorithm) become less reliable outside of normal market hours.

From our sample of trades classified as buys and sells, we construct our measure of abnormal net buying activity for each of the six trade size categories. For each category, we begin by subtracting the number of sell trades during the three trading days centered on the earnings announcement date from the number of buy trades over the same time period. If an earnings announcement occurs on a day when financial markets are closed, we use the next trading day as our event date. After computing the net buying activity for the *ith* trade size category in the event window ($NetEventBuy_i$), we compute similar statistics for the three-day trading window centered ten days prior to the earnings announcement date ($NetPreBuy_i$) and for the three-day trading window centered ten days following the earnings announcement date ($NetPostBuy_i$). Finally, we define the abnormal net buying activity in the *ith* trade size category, $NETBUY_i$, as follows:

$$NETBUY_i \;=\; NetEventBuy_i \;-\; \left(\frac{NetPreBuy_i \;+\; NetPostBuy_i}{2}\right).$$

To ensure our measure of abnormal net buying activity is reasonable, we require each earning announcement in our sample to have an average of ten trades per day in each of the three day trading windows.

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[9]Specifically, we eliminate trades with a Condition Code of 'Z' or 'G' and trades that have a Correction Code that is not equal to zero or one.

[10]Bessembinder and Kaufman (1997) is one of many papers that uses data screens similar to those employed in this paper.

To allow for outliers and non-linearities in the relationship between forecast errors and trading activity and to enhance the interpretation of our regression coefficients, each calendar quarter we rank all observations of AFE, SRWFE, and NETBUY and partition them into percentiles coded from 0 to 99. The percentile scores are then divided by 99 and 0.5 is subtracted. We test our hypotheses using these coded variables.

IV. Empirical Results

Descriptive Statistics

Table 1 provides descriptive statistics for the sample firms. The first variable, SIZE, is the market capitalization of the firm in thousands of dollars at the beginning of the calendar year of the earnings announcement. Perhaps more informative regarding market capitalization is the next variable, DECILE. DECILE is defined as the market-capitalization decile of the firm within Nasdaq for the calendar year of the earnings announcement. Note that our sample criteria result in a sample of firms that tend to be larger than the median Nasdaq firm. Specifically, the average (median) size decile is 8.44 (9.00). The next variable, PRICE, is the actual share price twenty days prior to the earnings announcement. The mean (median) value for PRICE is 21.64 (18.25). INST is the fraction of shares held, in the calendar quarter prior to the earnings announcement quarter, by institutions required to file Form 13f with the Securities and Exchange Commission. The mean (median) value of INST is 0.41 (0.39) indicating that institutions hold about 40% of the shares of the typical sample firm. ANUM is a measure of analyst following and is defined as the number of analysts reporting quarterly earnings forecasts to IBES in the 90 days prior to the earnings announcement. Since a measure of analyst earnings expectation is required for the hypotheses, the sample is constrained to firm-quarters for which at least one analyst reports to IBES. The mean (median) number of analysts reporting forecasts is 3.93 (3.00). Finally, TRADES is the average number of trades per day over the three-day interval centered on the earnings announcement day. We require an average of ten trades per day for the earnings announcement period and for two non-announcement benchmark periods to ensure that our test statistics are meaningful. During the three-day earnings announcement period, the mean (median) firm averages 248.1 (78.7) trades per day.

(Insert Table 1 about here)

Correlations

Table 2 presents correlations among the net buying activity measures for the six trade-size categories and the two measures of earnings surprise. $NETBUY_i$ is the net buying activity (or the buying versus selling imbalance) at the time of the earnings announcement for trading-size class i. AFE is the analysts' forecast error and SRWFE is the seasonal random walk forecast error.

(Insert Table 2 about here)

While Table 2 does not present formal hypothesis tests, some results displayed strongly suggest the data are consistent with our expectations. Note that for the three smallest-trade categories, those trading less than 1000 shares, the correlations between net buying activity and SRW errors are higher than between net buying activity and analyst forecast errors. On the other hand, for the three largest-trade categories, net buying activity is more highly correlated with analyst forecast errors than with SRW errors.[11]

Specifically, for those initiating the smallest trades (less than 500 shares) the correlation with SRW forecast errors is 0.078 and is significantly greater than zero at the 0.01 level, while the corresponding correlation with analyst forecast errors is only 0.022 (significant at the 0.05 level). For those initiating the largest trades, the direction is reversed and the correlation between net buying activity and analyst forecast errors is 0.055 and is significant at the 0.01 level, while the corresponding correlation with SRW error is only 0.026 (significant at the 0.05) level. Taken alone, these results suggest that both the smallest and largest

[11] For the two smallest trade-size categories and for the largest trade-size category, the differences in correlations (analyst forecast error versus SRW forecast error) are significant at the 0.01 level. For the other trade-size categories, the difference is not significant at traditional levels.

traders respond to both signals, but small (large) traders' expectations more closely resemble the SRW (analyst) forecast errors.

Means Tests with Consistent and Contradictory Earnings Signals

Table 3 presents results of means tests of net buying activity for the different trade-size categories as a function of the signs of the two earnings signals. Positive (negative) t-statistics on net buying activity indicate more (less) earnings-announcement period buying relative to selling than normal. Specifically, Panel A provides two types of t-statistics, traditional and time-series, for the hypothesis that net buying activity for the different trade-size categories is zero, when both earnings signals (analyst and SRW forecast errors) are negative. The time-series t-statistic treats the mean net buying activity within a trade-size category for each of the 15 calendar quarters as an independent observation (see Fama and MacBeth 1973). The time-series t-statistic is for the test that the mean of the 15 quarterly means is zero. Panels B through D present corresponding statistics for other possible cases: both errors are positive; analyst errors are negative and SRW errors are positive; and analyst errors are positive and SRW are negative, respectively. Figure 1 summarizes our predictions for Table 3.

(Insert Table 3 about here)

Note that in Panel A and Panel B the signs for net buying activity for all trade-size categories is as expected. When both signals are negative (see Panel A), the t-statistics for each trade size category is negative, indicating investors place fewer buy orders relative to sell orders than usual. Panel B, where both signals are positive, shows exactly the opposite. In this panel, the positive signs indicate that, for all trade-size categories, investors place more buy orders relative to sell orders when the earnings signals are positive. While the results presented in Panels A and B may not be surprising, they provide support for the empirical procedures. That is, interpretation of our results depend on information traders initiating trading (see Lee 1992) and on our ability to type trades as buy or sells. The results presented in Panels A and B of Table 3 suggest that these procedures are effective.

Panel C presents the case where analyst forecast errors are negative and SRW forecast errors are positive. In these cases those investors whose expectations more closely resemble analysts' (SRW) forecasts should view the announcement as bad (good) news and tend to initiate fewer (more) buy orders than usual relative to sell orders. So, we hypothesize that the sign of net buying activity should be negative (positive) for small (large) traders. When we examine the smallest and largest traders, the results are consistent with our hypothesis. Those trading fewer than 500 shares tend to buy when the SRW error is positive (indicated by the positive sign), even when the analyst forecast error is negative. For the largest traders, the opposite is true. They tend to sell when the analyst forecast error negative even when the SRW error is positive. Results for all intermediate size categories are indeterminate.

Results for Panel D of Table 3 mirror those of Panel C. When the analyst signal is positive and the SRW signal is negative, the largest traders tend to initiate more buys relative to sells and the smallest traders tend to initiate fewer buys relative to sells. In this case, results for the second smallest trade-size category is also significant in the expected direction. So far the results of univariate correlations and comparisons of means are consistent with our hypotheses that small traders' beliefs more closely resemble SRW forecasts and large traders' beliefs more closely resemble analysts' forecasts. We present one final test of these hypotheses.

Regression Tests of Net Buying Activity on Earnings Signals

Table 4 presents results of regression tests of net buying activity for each trade-size category on the two earnings signals: analyst and SRW forecast errors. Consider the first column of results for those trading fewer than 500 shares. The coefficient on the analyst forecast error (AFE) is not significantly different from zero (standard t-statistic = -1.11, time-series t-statistic = -1.21). This result indicates that, when controlling for SRW forecast error, the smallest traders do not respond at all to analyst forecast errors. Hence, the significantly positive correlation between analyst forecast error and net buying activity for this group (see Table 2) is attributable to the correlation between analyst and SRW forecast errors (0.41 for this sample, not tabulated). The coefficient on the SRW forecast error, on the other hand, is significantly positive. Both the standard t-statistic (7.28) and the time-series t-statistic (5.58) indicate the relation is significant at the 0.01 level. The coefficient of 0.083 for the SRW forecast error may be interpreted as indicating an expected increase of 1 percentile in sample rank of net buying activity for every 12 percentile (1 / 0.083) increase in sample rank of SRW error. The second column, for those who trade 500 shares, provides results that are similar but a little weaker than those for the smallest traders.

(Insert Table 4 about here)

At the other end of the spectrum the net buying activity of the largest traders, those who initiate trades for 5000 shares or more, is significantly positively related to analyst forecast errors (standard t-statistic = 4.62, time-series t-statistic = 4.48). Unlike the smallest traders, the largest traders respond to analyst forecast errors, but appear to completely ignore SRW errors (standard t-statistic = 0.40, time-series t-statistic = 0.20). Results regarding the second largest traders, those trading 1100 to 4900 shares, are mixed. Both t-statistics suggest their expectations do not resemble SRW forecasts (standard t-statistic = 1.02, time-series t-statistic = 1.01). But the standard t-statistic (t = 2.12) indicates a significantly positive (at the 0.05 level) relationship with analyst forecast errors, while the time-series t-statistic (t = 1.25) fails to indicate significance.

Finally, notice that the 1000 share traders respond positively to both earnings signals. It is possible that this level of trade size, for most of our sample period the smallest trade size for which the posted quote is guaranteed, attracts some sophisticated investors and some unsophisticated traders. The results presented in Tables 2, 3, and 4 consistently show that at least one subset of investors, those who initiate the smallest trades, holds earnings expectations that resemble SRW forecasts. These expectations are clearly naive in the sense that they are less accurate than analysts' forecasts. The results also consistently show that those investors who initiate the largest trades base their buy and sell decisions on expectations that more closely resemble analysts' forecasts. We conclude that different classes of investors, categorized by trade size, base their buy and sell decisions on significantly different information sets. Our results clearly support our alternative statements of the first and second hypotheses. The next subsection examines which trades are responsible for the cumulative price movements in the three-day window around earnings announcements.

Barclay-Warner Cumulative Price Change Analysis

Following Barclay and Warner (1993), we attribute the fraction of the stock's three-day announcement-period cumulative price change to trades of the different size classes. We do this primarily to determine if trades of any size categories move opposite to the cumulative price change over the interval. Some researchers believe that investors who hold naive beliefs trade opposite to the direction prices *should* move and this gives rise to post-earnings-announcement drift. This is our third hypothesis: Transactions of small traders run counter to price movements that occur at the time of earnings announcements.

Table 5 displays the results of the Barclay-Warner analysis. The most salient point from Table 5 is that the smallest traders, those initiating trades of less than 500 shares, tend to move prices in the *wrong* direction. That is, say that in a particular case a stock price moved up a total of 4% in the three days around an earnings announcement. On average, the cumulative price change occurring on transactions initiated by the smallest traders (compared to the prices of the preceding trades) would be *down* about 1% (-26.2% x 4% = -1.048%). While this does not prove that small traders actually impede stock prices from moving to where they *should* be, it at least leaves the door open to that possibility.

(Insert Table 5 about here)

Also note that it is the 1000 share trades that move prices the most. 1000 share trades make up 29.5% of all transactions and are responsible for 80.7 % of the total three-day cumulative price movement. This result is consistent with Harris and Schultz (1997). Note that the largest trades make up 8.1% of all transactions but are responsible for only 3.9% of the total cumulative price movement. These results seem inconsistent with the those of the prior tests that show the largest traders have earnings expectations that most closely resemble analysts forecasts. One possibility is that many of these trades are negotiated beforehand so that market makers have time to arrange for offsetting trades, thereby reducing price impact.

Regression Tests of Association Between Net Buying Activity and Stock Returns

Table 6 presents the results of simple regressions of abnormal stock returns on the net buying activity of different trade-size categories. Panel A of Table 6 presents results with ANCAR, the three-day announcement-period size-adjusted return, as the dependent variable. These tests show whether the net buying activity of the different trade-size categories is associated with the overall announcement period price movement. Although these tests are not identical to the Barclay-Warner cumulative price change analysis, the results are completely consistent. The association between the announcement-period abnormal returns and net buying activity is (significantly) positive for all trade-size categories except for the smallest. This indicates that on average investors using each of the five larger order sizes initiate trades that are in the direction of the overall announcement-period price movement. Results for the smallest group indicate that those initiating trades of less than 500 shares tend to do more net buying when the return is lower and less net buying when the return is higher. Consistent with the Barclay-Warner analysis, the smallest traders tend to act in the *wrong* direction.

(Insert Table 6 about here)

A natural question is how do the stocks which the different groups buy tend to perform *after* the three-day announcement period over which net buying activity is measured. Panel B of Table 6 examines this issue. For this panel the dependent variable is the size-adjusted return beginning the third day after the announcement and ending on the day of the subsequent announcement.[12] Results for four of the six trade-size

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[12] Net buying activity is measured using days -1, 0, and +1 relative to the Compustat announcement date. The post-announcement returns skip day +2 and begin on day +3 in order to avoid any bias from bid-ask bounce. That is, for a firm with a high level of buying activity over the three day announcement period, there is a greater than even chance that the last transaction price of day +1 is at (or near) the ask price. If the last transaction on day +2 is at (or near) the bid and ask price with equal probability, then the firms return on day +2 is biased downward. Omitting day +2 avoids this potential bias. Results are very similar and inferences are unaltered if the end of the cumulation period is defined as 63 trading days (approximately one quarter) after its beginning.

categories are insignificant. Stocks for which there was abnormally high buying activity for those initiating trades of 500 or 1000 shares, however, performed worse than average over the subsequent quarter. For example, the coefficient of -2.00 for 500 share traders may be interpreted as follows. Stocks in the top percentile, in terms of 500-share net buying activity during the announcement period, exhibit an estimated abnormal return over the following quarter of 2.00% less than those in the bottom percentile. The other trade-size category with significant results, those initiating trades of 1000 shares, also exhibits negative performance.

The results of Table 6 indicate that the smallest investors trade opposite to overall price movements around earnings announcements. But those stocks purchased the most by those whose trading has highest association with announcement-period price movements, 1000-share traders, perform the worst over the following quarter. It is difficult to interpret these results in terms of their implications for post-earnings announcement drift.

V. Conclusion

In this paper we present results indicating that different types of investors (identified by trade size) use different information sets when making their buy and sell decisions. Those investors who initiate small trades seem to base their decisions on more naive or less sophisticated information than those who initiate large trades. Specifically, we find that small traders tend to ignore earnings signals based on analysts' forecasts while responding to signals of a less accurate time-series model. Large traders on the other hand ignore the naive time-series signals and respond to analysts' forecast errors.

Bernard and Thomas (1990) hypothesize that post-earnings announcement drift is caused by investors whose beliefs resemble SRW forecasts. Other researchers, e.g., Walther (1997) and Bhattacharya (2001), suggest that it is probably small investors who hold these beliefs. Our results support and extend the idea that small investors do indeed hold beliefs that resemble SRW forecasts. We show further that the trades of small investors around earnings announcements are opposite to the direction of stock price movements. While this result is consistent with the idea that small traders impede stock-price movements at the time of earnings announcements and, therefore, play a role in causing post-earnings-announcement drift, our analysis falls far short of proving that to be the case. While we believe this paper contributes to the discussion of the relative level of sophistication of investors, we also believe this remains a fertile area for future research.

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Table 1
Sample Descriptive Statistics, 1993-1996

SIZE is the market capitalization of the firm in thousands of dollars at the beginning of the calendar year. DECILE is the market capitalization decile of the firm within Nasdaq as assigned by CRSP. PRICE is the stock price twenty days prior to the earnings announcement. INST is the fraction of the firm's shares held by institutions that file Form 13f with the SEC in the calendar quarter prior to the earnings surprise. ANUM is the number of analysts providing quarterly earnings forecasts to I/B/E/S in the 90 days prior to the earnings surprise. TRADES is the average number of trades per day over the three-day interval centered on the earnings announcement day.

Variable	Mean	Standard Deviation	Quartile 1	Median	Quartile 3
SIZE ('000's)	634,885	2,176,392	105,808	219,419	503,890
DECILE	8.44	1.71	7.00	9.00	10.00
PRICE	21.64	14.60	11.38	18.25	28.13
INST	0.41	0.21	0.25	0.39	0.57
ANUM	3.93	3.83	2.00	3.00	5.00
TRADES	248.1	720.9	37.0	78.7	190.0

N = 9,426

TABLE 2
Correlations between forecast errors and net buying activity for different trade-size categories.

AFE is the analysts' forecast error and is defined as actual earnings per share minus the average of all forecasts reported to IBES in the 90 days prior to the earnings announcement deflated by price. SRWFE is the seasonal random walk forecast error and is defined as actual earnings per share minus reported earnings per share for the same fiscal quarter of the prior year deflated by price. $NETBUY_1$ - $NETBUY_6$ are adjusted net purchases for different trade-size categories as noted. $NETBUY_i$ is (average daily event-period purchases minus average daily event-period sales for category i) minus (average daily non-event period purchases minus average daily non-event period sales for category i) divided by (average daily non-event period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The non-event period is two three-days periods centered two weeks before and after the earnings announcement date.

Variable	<500 sh. $NETBUY_1$	500 sh. $NETBUY_2$	600-900 sh. $NETBUY_3$	1000 sh. $NETBUY_4$	1100-4900 sh. $NETBUY_5$	$\geq$ 5000 sh. $NETBUY_6$
AFE	0.022*	0.011	0.004	0.054**	0.029**	0.055**
SRWFE	0.078**	0.040**	0.006	0.042**	0.022*	0.026*
$NETBUY_1$	1.000	0.406**	0.285**	0.203**	0.167**	-0.015
$NETBUY_2$		1.000	0.224**	0.311**	0.253**	0.058**
$NETBUY_3$			1.000	0.215**	0.254**	0.079**
$NETBUY_4$				1.000	0.387**	0.149**
$NETBUY_5$					1.000	0.193**
$NETBUY_6$						1.000

N = 9,426
** and * indicate significantly different from zero at the .01 and .05 level, respectively.

TABLE 3
Net buying activity for different trade size categories:
Confirmatory and contradictory earnings signals

AFE is the analysts' forecast error and is defined as actual earnings per share minus the average of all forecasts reported to IBES in the 90 days prior to the earnings announcement deflated by price. SRWFE is the seasonal random walk forecast error and is defined as actual earnings per share minus reported earnings per share for the same fiscal quarter of the prior year deflated by price. $NETBUY_1$ - $NETBUY_6$ are adjusted net purchases for different trade-size categories as noted. $NETBUY_i$ is (average daily event-period purchases minus average daily event-period sales for category i) minus (average daily non-event period purchases minus average daily non-event period sales for category i) divided by (average daily non-event period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The non-event period is two three-days periods centered two weeks before and after the earnings announcement date.

Panel A: AFE Negative, SRWFE Negative

Trade size		t-statistic	Time-series t-statistic	Quarters positive
< 500 sh.	$NETBUY_1$	-3.73**	-3.37**	3/15
500sh.	$NETBUY_2$	-1.69	-1.54	7/15
600-900 sh.	$NETBUY_3$	-0.28	0.70	8/15
1000 sh.	$NETBUY_4$	-3.42**	-3.65**	3/15
1100-4900 sh.	$NETBUY_5$	-2.68**	-2.23*	4/15
$\geq$ 5000 sh.	$NETBUY_6$	-3.19**	-3.78**	1/15

N =3,053
** and * indicate significantly different from zero at the .01 and .05 level, respectively.

TABLE 3 (Continued)

Panel B: AFE Positive, SRWFE Positive

Trade size		t-statistic	Time-series t-statistic	Quarters positive
< 500 sh.	$NETBUY_1$	3.70**	3.54**	13/15
500 sh.	$NETBUY_2$	2.71**	3.10**	11/15
600-900 sh.	$NETBUY_3$	0.35	-0.03	7/15
1000 sh.	$NETBUY_4$	5.08**	9.38**	15/15
1100-4900 sh.	$NETBUY_5$	1.55	1.65	10/15
$\geq$ 5000 sh.	$NETBUY_6$	3.25**	4.43**	12/15

N =3, 053

** and * indicate significantly different from zero at the .01 and .05 level, respectively.

Panel C: AFE Negative, SRWFE Positive

Trade size		t-statistic	Time-series t-statistic	Quarters positive
< 500 sh.	$NETBUY_1$	3.44**	3.45**	12/15
500sh.	$NETBUY_2$	1.44	1.25	10/15
600-900 sh.	$NETBUY_3$	0.33	0.46	7/15
1000 sh.	$NETBUY_4$	-1.70	-1.92	5/15
1100-4900 sh.	$NETBUY_5$	0.49	0.37	8/15
$\geq$ 5000 sh.	$NETBUY_6$	-2.55*	-2.31*	3/15

N =1,575

** and * indicate significantly different from zero at the .01 and .05 level, respectively.

TABLE 3 (Continued)

Panel D: AFE Positive, SRWFE Negative

Trade size		t-statistic	Time-series t-statistic	Quarters positive
< 500 sh.	$NETBUY_1$	-3.60**	-2.50*	4/15
500sh.	$NETBUY_2$	-2.76**	-2.36*	5/15
600-900 sh.	$NETBUY_3$	-0.39	-1.20	6/15
1000 sh.	$NETBUY_4$	-0.47	-1.59	4/15
1100-4900 sh.	$NETBUY_5$	1.13	0.83	9/15
$\geq$ 5000 sh.	$NETBUY_6$	2.60**	3.16**	11/15

N = 1,565

** and * indicate significantly different from zero at the .01 and .05 level, respectively.

TABLE 4
Regressions of net buying activity for different trade size categories on analyst forecast errors and seasonal random walk forecast errors.

AFE is the analysts' forecast error and is defined as actual earnings per share minus the average of all forecasts reported to IBES in the 90 days prior to the earnings announcement deflated by price. SRWFE is the seasonal random walk forecast error and is defined as actual earnings per share minus reported earnings per share for the same fiscal quarter of the prior year deflated by price. $NETBUY_1$ - $NETBUY_6$ are adjusted net purchases for different trade-size categories as noted. $NETBUY_i$ is (average daily event-period purchases minus average daily event-period sales for category i) minus (average daily non-event period purchases minus average daily non-event period sales for category i) divided by (average daily non-event period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The non-event period is two three-days periods centered two weeks before and after the earnings announcement date.

	<500 sh. $NETBUY_1$	500 sh. $NETBUY_2$	600-900 sh. $NETBUY_3$	1000 sh. $NETBUY_4$	1100-4900 sh. $NETBUY_5$	$\geq$ 5000 sh. $NETBUY_6$
AFE	-0.013	-0.007	0.002	0.044	0.024	0.053
t-statistic	-1.11	-0.57	0.18	3.83^{**}	2.12^{*}	4.62^{**}
time-series t-statistic	-1.21	-0.03	-0.51	4.11^{**}	1.25	4.48^{**}
Quarters +'ve	4/15	5/15	7/15	13/15	10/15	14/15
SRWFE	0.083	0.043	0.005	0.024	0.012	0.005
t-statistic	7.28^{**}	3.73^{**}	0.43	2.12^{**}	1.02	0.40
time-series t-statistic	5.58^{**}	2.83^{**}	0.29	2.68^{**}	1.01	0.20
Quarters +'ve	14/15	13/15	8/15	13/15	9/15	7/15
Adj. R-square	0.60%	0.14%	0.00%	0.31%	0.01%	0.28%

N = 9,426
** and * indicate significantly different from zero at the .01 and .05 level, respectively.

TABLE 5
Results of Barclay-Warner cumulative price change analysis

Mean percentage of cumulative stock-price change that occur on trades of each trade-size category and the percentage of trades in each trade-size category. $NETBUY_1$ - $NETBUY_6$ are adjusted net purchases for different trade-size categories as noted. $NETBUY_i$ is (average daily event-period purchases minus average daily event-period sales for category i) minus (average daily non-event period purchases minus average daily non-event period sales for category i) divided by (average daily non-event period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The non-event period is two three-days periods centered two weeks before and after the earnings announcement date.

Statistic		Percentage of cumulative price change	Percentage of Trades
< 500 sh.	$NETBUY_1$	-26.2	29.4
500 sh.	$NETBUY_2$	14.5	10.9
600-900 sh.	$NETBUY_3$	2.5	5.0
1000 sh.	$NETBUY_4$	80.7	29.5
1100-4900 sh.	$NETBUY_5$	24.4	17.1
≥ 5000 sh.	$NETBUY_6$	3.9	8.1

N = 9,426

TABLE 6
Simple regressions of abnormal stock returns, at the time of and following earnings announcements, on net buying activity for different trade-size categories.

ANCAR, the three-day abnormal return around the earnings announcement. It is the three-day cumulated firm return minus the equally-weighted return for the same period for the Nasdaq market-capitalization decile assigned by CRSP. POSTCUM is the abnormal return following the earnings announcement. It is firm's compound return three days after the earnings announcement through the day of the next earnings announcement minus the equally weighted return for the same period for the Nasdaq market-capitalization decile assigned by CRSP. $NETBUY_1$ - $NETBUY_6$ are adjusted net purchases for different trade-size categories as noted. $NETBUY_i$ is (average daily event-period purchases minus average daily event-period sales for category i) minus (average daily non-event period purchases minus average daily non-event period sales for category i) divided by (average daily non-event period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The non-event period is two three-days periods centered two weeks before and after the earnings announcement date.

Panel A: Dependent Variable: ANCAR, the announcement period abnormal return

Trade-Size Category		Coefficient	t-statistic	Time-series t-statistic
<500 sh.	$NETBUY_1$	-0.72	-2.27*	-2.00*
500 sh.	$NETBUY_2$	2.12	6.71**	2.33*
600-900 sh.	$NETBUY_3$	1.46	4.61**	5.01**
1000 sh.	$NETBUY_4$	10.47	35.14**	20.66**
1100-4900 sh.	$NETBUY_5$	4.70	15.00**	10.14**
>= 5000 sh.	$NETBUY_6$	4.98	15.90**	13.14**

Panel B: Dependent Variable: POSTCUM, the announcement period abnormal return

Trade-Size Category		Coefficient	t-statistic	Time-series t-statistic
<500 sh.	$NETBUY_1$	-0.47	-0.53	-1.03
500 sh.	$NETBUY_2$	-2.00	-2.25*	-3.41**
600-900 sh.	$NETBUY_3$	-0.56	-0.63	-1.21
1000 sh.	$NETBUY_4$	-2.28	-2.55*	-2.10*
1100-4900 sh.	$NETBUY_5$	-0.77	-0.86	-0.83
>= 5000 sh.	$NETBUY_6$	0.79	0.89	1.41

N = 9,426
** and * indicate significantly different from zero at the .01 and .05 level, respectively.