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Earnings expectations, investor trade size, and anomalous returns around earnings announcements☆

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Abstract

We provide evidence that identifiable subsets of investors use significantly different information sets. Investors initiating large trades respond to analysts' earnings forecast errors, while investors initiating small trades respond to a less-sophisticated signal that underestimates the implications of current earnings innovations for future earnings levels. This suggests small investors exhibit the behavior that Bernard and Thomas [Journal of Accounting and Economics 13, 305–340] theorize causes post-earnings announcement drift. We also use analysts' forecasts to significantly improve the predictability of returns around earnings announcements previously documented by Bernard and Thomas. Finally, results attempting to link return predictability to the prevalence of small-investor trading are mixed.

JEL classification: G14

Keywords: Investor clienteles; Biased expectations; Earnings expectations

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1. Introduction

This paper investigates whether different types of investors base their buy and sell decisions on different information sets, whether some investor types hold beliefs that are systematically biased, and, if so, whether investors who hold these biased expectations affect stock prices. Each of these questions is motivated by prior research. Hand (1989) and Bernard and Thomas (1990) suggest that earnings expectations held by some investors may resemble the simplistic seasonal random walk (SRW) model (i.e., earnings this quarter will be the same as earnings for the same fiscal quarter last year). The SRW model is considered to be unsophisticated or naive both because its errors exhibit a distinctive autocorrelation pattern (Foster, 1977), which sophisticated investors presumably would recognize, and because its predictions are significantly less accurate than analysts' forecasts.[1] Combining the suggestions of Hand and Bernard and Thomas with Easley and O'Hara's (1987) proposition that information sets used by investors initiating small trades may be systematically inferior to those used by investors initiating large trades, we hypothesize that small investors may hold earnings beliefs that resemble SRW forecasts.

This paper presents direct evidence that investors initiating small trades hold earnings expectations that are systematically biased towards SRW forecasts, while those initiating large trades show no such bias. Further, since SRW forecast errors exhibit significantly positive serial correlation, the small investors whose beliefs resemble SRW forecasts significantly underestimate the implications of current earnings innovations for future earnings levels. In other words, we document that small investors display precisely the behavior that Bernard and Thomas hypothesize causes post-earnings announcement drift. Post-earnings announcement drift (also referred to as the SUE (Standardized Unexpected Earnings) effect) is the well-documented tendency for stock returns to rise (fall) in the weeks following earnings announcements that exceed (fall short of) a proxy for the market's expectation of earnings. (See, e.g., Ball and Brown, 1968; Latané and Jones, 1979; Rendleman et al., 1982; Foster et al., 1984; and Bernard and Thomas, 1989.)

Perhaps because most papers that document the drift use time-series models (often the SRW model), it appears to be a commonly held belief that the drift is a time-series (e.g., SRW) result. Livnat and Mendenhall (2003), however, show that the drift is larger when the earnings surprise is defined using analysts' forecast errors. This is true for our sample as well. This suggests that sophisticated investors seeking to exploit the post-earnings announcement drift should use analyst forecast errors, not the SRW model, to formulate their trading strategies.

[1] See for example, Brown et al. (1987). For the sample used in this paper, the mean analyst forecast from I/B/E/S is more accurate than the SRW forecast in 76.4% of the observations. The SRW model is more accurate 22.0% of the time, while for 1.7% of the observations the predictions of the two models are the same. For our sample, analyst superiority does not depend on firm size, analyst following, or institutional holding. Independently, we divide the sample into quartiles based on each of these three variables. For each quartile based on each variable, analysts' forecasts are significantly more accurate than the SRW model.

While Hand (1989) and Bernard and Thomas (1990) suggest that some investors hold naive earnings expectations, a few recent papers attempt to address this issue more directly. Walther (1997) regresses the abnormal returns around earnings announcements on both SRW and analysts' forecast errors and presents results that "are consistent with market participants placing more weight on the analyst forecast relative to the SRW forecast as institutional ownership and analyst following increase" (p. 178). Bhattacharya (2001) 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. Using the same methods, however, he finds the puzzling result that the number of large trades around earnings announcements, while uncorrelated with SRW errors, is negatively correlated with the absolute value of analyst forecast errors. Bhattacharya does not show that small traders tend to buy (sell) when the errors are positive (negative), only that they trade more 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 relation 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. That is, the greater (more positive) the SRW forecast error, the more likely small traders are to buy. Further, we show that large traders' buying activity is positively associated with signed analysts' forecast errors. Indeed, the correlation between the net buying activity around earnings announcements of the smallest and largest investors is small (-0.003) and not significantly different from zero. These results show that, on average, investors initiating small trades hold, or at least behave as if they hold, earnings expectations that resemble an inefficient and inferior model of earnings, while those initiating large trades do not. We do not assert that this behavior is necessarily illogical. The magnitudes of both the costs and the benefits associated with obtaining different types of forecasts are obviously different for large and small investors. We simply document that the different groups behave in predictably different ways.

We next use both past SRW errors and current analysts' forecasts to dichotomize SRW forecast errors into predictable and unpredictable components. In each case the predictable component of the SRW forecast error is significantly positively associated with the propensity of small traders to buy stock. Bernard and Thomas (1990) use past SRW errors to predict returns around earnings announcements. From this, they hypothesize that a significant subset of investors is unaware of the time-series properties of earnings and that their actions give rise to post-earnings announcement drift. Our ability to use past SRW errors to predict small-trader buying behavior around earnings announcements mirrors Bernard and Thomas's result and indicates that small traders exhibit the investor behavior that Bernard and Thomas theorize causes post-earnings announcement drift.

We confirm Bernard and Thomas's result that stock returns around earnings announcements are predictable on the basis of past SRW errors, though after imposing sample restrictions necessary to test our hypotheses (e.g., availability of analysts' forecasts and a minimum number of trades per day), the result is statistically insignificant. We then extend the Bernard and Thomas result, however, by showing that current analysts' forecasts provide much better predictions than do past SRW errors of: (1) the upcoming SRW forecast error; (2) small-trader buying behavior around the upcoming earnings announcement; and, (3) stock returns around the upcoming earnings announcement. Not only do post-earnings-announcement stock prices fail to reflect the time-series properties of earnings, but they also fail to impound a significant amount of additional information possessed by analysts. Finally, using analysts' forecasts, we provide evidence suggesting that the ability to predict stock returns around earnings announcements increases in the proportion of overall trading attributable to small traders.

Although results indicate that stock returns around earnings announcements are predictable ex ante, we do not attempt to show that these returns exceed trading costs and, therefore, we do not claim that they represent a profitable trading rule. Similarly, although our results suggest that large traders use an information set that is superior to that of small traders, we do not attempt to show that they benefit at the expense of small traders over longer windows. The purpose of this paper, rather, is to show that investors, who can be classified ex ante on the basis of their trade size, hold and act on systematically different beliefs. Further, the group of investors that we expect to be least sophisticated holds systematically inferior earnings expectations–earnings expectations identical to those hypothesized to give rise to post-earnings announcement drift. Finally, some evidence suggests that this group of investors may affect stock prices.

The rest of this paper is organized as follows. In the next section we motivate and state specific testable hypotheses. In Section 3 we lay out the data, sample, and research methods. Section 4 presents the empirical results and Section 5 concludes.

2. Hypotheses

The model we have in mind is a simple one which most resembles Varian (1986). Prior to observing the earnings announcement, each investor holds the amount of stock that he or she has determined to be optimal. The optimal amount of stock is given by the investor's demand function, which is increasing in the difference between the investor's estimate of share value and the market price. The investor's estimate of share value is an increasing function of his or her earnings expectation. Upon observing the earnings announcement, each investor revises his or her estimate of firm value. When observed earnings is higher (lower) than the investor's expectation, investors revise their estimates of share value upward (downward), which causes them to attempt to buy (sell) shares of stock. While investors observe an identical earnings signal, they revise their estimates of value differently—and therefore trade differently—because of divergent prior beliefs.[2]

We propose two available earnings estimates as proxies for investors' prior earnings beliefs. As stated in the introduction, prior research suggests that stock prices may reflect earnings expectations that are biased toward SRW forecasts. Both Hand (1989) and Bernard and Thomas (1990) conjecture that this is attributable to the historical tendency of the financial press to focus its attention on year-to-year quarterly earnings changes. Also as discussed above, the SRW model is significantly less accurate than the best available estimate of earnings–analysts' forecasts. Combining the results of Hand and Bernard and Thomas with the analysis of Easley and O'Hara (1987), who suggest that investors initiating small trades are less well informed than those initiating larger trades, we hypothesize that the earnings expectations of small traders more closely resemble the less accurate SRW predictions rather than they do analysts' forecasts.

We test this by examining the *net buying activity* of investors in response to earnings announcements. Net buying activity, defined formally in the next section, is a measure of the buy-sell imbalance around an earnings announcement for a particular trade-size category (e.g., less than 500 shares). If small traders' earnings expectations resemble SRW forecasts, then SRW forecast errors (as opposed to analyst forecast errors) should trigger trading among this group. Specifically, the revision of perceived share value and therefore the net buying activity of small investors should be positively correlated with SRW forecast errors. 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, we expect investors who place large orders to be better informed. We therefore hypothesize that their prior earnings 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, the net buying activity of large traders should be positively correlated with analyst forecast errors. The second hypothesis is then

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.*

[2]The real situation is slightly more complex than described here. First, even though announced earnings is the same for all investors, more and less sophisticated investors may view earnings differently. Specifically, more sophisticated investors may back out nonvalue-relevant or less persistent components of earnings. Second, following an earnings announcement, the market price as well as the investor's perceived value will normally change. Generally, these price movements will not alter the predicted direction of trades as described above, but they can have implications. We discuss findings related to both of these issues in the results section.

We recognize that analysts' forecasts are not perfect. For example, they exhibit significant first-order autocorrelation (e.g., Mendenhall, 1991; Abarbanell and Bernard, 1992). But in addition to being significantly more accurate than time-series models (see footnote 1), analysts' forecast errors exhibit significantly less serial correlation than those of SRW forecasts, i.e., analysts exhibit significantly less underreaction. For example, Abarbanell and Bernard (Table 1) report median firm-specific first-order autocorrelations of 0.44 for SRW errors, but only 0.10 for analysts' errors.

We summarize the predictions of the first two hypotheses in Fig. 1 below.

If we find that small traders respond to SRW errors, the next question is whether their buying activity can be predicted ex ante. Foster (1977) shows that SRW forecast errors exhibit a significant autocorrelation pattern for up to four lags. This means, of course, that the current SRW error is partially predictable on the basis of the most recent four errors. Bernard and Thomas (1990) hypothesize that some

Table 1

Descriptive statistics for firm-specific variables

SMALL TRADES is the fraction of all shares traded in the three-day earnings announcement window that are traded by investors initiating trades of less than 500 shares. 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. INST. FRAC. 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 announcement. ANALYSTS is the number of analysts providing quarterly earnings forecasts to I/B/E/S in the 90 days prior to the earnings announcement. PRICE is the stock price twenty days prior to the earnings announcement. DVOL is the average daily dollar volume of trading in the year ending twenty days prior to the earnings announcement.

Variable	Mean	Standard Deviation	Quartile 1	Median	Quartile 3
Panel A: distributional statistics of firm-specific variables					
SMALL TRADES	0.043	0.035	0.021	0.034	0.054
SIZE ('000s)	665,408	2,280,152	106,265	225,600	529,472
DECILE	8.45	1.73	7.00	9.00	10.00
INST. FRAC.	0.42	0.21	0.26	0.40	0.57
ANALYSTS	4.05	3.91	2.00	3.00	5.00
PRICE	21.58	14.79	11.13	18.06	28.25
DVOL ('000s)	7,035.7	26,934.6	681.6	1,621.2	4,113.1

Panel B: spearman rank order correlations appear above the diagonal. Pearson product moment correlations appear below the diagonal

	SMALL TRADES	SIZE	INST. FRAC.	ANALYSTS	PRICE	DVOL
SMALL TRADES	1.000	−0.105**	−0.293**	−0.130**	0.003	−0.156**
SIZE	−0.026**	1.000	0.480**	0.574**	0.688**	0.799**
INST. FRAC.	−0.261**	0.125**	1.000	0.422**	0.503**	0.529**
ANALYSTS	−0.127**	0.530**	0.352**	1.000	0.425**	0.606**
PRICE	−0.010	0.400**	0.445**	0.425**	1.000	0.599**
DVOL	−0.038**	0.907**	0.170**	0.586**	0.378**	1.000

$N = 9{,}005$. ** and * indicate significantly different from zero at the .01 and .05 level, respectively.

	Positive Analyst Forecast Error	Negative Analyst Forecast Error
Positive SRW Forecast Error	Large Traders Buy Small Traders Buy	Large Traders Sell Small Traders Buy
Negative SRW Forecast Error	Large Traders Buy Small Traders Sell	Large Traders Sell Small Traders Sell

Fig. 1. Empirical predictions of the first two hypotheses.

investors behave as if they are unaware of the autocorrelation in SRW forecast errors. These investors underestimate the implications of current earnings for future earnings and this gives rise to post-earnings announcement drift. We attempt to directly test Bernard and Thomas's hypothesis that some investors ignore the autocorrelation in SRW errors by examining the net buying behavior of investors in different trade-size categories. If small traders are on average the type of investors that Bernard and Thomas (1990) have in mind, then they should respond to both predictable and unpredictable components of SRW errors because they cannot distinguish between them. Conversely, since large investors are more likely to be sophisticated, the predictable component of the current SRW error should not be new information. We therefore hypothesize that small traders respond to both components of the SRW error—that which is predictable using past SRW errors and that which is not—while large traders respond only to the unpredictable component.

H_{3A}: *The level of small-trader buying activity around earnings announcements is positively associated with both the component of the SRW forecast error that is related to past SRW errors and the component that is not.*

H_{4A}: *The level of large-trader buying activity around earnings announcements is not associated with the component of the SRW forecast error that is related to past SRW errors, but is positively associated with the component that is not.*

Past SRW forecast errors represent only a fraction of the information that investors could use to predict the upcoming SRW error. Extending the logic leading to Hypotheses 3A and 4A, we attempt to predict the net buying behavior of investors in different trade-size classes using analysts' forecasts. That is, since analysts presumably use much more information than is contained in past time-series errors, by comparing analyst and SRW forecasts we should obtain better predictions of the upcoming SRW error. If so, this provides additional tests of the sophistication of small and large traders. For these tests, we partition the SRW forecast error into predictable and unpredictable components on the basis of analysts' forecasts rather than past time-series errors. It turns out that the predictable component of the SRW error is the difference between the analyst and SRW forecasts, while the unpredictable component is simply the analysts' forecast error. Unlike the case above, here we expect small traders to respond only to the predictable component of the SRW error, because they are not cognizant of the analysts' forecasts and therefore do not observe the unpredictable component of the SRW error—the analyst forecast error.

H_{5A}: *The level of small-trader buying activity around earnings announcements is positively associated with the component of the SRW forecast error that is predictable on the basis of analysts' forecasts, but is unrelated to the component that is not.*

We further hypothesize that large investors' expectations are as sophisticated as those of analysts. If so, their buying behavior will again respond only to the unpredictable component of the SRW forecast error.

H_{6A}: *The level of large-trader buying activity around earnings announcements is not associated with the component of the SRW forecast error that is predictable on the basis of analysts' forecasts, but is positively associated with the component that is not.*

If small-investor buying behavior is predictable and if small investors have sufficient market power to affect stock prices, then returns should be predictable on the basis of both past SRW forecast errors and analysts forecasts. Bernard and Thomas (1990) show that returns around earnings announcements are partially predictable on the basis of past SRW errors. After replicating that finding for our sample, we extend Bernard and Thomas by using the predictable component of the SRW forecast error based on a comparison of the current SRW and analyst forecasts.

Following the logic used to motivate Hypotheses 5A and 6A, we hypothesize that since analysts should have more ability than past SRW forecast errors to predict upcoming SRW errors, they will also have greater ability to predict price movements around the upcoming earnings announcement. Bernard and Thomas (1990) hypothesize that investors who ignore the time-series properties of earnings may give rise to the drift. It seems equally plausible to us, however, that the apparent ignorance (or underweighting) of past SRW errors is only one symptom of a more general underreaction to the information in earnings. We therefore hypothesize that analysts, with the broader information set available to them, have greater ability to predict stock price movements around earnings announcements than do past SRW errors.

H_{7A}: Bernard and Thomas (1990) *show that stock returns around earnings announcements are predicable on the basis of past SRW errors. We* *hypothesize that analysts' forecasts have greater ability to predict returns around earnings announcements than do past SRW errors.*

Finally, we propose that the prevalence of small-investor trading may affect the ability of past time-series errors and analysts to predict stock returns around earnings announcements. That is, if the predictability of future stock returns represents systematic mispricing, then there may be greater stock mispricing for cases in which small investors exhibit greater influence.

H_{8A}: *We hypothesize that past SRW forecast errors and analysts' forecasts have greater ability to predict returns around earnings announcements when the fraction of shares traded by small investors is large.*

3. Description of the variables and sample

Our sample begins with all earnings announcements identified by Compustat for Nasdaq stocks between April 1, 1993 and December 31, 1996. Two features of the Nasdaq trading environment during this time period make it an attractive laboratory for our experiment. The first 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. The rules governing the usage of SOES during our sample period make it very unlikely that sophisticated investors with information placed small trades. The second is the mechanism used by Nasdaq to open and close trading in its stocks each day. In contrast to other markets that use single-price auctions to open and/or close trading, Nasdaq market participants simply begin executing and reporting trades when the market opens and stop when it closes. Focusing on earnings announcements in Nasdaq stocks allows us to analyze all trades during normal market conditions. We describe each of these features in more detail below before discussing our variables and sample selection criteria.

3.1. Why Nasdaq data from 1993 through 1996?

After the market crash of 1987, Nasdaq officials made market maker participation in SOES mandatory. As a result, Nasdaq market makers were required to post and honor bid and ask prices for a pre-set number of shares (typically 1,000).[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

[3]For stocks averaging three or more transactions per day, market makers were required to honor their quoted prices for up to 1,000 shares between January 1, 1993 and January 31, 1994, 500 shares between February 1, 1994 and March 27, 1995, and 1,000 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 et al. (1997) for more information on SOES and its affect on trading in the Nasdaq market.

brokers) at posted prices. For more information on the Order Handling Rules, see Barclay et al. (1999).

In this trading environment, it is unlikely that wealthy investors who have or think they have value-relevant information would place market orders for less than the number of shares guaranteed by SOES. Conversely, since Nasdaq market makers are not obligated to transact orders larger than the SOES minimum at quoted prices, an investor purchasing (selling) more shares than are guaranteed by SOES will typically transact at a price that is higher (lower) than the posted ask (bid). This suggests that a sophisticated investor would never place an order for a few hundred shares more or a few hundred shares less than the number of shares guaranteed by SOES. Obviously, as suggested by Easley and O'Hara (1987), there are instances in which sophisticated investors have information that justifies bearing the execution price risk associated with acquiring positions well in excess of the SOES maximum. While one might expect these investors to break up their orders and execute them via SOES, access to SOES was limited to nonprofessional, retail investors during our sample period. In fact, the NASD (1988, 1990, 1991, 1994) introduced several rules throughout the nineties that made it difficult for institutional investors to break up large orders and execute them using SOES. See NASD Notices to Members 88-103 (no professional trading on SOES), 90-57 (no market maker agency orders on SOES), 91-67 (time parameters limiting frequency of order entry), and 94-1 (temporary reduction in order size parameters).

Following this reasoning, we examine six groups of trades based on size: 100–400 shares, 500 shares, 600–900 shares, 1,000 shares, 1,100–4,900 shares, and 5,000 and more shares. We examine 500-share and 1,000-share trades separately, since the number of shares that market makers are required to transact at their quotes via SOES vacillates between 500 and 1,000 shares during our sample period. We select 5,000 shares as the cutoff for our largest trade-size category reasoning that SOES was unavailable for orders this large. We expect that trades in the 100 to 400 share category correspond to the trading interests of naive, unsophisticated investors with little information and trades in the 5,000 and more shares category correspond to the trading interests of wealthy, sophisticated investors with access to superior information.

In contrast to the Nasdaq market prior to 1997, a trader sending a market order to the NYSE could expect it to be manually executed at the posted price as long as the order's size did not exceed the quoted depth (which may have changed while the order was in transit). (In April of 2001, the NYSE began offering immediate executions in all of its securities.) Since the depths on the floor of the NYSE vary widely across stocks and over time, there are no natural trade-size bins that isolate the trading interests of sophisticated and naive investors. Indeed, the introduction of the Order Handling Rules in January of 1997, which reduced the guaranteed minimum number of shares at the inside quotes to 100 shares, eliminated "natural" trade-size bins from the Nasdaq market.

The second advantage of using data from Nasdaq rather than the NYSE centers on the way in which each market begins and ends trading in its stocks. The NYSE uses a single-price call auction that transforms multiple trades into a single reported transaction to open and close trading, while Nasdaq reports individual trades separately throughout the trading day. Since researchers cannot decompose the results of a NYSE call auction into its component trades from publicly available data, data from the opening and closing auctions on the NYSE cannot be used to study investor behavior. 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 both the potential for strategic trading at the open (see Brooks and Su, 1997) and the frequency of after-hours earnings announcements (see Greene and Watts, 1996), the exclusion of trades participating in the NYSE's opening and closing call auctions may lead to biased inferences. For these reasons, Nasdaq trading data prior to 1997 provides a more powerful test of our hypotheses than data from the NYSE or more recent data from Nasdaq.

For less sophisticated investors, the relative cost of obtaining analyst forecasts rather than historical earnings numbers has clearly declined over time. Today, analyst forecasts are freely available over the Internet and press releases are more likely to emphasize how a firm's earnings compare to consensus analyst forecasts. During our sample period, the Internet was in its infancy and news reports were more likely to compare current earnings numbers to historical numbers. This suggests less sophisticated investors are more likely to rely on SRW forecasts before (rather than after) 1997, which further increases the power of our tests.

3.2. Construction of earnings variables

As noted earlier, our initial sample begins with earnings announcements available from Compustat for Nasdaq stocks between April 1, 1993 and December 31, 1996. We calculate the seasonal random walk forecast error (SRWFE) as the difference between actual earnings per share and the actual earnings per share of the same fiscal quarter of the prior year, deflated by share price. So, if the earnings announcement date, the actual reported earnings figure, or the actual reported earnings of the same fiscal quarter of the prior year are not available from Compustat, we eliminate the earnings announcement from our sample. We also eliminate the observation if the share price twenty trading days prior to the earnings announcement date is not available from CRSP. As discussed below, we require the four most recent SRWFEs in order to estimate the component of the current SRW error that is predictable on the basis of the time series of earnings. We therefore eliminate all observations for which we cannot estimate the four most recent SRWFEs.

We compute analysts' forecast errors (AFE) as the difference between Compustat actual earnings per share and the mean of analysts' earnings per share forecasts immediately prior to the earnings announcement, deflated by share price. Thus, if at least one analyst forecast (not more than 90 days old) is not available from I/B/E/S, we eliminate the earnings announcement from our sample. Since we use the Compustat earnings announcement date as the event date in our analysis, to ensure that the I/B/E/S forecasts are aligned with Compustat earnings (as well as with transactions and returns data), we eliminate earnings announcements from our sample if the I/B/E/S earnings announcement date is missing or if the Compustat announcement date and the I/B/E/S date are not within two days of each other.

The I/B/E/S dataset adjusts for stock splits over time. In order to use a common actual earnings per share figure for both the SRW model and for analysts' forecasts, we unadjust all I/B/E/S forecasts and use unadjusted earnings, as reported on Compustat, as actual earnings per share for both types of errors. (For the SRW model, the earnings forecast from Compustat is adjusted for splits that occur between it and quarter-zero earnings.) As the deflator for both forecast errors, we use unadjusted share prices from CRSP. So, forecasts, actual earnings per share, and prices are what investors would have actually observed.

Finally, we partition the current SRW forecast error into predictable and unpredictable components in two ways. First, we define $\mathrm{PSRWFE}_{\text{time-series}}$ as the portion of the current SRW error that is related to the prior four SRW errors; we define the remaining portion of the error as the unpredictable component-$\mathrm{USRWFE}_{\text{time-series.}}$ Specifically, $\mathrm{PSRWFE}_{\text{time-series}}$ is the prediction of the current coded SRW error from a pooled cross-sectional regression of coded SRW errors on the prior four coded SRW errors. $\mathrm{USRWFE}_{\text{time-series}}$ is the residual for the current observation from the same regression. This estimate of the predictable component of the SRWFE assumes that an investor could know the true SRW autocorrelation pattern observed for our sample (Table 6). To ensure our results are not attributable to hindsight bias, we replicate all tests assuming three different SRWFE autocorrelation patterns that would have been available to investors: the pattern reported in Foster (1977, Table 2); the pattern reported in Bernard and Thomas (1990, Table 1); and the pattern estimated using all sample observations occurring in the prior calendar quarter. As might be expected given the consistency among the autocorrelation structures cited, results are nearly identical to those presented.

We next use analysts' forecasts to partition the current SRW error into predictable and unpredictable components. We define $\mathrm{PSRWFE}_{\text{analysts}}$ as the analyst forecast minus the SRW forecast deflated by price. That is, by adding the analyst forecast to and subtracting it from the SRW forecast error,

$$\frac{E-\hat{E}_{\text{SRW}}}{P}=\frac{E}{P}-\frac{\hat{E}_{\text{Analysts}}}{P}+\frac{\hat{E}_{\text{Analysts}}}{P}-\frac{\hat{E}_{\text{SRW}}}{P}, \tag{1}$$

the SRW forecast error can be bifurcated into predictable and unpredictable components:

$$\frac{E-\hat{E}_{\text{SRW}}}{P}=\left(\frac{E-\hat{E}_{\text{Analysts}}}{P}\right)+\left(\frac{\hat{E}_{\text{Analysts}}-\hat{E}_{\text{SRW}}}{P}\right). \tag{2}$$

The second term of the right side of the above equation is the predictable component of the SRW forecast error. Note that this variable is known with certainty prior to the earnings announcement–it does not depend on announced earnings.

To allow for outliers and nonlinearities in the relations among forecast errors, trading activity, and returns, we follow Bernard and Thomas (1990) and code AFE and SRWFE by within-quarter decile. To aid in the economic interpretation of our regression results, we follow Affleck-Graves and Mendenhall (1992) and equally space the coded scores from -0.5 (lowest decile) to $+0.5$ (highest decile).

3.3. Construction of return and control variables

To investigate the relation between trading by different investor clienteles and returns around earnings announcements, we require daily return data from CRSP. Our return variable, 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. We eliminate from our sample earnings announcements for which the data needed to compute ANCAR are not available. We also use three variables to control for firm-specific factors identified by Bhushan (1994) and Walther (1997) as being associated with investor sophistication. The first, SIZE, is the market capitalization of the firm in thousands of dollars at the beginning of the calendar year taken from CRSP. The second, INST. FRAC., is taken from CDA Spectrum and 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 announcement. The third, ANALYSTS, is the number of analysts providing quarterly earnings forecasts to I/B/E/S in the 90 days prior to the earnings announcement. In addition, Bhushan argues that share price and recent dollar trading volume proxy for trading costs. We therefore define PRICE as the stock price twenty days prior to the earnings announcement and DVOL as the daily average dollar trading volume in the stock in the year ending twenty days prior to the announcement.

3.4. Construction of microstructure variables

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 Stock Market. Each quote record indicates the underlying stock, the trading venue posting the quote, the date and time of the quote, the bid and ask prices and quantities, and a condition code indicating whether the quote is an opening or a closing quote. 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. (See the NYSE's TAQ2 User's Guide for an in-depth description of the TAQ database.) 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 qualifying 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 is initiated by a buyer or seller.[4] 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 an 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 et al. (2000), we then use the execution-time NBBO with no lag as our benchmark quotes.[5]

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. 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. We also eliminate any trade

[4] Lee and Radhakrishna (2000), 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 improves the trade typing success rate by only 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.

[5] 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 et al. (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.

with a transaction price more than $5.00 away from the previous price on that day and trades with no reported quantities—“obvious” data errors. 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 a.m. and 4:00 p.m. since the time-stamps for trades (needed for the LR algorithm) become less reliable outside of normal market hours. See, e.g., Bessembinder and Kaufman (1997), who use data screens similar to ours.

From our sample of trades classified as buys and sells, we construct a 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 *i*th trade-size category in the event window ($\text{NetEventBuy}_\text{i}$), we compute similar statistics for the three-day trading window centered ten trading days prior to the earnings announcement date ($\text{NetPreBuy}_\text{i}$) and for the three-day trading window centered ten trading days following the earnings announcement date ($\text{NetPostBuy}_\text{i}$).[6] We then subtract the average of NetPreBuy and NetPostBuy from NetEventBuy and deflate by the average number of nonevent trades (Avg. # of Nonevent Trades). The Avg. # of Nonevent Trades is the sum of the stock's category i (buy and sell) transactions in the three-day pre- and post-nonevent windows divided by two. Formally, the abnormal net buying activity in the *i*th trade-size category, NETBUY_i, is as follows:

$$\text{NETBUY}_i = \left[\text{NetEventBuy}_i - \left(\frac{\text{NetPreBuy}_i + \text{NetPostBuy}_i}{2}\right)\right] \times \left(\frac{1}{\text{Avg. \# of Non-Event Trades}_i}\right). \tag{3}$$

NETBUY_i may be interpreted as the abnormal buy–sell imbalance as a fraction of total nonevent trades. Thus, if the number of event buys exceeds nonevent buys by 10% of normal trade volume (both buys and sells) and event sells are at the normal nonevent level, then NETBUY_i equals 10%. To ensure our measure of abnormal net buying activity is reasonable, we require each earnings announcement in our sample to have an average of ten trades per day in each of the three-day trading windows.

Finally, we use the total shares traded by investors initiating trades less than 500 shares in the three-day announcement period divided by the total number of shares traded in the same period as a measure of small-trader influence. We name this variable SMALL TRADES. The final sample consists of 9,005 quarterly earnings announcements representing 1,608 distinct firms.

[6]Results presented in Lee (1992) suggest using a nonevent period centered ten trading days away from the earnings announcement is more than adequate. Moving the nonevent period to 20 trading days before and after the announcement does not alter our results.

4. Empirical results

4.1. Descriptive statistics

Panel A of Table 1 provides descriptive statistics for the sample firms. The first variable, SMALL TRADES, is the fraction of shares traded during the three-day earnings announcement period that are initiated by investors trading fewer than 500 shares. For our sample, these small trades on average make up 29.0% (not tabulated) of all trades and are responsible for 4.3% of all shares traded during the three-day earnings announcement period. Next, SIZE is the market capitalization of the firm in thousands of dollars at the beginning of the calendar year of the earnings announcement. We define DECILE as the market-capitalization decile of the firm within Nasdaq for the calendar year of the earnings announcement. Note that our criteria result in a sample of firms that tend to be larger than the median Nasdaq firm. Specifically, the average (median) size decile is 8.45 (9.00). The next variable, INST. FRAC., 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. FRAC. is 0.42 (0.40) indicating that institutions hold about 40% of the shares of the typical sample firm. As a measure of analyst following, we define ANALYSTS as the number of analysts reporting quarterly earnings forecasts to I/B/E/S 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 I/B/E/S. The mean (median) number of analysts reporting forecasts is 4.05 (3.00). The next variable, PRICE, is the actual share price from CRSP 20 days prior to the earnings announcement. The mean (median) value for PRICE is 21.58 (18.06). Finally, DVOL is the average daily dollar trading volume for the stock in the year ending 20 days prior to the earnings announcement.

Panel B of Table 1 presents the Pearson (below the diagonal) and Spearman correlations among the variables. As expected, the firm-specific variables, SIZE, INST. FRAC, ANALYSTS, PRICE, and DVOL are all positively correlated, while our measure of small-trader activity, SMALL TRADES, is negatively correlated with most of these firm-specific variables. (The lone exception is PRICE.) We also find SMALL TRADES, the fraction of all shares traded in trades initiated by investors trading less than 500 shares, is most highly negatively correlated with the fraction of shares held by institutions (Pearson = −0.261; Spearman = −0.293).

Most of our analysis relies on measures of net buying activity by investors who initiate trades of different sizes. Table 2 indicates distributional statistics for each of the six trade-size classifications. Not surprisingly, we find that small traders are net buyers during earnings announcement periods. The mean (median) value of NETBUY_1 (the net buying activity of those initiating trades of less than 500 shares) is 0.065 (0.031), which is significantly greater than zero at traditional levels. This phenomenon was first documented by Lee (1992), who speculates that earnings announcements may draw the attention of individual investors. (Note that we observe this for those initiating 500 share trades and those initiating 1,000 share trades as well.)

Table 2
Descriptive statistics for net buying activity of different trade-size categories

$NETBUY_1$—$NETBUY_6$ 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 nonevent-period purchases minus average daily nonevent-period sales for category i) divided by (average daily nonevent-period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The nonevent period is two three-day periods centered ten trading days before and after the earnings announcement date.

Variable	Mean	Standard Deviation	Quartile 1	Median	Quartile 3
$NETBUY_1$ (<500 shrs.)	0.065	0.541	−0.228	0.031	0.313
$NETBUY_2$ (500 shrs.)	0.120	0.838	−0.309	0.034	0.442
$NETBUY_3$ (600–900 shrs.)	−0.039	0.792	−0.398	−0.003	0.335
$NETBUY_4$ (1,000 shrs.)	0.091	0.787	−0.285	0.0284	0.402
$NETBUY_5$ (1,100–4,900 shrs.)	−0.043	0.571	−0.305	−0.021	0.248
$NETBUY_6$ ($\geqslant$5,000 shrs.)	−0.071	1.032	−0.357	0.000	0.333

$N = 9,005$.

Conversely, large traders tend to sell during earnings announcements. On average, investors initiating trades in the 1,100–4,900 range and those initiating trades of 5,000 shares or more exhibit a significant tendency to sell during the earnings announcement period. (Note that the median value of $NETBUY_6$ is, however, 0.0.) We did not anticipate this mean effect for large traders and are not sure why it occurs. It is possible that large investors, knowing that small investors tend to be net buyers around earnings announcements, use this opportunity to sell shares. (We thank an anonymous reviewer for this insight.) Rather than explore possible explanations for the propensity of large traders to sell or the propensity of small traders to buy during earnings announcement periods, we focus on the differences in net buying activity across the signs of the two types of forecast errors for the two types of traders.

4.2. Correlations among forecast errors and net buying activity

Table 3 displays correlations among the net buying activity measures for the six trade-size categories, the two measures of earnings surprise, and the two measures of both the predictable and unpredictable components of the SRWFE. The results strongly suggest that the data are consistent with our expectations. Note that for the two smallest trade-size categories, those trading 500 shares or less, 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 two largest trade-size categories, net buying activity is more highly correlated with analyst forecast errors than with SRW errors.

Table 3
Correlations among 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 I/B/E/S 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. $PSRWFE_{time\text{-}series}$ ($USRWFE_{time\text{-}series}$) is the portion of the current SRW forecast error that is (is not) related to past SRW forecast errors. $PSRWFE_{analyst}$ ($USRWFE_{analyst}$) is the portion of the current SRW forecast error that is (is not) predictable on the basis of analyst's forecasts. $NETBUY_1$—$NETBUY_6$ 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 nonevent-period purchases minus average daily nonevent-period sales for category i) divided by (average daily nonevent-period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The nonevent period is two three-day periods centered ten trading days before and after the earnings announcement date.

	$NETBUY_1$ (<500 shrs.)	$NETBUY_2$ (500 shrs.)	$NETBUY_3$ (600–900 shrs.)	$NETBUY_4$ (1,000 shrs.)	$NETBUY_5$ (1,100–4,900 shrs.)	$NETBUY_6$ (≥5,000 shrs.)
Panel A: correlations between forecast errors and NETBUY variables						
AFE	0.000	0.017	0.008	0.036**	0.041**	0.057**
SRWFE	0.057**	0.029**	0.003	0.043**	0.032**	0.041**
$PSRWFE_{time\text{-}series}$	0.053**	0.020*	0.012	0.003	−0.014	0.006
$USRWFE_{time\text{-}series}$	0.034**	0.020*	−0.003	0.049**	0.046**	0.043**
$PSRWFE_{analyst}$	0.069**	0.025*	0.010	0.024**	0.008	0.015
$USRWFE_{analyst}$	0.000	0.017	0.008	0.036**	0.041**	0.057**
Panel B: correlations among NETBUY variables						
$NETBUY_1$ (<500 shrs.)	1.000					
$NETBUY_2$ (500 shrs.)	0.412**	1.000				
$NETBUY_3$ (600–900 shrs.)	0.308**	0.193**	1.000			
$NETBUY_4$ (1,000 shrs.)	0.138**	0.213**	0.156**	1.000		
$NETBUY_5$ (1,100–4,900 shrs.)	0.167**	0.262**	0.268**	0.304**	1.000	
$NETBUY_6$ (≥5,000 shrs.)	−0.003	0.063**	0.095**	0.129**	0.213**	1.000

$N = 9{,}005$. ** and * indicate significantly different from zero at the 0.01 and 0.05 level, respectively.

Specifically, for those initiating the smallest trades (less than 500 shares), the correlation with SRW forecast errors is 0.057 and is significantly greater than zero at the 0.01 level, while the corresponding correlation with analyst forecast errors is not significantly different from zero. For those initiating the largest trades, the ordering is reversed and the correlation between net buying activity and analyst forecast errors is 0.057, while the corresponding correlation with SRW error is only 0.041. Both correlations are significant at the 0.01 level. Taken alone, these results suggest that the smallest traders respond only to SRW signals, while the largest traders respond to both signals.

Note, however, the correlations among the net-buying measures and the predictable and unpredictable components of the SRW forecast error. Traders in each of the two smallest trade-size categories, $NETBUY_1$ and $NETBUY_2$, respond to the components that are and are not predictable on the basis of the time series of earnings. Traders in these two groups, however, respond only to the component that is predictable on the basis of analysts' forecasts. This is consistent with our expectations, because the smallest traders are not cognizant of analysts' forecasts and therefore do not observe $PSRWFE_{analyst}$. Traders in the two smallest trade-size categories respond to components of the SRWFE that should be known in advance. On the other hand, traders in the two largest trade-size categories, $NETBUY_5$ and $NETBUY_6$, respond only to the unpredictable components of the SRW forecast error.

4.3. Means tests with consistent and contradictory earnings signals

The four interior cells of Table 4 present the net buying activity of small and large traders for each combination of the signs of SRW and analyst forecast errors. The upper-left interior cell indicates that when both the SRW and analyst forecast errors are positive, small traders are significant net buyers ($NETBUY_1 = 0.077$, significant at the 0.01 level) and large traders are neither net buyers or sellers ($NETBUY_6 = 0.007$, insignificantly different from zero). Moving one cell to the right, results indicate that for cases in which the SRW forecast error is held positive but the analyst forecast error is negative, small traders remain net buyers ($NETBUY_1 = 0.110$, significant at the 0.01 level) and large traders become significant net sellers ($NETBUY_6 = -0.173$, significant at the 0.01 level).

The last column of the first row indicates that when holding SRW forecast errors positive and allowing the analyst forecast error to go from positive to negative, large traders become significantly greater sellers ($t = 4.54$; $z = 3.72$), but the results for small traders are insignificant ($t = -1.81$; $z = -0.96$). (Throughout our analysis, z-statistics are based on the large-sample approximation of the Wilcoxon Rank Sum Test.) Taken alone, the results presented in the first row suggest that while large traders respond to analyst forecast errors in the expected direction, at best small traders ignore analysts' forecast errors.

The second row holds the SRW error negative while again allowing the sign of the analyst forecast error to change. The results for large traders are similar to those of the first row—they are neutral when the analyst forecast error is positive ($NETBUY_6 = 0.018$, not significant) and they are strong net sellers when the analyst forecast error is negative ($NETBUY_6 = -0.177$, significant at the 0.01 level). Again the cell in the rightmost column indicates that when holding the sign of the SRW forecast error constant (negative for the second row), the activity of large traders depends significantly on the sign of the analyst forecast error ($t = 3.55$; $z = 3.67$). In contrast, tests whose results are reported in the table's bottom row indicate that when holding the sign of the analyst forecasts constant, changing the sign of the SRW forecast has a very small and insignificant effect on the buying behavior of large traders.

Comparison of the first and second rows also indicates that small traders exhibit much less propensity to buy when the SRW forecast error is negative. The table's bottom row shows this difference to be highly significant both when the analyst

Table 4
Net buying activity for different trade-size categories: Confirmatory and contradictory earnings signals

Mean values of NETBUY1 (Small) and NETBUY6 (Large) by the sign of the analyst forecast error (AFE) and the seasonal random walk forecast error (SRWFE).

	Positive analyst forecast error	Negative analyst forecast error	Difference (positive–negative)
Positive seasonal randomwalk forecast error	Small: 0.077**	Small: 0.110**	Small: −0.028 ($t = -1.81$; $z = -0.96$)
	Large: 0.007 ($N = 4,050$)	Large:−0.173** ($N = 1,826$)	Large: 0.132 ($t = 4.54^{**}$; $z = 3.72^{**}$)
Negative seasonal randomwalk forecast error	Small:−0.034	Small: 0.027*	Small: −0.061 ($t = -2.66^{*}$; $z = -1.59$)
	Large: 0.018 ($N = 748$)	Large:—0.177** ($N = 2,381$)	Large: 0.195 ($t = 3.55^{**}$; $z = 3.67^{**}$)
Difference (positive–negative)	Small: 0.111 ($t = 5.19^{**}$; $z = 4.84^{**}$) Large: −0.011 ($t = -0.21$; $z = -1.16$)	Small: 0.084 ($t = 4.10^{**}$; $z = 4.87^{**}$) Large: 0.004 ($t = 0.09$; $z = 0.37$)	

** and * indicate significantly different from zero at the 0.01 and 0.05 level, respectively.

forecast error is positive ($t = 5.19$; $z = 4.84$) and when the analyst forecast error is negative ($t = 4.10$; $z = 4.87$). Results presented in the rightmost column are mixed, with the t-statistic suggesting that small traders respond in the opposite direction of analyst forecast errors ($t = -2.66$) and the z-statistic suggesting that small traders ignore analyst forecast errors ($z = -1.59$).

Even with this crude control based only on the sign of the two types of errors, it seems apparent that small investors respond to SRW errors and large investors respond to analysts' errors. In other words, the evidence presented in Table 4 strongly supports hypotheses 1A and 2A, respectively. In the next section we use regression analysis to examine these two hypotheses while controlling for both the sign and the magnitude of the two types of errors.

4.4. Regression tests of net buying activity on earnings signals

Table 5 presents results of regression tests of net buying activity for each trade-size category on the two earnings signals, namely, 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 significantly less than zero (standard t-statistic $= -3.17$; time-series t-statistic $= -3.26$), suggesting that when controlling for SRW forecast error, the smallest traders respond in the opposite direction of analyst forecast errors.[7] The coefficient on the SRW forecast error, on the other hand, is significantly positive (standard t-statistic $= 6.24$; time-series t-statistic $= 4.00$). The SRW coefficient of 0.145 indicates that the difference in the announcement period buy-sell imbalance between observations in top and bottom SRW-error deciles is 14.5% of normal nonannouncement trades—after controlling for analyst forecast errors. For the SRW errors, the second column provides results, for those who trade 500 shares, that are similar to (but weaker than) the smallest traders, but gives little indication that these investors trade in the opposite direction of analyst forecast errors.

At the other end of the spectrum, the net buying activity of the largest traders—those who initiate trades for 5,000 shares or more—is significantly positively related to analyst forecast errors (standard t-statistic $= 4.05$; time-series t-statistic $= 7.31$). The coefficient on the analyst forecast errors is 0.223 and may be interpreted as described above. Unlike the smallest traders, the largest traders respond to analyst forecast errors, but appear to ignore SRW errors (standard t-statistic $= 1.23$; time-series t-statistic $= 1.63$). Results for the second largest traders, those trading 1,100 to 4,900 shares, are similar to but somewhat weaker than those of the largest traders–they seem to respond positively to analyst forecast errors (standard t-statistic $= 2.63$; time-series t-statistic $= 4.09$), but not to SRW forecast errors (standard t-statistic $= 1.23$, time-series t-statistic $= 1.61$).[8]

[7] Fama and MacBeth (1973) describe the time-series t-statistic.

[8] We replicate Table 5 on sample quartiles based on firm size. In each case the results are similar to those reported for the complete sample. Specifically, for small-trader net buying, the coefficient on SRWFE is positive and significant at least at the 5% level in all four cases, while the coefficient on AFE is insignificant

Table 5

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 I/B/E/S 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 nonevent-period purchases minus average daily nonevent-period sales for category i) divided by (average daily nonevent-period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The nonevent period is two three-day periods centered ten trading days before and after the earnings announcement date.

	$NETBUY_1$ (<500 shrs.)	$NETBUY_2$ (500 shrs.)	$NETBUY_3$ (600–900 shrs.)	$NETBUY_4$ (1,000 shrs.)	$NETBUY_5$ (1,100–4,900 shrs.)	$NETBUY_6$ (≥5,000 shrs.)
Intercept	0.061	0.121	−0.040	0.098	−0.046	−0.077
t-statistic	9.57**	10.92**	−3.97**	8.49**	−7.43**	−5.12**
AFE	−0.074	0.008	0.028	0.067	0.069	0.223
t-statistic	−3.17**	0.20	0.08	1.58	2.63**	4.05**
Time-series *t*-statistic	−3.26**	0.17	0.44	0.77	4.09**	7.31**
SRWFE	0.145	0.091	−0.005	0.093	0.032	0.068
t-statistic	6.24**	2.25**	−0.12	2.68**	1.23	1.23
Time-series *t*-statistic	4.00**	1.65	0.06	3.22**	1.61	1.63
Adj. *R*-square	0.41%	0.08%	−0.00%	0.19%	0.16%	0.32%

$N = 9,005$. ** and * indicate significantly different from zero at the 0.01 and 0.05 level, respectively.

As mentioned in footnote 2, even though investors see the same earnings figure, different investors may interpret it differently. For this study we use earnings provided by Compustat for both forecast errors. Alternatively, I/B/E/S provides earnings that have been "adjusted by I/B/E/S Data Research to be comparable to the estimates made by analysts" (from documentation provided by I/B/E/S). When we replace Compustat actual earnings with earnings that I/B/E/S believes are more value relevant, the relation between the largest traders' net buying activity and analyst forecast errors becomes stronger. The coefficient on AFE in Table 5 increases from 0.223 to 0.274, while the relations between small traders' net buying activity and both forecast errors are essentially unchanged. We interpret this as a test of the joint hypothesis that I/B/E/S succeeds in providing more value-relevant earnings figures (confirmed by nontabulated tests of association between errors and returns) and that large traders successfully back out at least some nonvalue-relevant or less persistent components of announced earnings.

(*footnote continued*)

in three cases and negative and significant for the largest quartile. For large-trader net buying, the coefficients on SRWFE are all insignificant, while the coefficients on AFE are all positive and are significant at least at the 5% in three cases. Inferences are identical when we form quartiles based on analyst following or fraction of shares held by institutions instead of market capitalization.

The results presented in Tables 3, 4, and 5 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.

Why is the net buying activity of small traders negatively correlated to analysts' forecast errors when controlling for SRW forecast errors? We offer what we believe is one possible interpretation of these results. Price movements are more highly associated with analyst forecast errors (signals seen by large traders) than with SRW forecast errors. (We confirmed this for our sample in nontabulated results.) As the price moves in response to the analyst forecast errors, this may have an inverse effect on small traders' demand functions. For example, suppose that announced earnings equals the SRW forecast but is above the analyst forecast. The positive analyst forecast error causes an increase in large-trader demand and their trading causes prices to rise. Thus, while small traders' subjective value of the stock does not change, their demand declines as the price rises, inducing them to sell.

More formally, Varian (1986) specifies investor demand as $D_i = \tau\alpha\,(v_i - P)$, where τ is the investor's risk aversion, α is the precision of the investor's information, v_i is the investors's subjective valuation, and P is the market price. For small traders, holding SRWFE constant holds v_i constant, while increasing AFE increases P, thereby decreasing demand and decreasing the net buying of small traders. Consistent with this interpretation, when we add the three-day abnormal return around the earnings announcement (ANCAR) as an independent variable to the first regression reported in Table 5, the coefficient on ANCAR is significantly negative and the coefficient on AFE is no longer significantly different from zero. This may be why, conditional on SRW forecast error, small traders appear to trade opposite to analysts' forecast errors.

We next explore the relations among the net buying measures and the predictable and unpredictable components of the SRW forecast error. Table 6 presents the results of attempting to predict the current SRW forecast error using past SRW forecast errors and using analysts' forecasts. The first column shows that seasonal random walk errors exhibit positive and declining first-, second-, and third-order autocorrelation and negative fourth-order autocorrelation. Our results are very similar to those reported in prior research. See, e.g., Table 1 of Bernard and Thomas (1990) and Table 1 of Ball and Bartov (1996). The information in the four most-recent SRW forecast errors explains 25.04% of the variation in the upcoming SRW forecast error. The second column reports that comparing the current analyst forecast to the current SRW forecast does a much better job of predicting the upcoming SRWFE than the information in the four most-recent SRW forecast errors (adjusted $R^2 = 56.92\%$). Analysts possess more information about upcoming earnings than do past SRW errors. Since we use decile variables coded from -0.5 to

Table 6
Regressions relating the current seasonal random walk forecast error to past errors and the prediction of the current seasonal random walk error based on analysts' forecasts

SRWFE is the current seasonal random walk forecast error. $SRWFE_{-t}$ is the seasonal random walk error for earnings announced t quarters ago. $PSRWFE_{analyst}$ is the prediction of the current seasonal random walk forecast error based on analysts' forecasts.

Dependent variable	SRWFE	SRWFE
Intercept	0.001	0.000
	(0.01)	(0.00)
$SRWFE_{-1}$	0.416	
	(40.14)**	
$SRWFE_{-2}$	0.116	
	(10.32)**	
$SRWFE_{-3}$	0.051	
	(4.56)**	
$SRWFE_{-4}$	−0.215	
	(−20.86)	
$PSRWFE_{analysts}$		0.754
		(109.07)**
Adj. R^2	25.04%	56.92%

$N = 9,005$. ** and * indicate significantly different from zero at the .01 and .05 level, respectively.

+0.5 for this test, the coefficient of 0.754 on $PSRWFE_{analyst}$ indicates that an increase of one decile in the rank of $PSRWFE_{analyst}$ increases the expected rank of the actual SRW forecast error by about three-quarters of one decile.

Table 7 presents results of regressions of net buying activity on the components of the SRW forecast error. If small traders systematically use an inferior earnings expectation model, then their buying behavior should be predictable. The regression results are consistent with the correlations presented in Table 3 above. The first column results support the alternative statement of the third hypothesis: Small traders respond significantly to both components of the SRW forecast error. While it is not surprising that investors respond to the unpredictable component of earnings, the result that small investors respond to that component of the SRW forecast error that is predictable on the basis of past SRW errors is important. This result indicates that these small investors fail to recognize the time-series properties of earnings and therefore fail to incorporate past SRW forecast errors into their prediction of upcoming earnings. This is precisely the investor behavior that Bernard and Thomas (1990) hypothesize gives rise to post-earnings announcement drift. So, results presented here represent the first direct documentation that at least one set of investors, those initiating small trades, behaves in the manner that many believe is responsible for the SUE effect.

Results in the second column are consistent with the alternative statement of the fifth hypothesis: When we dichotomize the SRW forecast error into components based on analysts' forecasts, small traders respond to only the predictable component. This is consistent with results presented throughout this paper

Table 7
Regressions of net buying activity and three-day abnormal stock returns at the time of earnings announcements on the predicted component of seasonal random walk (SRW) forecast errors and small-trader activity

$NETBUY_1$ and $NETBUY_6$ 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 nonevent-period purchases minus average daily nonevent-period sales for category i) divided by (average daily nonevent-period trades for category i). The event period is the three-day interval centered on the earnings announcement date as reported on Compustat. The nonevent period is two three-day periods centered two weeks before and after the earnings announcement date. $PSRWFE_{time\text{-}series}$ ($USRWFE_{time\text{-}series}$) is the portion of the current seasonal random walk forecast error that is (is not) related to past seasonal random walk forecast errors. $PSRWFE_{analyst}$ ($USRWFE_{analyst}$) is the portion of the current seasonal random walk forecast error that is (is not) predictable on the basis of analyst's forecasts.

Dependent variable	$NETBUY_1$ (<500 shrs.)	$NETBUY_1$ (<500 shrs.)	$NETBUY_1$ (<500 shrs.)	$NETBUY_6$ (≥5,000 shrs.)	$NETBUY_6$ (≥5,000 shrs.)	$NETBUY_6$ (≥5,000 shrs)
Intercept	0.061	0.061	0.061	−0.077	−0.077	−0.077
	(9.57)**	(9.57)**	(9.57)**	(−5.12)**	(−5.12)**	(−5.12)**
$PSRWFE_{time\text{-}series}$	0.199		0.133	0.054		−0.088
	(5.08)**		(2.24)*	(0.59)		(−0.63)
$USRWFE_{time\text{-}series}$	0.075		0.040	0.224		0.050
	(3.23)**		(0.88)	(4.07)**		(0.47)
$PSRWFE_{analysts}$		0.132	0.079		0.057	0.055
		(6.58)**	(2.04)*		(1.20)	(0.60)
$USRWFE_{analysts}$		−0.005	−0.032		0.255	0.243
		(−0.27)	(−1.11)		(5.39)**	(3.52)**
Adj. R^2	0.38%	0.46%	0.50%	0.17%	0.32%	0.32%

$N = 9,005$. ** and * indicate significantly different from zero at the .01 and .05 level, respectively.

suggesting that small investors behave as if they are unaware of analysts' forecasts and form earnings expectations that are much less sophisticated. The third column simply uses each of the predictable and unpredictable components as explanatory variables.

The last three columns of Table 7 perform the same analyses for large investors. Note that consistent with the alternative statements of Hypotheses 4 and 6, in all cases large investors respond only to the unpredictable component of the SRW forecast error. The last column indicates that when including all error components, large investors respond only to the component that is unpredictable on the basis of analysts' forecasts. Large traders seem to exhibit a level of sophistication well beyond that of small traders.

4.5. Small-trader activity and the stock-price response to earnings

The first six hypotheses address the trading behavior, and therefore the earnings expectations, of investors of different trade-size classes. Bernard and Thomas (1990) provide results suggesting that the earnings expectations embedded in stock prices do not adequately reflect the time-series properties of earnings. In other words, they show that stock returns around earnings announcements are predictable on the basis of past SRW forecast errors. In this section, we attempt to extend the findings of Bernard and Thomas and link them to the prevalence of small-investor trading.

If, as shown above, small traders' expectations are predictable and if small traders (or all who share their earnings expectations) affect prices, then stock price movements at the time of earnings announcements should also be predictable. In the first column of Table 8 we attempt to predict stock price movements around sample earnings announcements using the same techniques used for the tests predicting buying behavior in Table 7. (We thank an anonymous reviewer for suggesting this set of tests.) The coefficient on the predictable component of the current SRW error (based on the past SRW errors) is 0.905 and falls just short of being significant at the 5% level based on a one-tail test. Because of the decile coding, the 0.905 coefficient may be interpreted as a difference in announcement abnormal return of just under 1% between the top and bottom $\mathrm{PSRWFE}_{\text{time-series}}$ deciles.

Bernard and Thomas (1990) obtain significant results when using SRW errors to predict returns around earnings announcements. Why are our results so weak? First, while we study about 9,000 firm-quarter observations, Bernard and Thomas study between 72,000 and 86,000. Our sample size is smaller in part because we restrict our sample to Nasdaq firms during the period between the beginning of TAQ availability and implementation of Nasdaq Order Handling rules. As we discuss above, we impose these limitations in order to form the most powerful and accurate tests of our hypotheses.

Our sample is also biased towards firms whose future returns are less predictable. To test our hypotheses we must require at least one analyst forecast from I/B/E/S. We also require an average of at least ten trades per day during the earnings announcement and control periods to make our net buying measures more meaningful. Each of these requirements tends to rule out the smaller, less followed,

Table 8

Regressions of the three-day abnormal stock return at the time of earnings announcements on the predictable component of seasonal random walk (SRW) forecast error and small-trader activity

ANCAR 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. $\mathrm{PSRWFE}_{\text{time-series}}$ is the portion of the current seasonal random walk forecast error that is related to past seasonal random walk forecast errors. $\mathrm{PSRWFE}_{\text{analyst}}$ is the portion of the current seasonal random walk forecast error that is predictable on the basis of analyst's forecasts. SMALL TRADES is the fraction of all shares traded in the three-day earnings announcement window that are traded by investors initiating trades of less than 500 shares. SIZE is the market capitalization of the firm in thousands of dollars at the beginning of the calendar year. INST. FRAC. 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 announcement. DVOL is the average daily dollar volume of trading in the year ending twenty days prior to the earnings announcement. SMALL TRADES, SIZE, INST. FRAC., ANUM, and DVOL are decile coded over a range of 0.0 to 1.0.

	Time-series prediction			Analyst prediction		
Dependent variable	ANCAR	ANCAR	ANCAR	ANCAR	ANCAR	ANCAR
Intercept	0.221	0.220	0.209	0.221	0.235	0.220
	(2.44)*	(2.43)*	(2.29)*	(2.44)*	(2.59)**	(2.44)*
PSRWFE	0.905	0.611	1.373	1.337	0.376	1.475
	(1.64)	(0.60)	(0.91)	(4.71)**	(0.72)	(1.91)
PSRWFE*		0.598	0.545		1.960	1.912
SMALL TRADES		(0.34)	(0.30)		(2.20)*	(2.09)*
PSRWFE*			3.178			−1.302
SIZE			(1.04)			(−0.84)
PSRWFE*			1.929			0.739
INST. FRAC			(0.90)			(0.68)
PSRWFE*			0.571			1.276
ANUM			(0.24)			(1.07)
PSRWFE*			−7.204			−3.233
DVOL			(−2.37)*			(−2.10)*
Adj.R^2	0.02%	0.01%	0.04%	0.23%	0.28%	0.40%

$N = 9{,}005$. ** and * indicate significantly different from zero at the .01 and .05 level, respectively.

less active stocks for which future returns are probably more predictable. For example, Bernard and Thomas (1990) find greater return predictability for small stocks and Bhushan (1994) finds a larger SUE effect for stocks with lower recent trading volume. In untabulated tests, simply eliminating the ten-trade per day constraint increases the sample from 9,005 to 13,299 observations and nearly doubles the coefficient on $\mathrm{PSRWFE}_{\text{time-series}}$ from 0.905 to a statistically significant 1.700 ($t = 3.85$). This suggests that the return predictability documented in prior studies may be heavily concentrated in illiquid stocks and therefore be largely unexploitable. The very data necessary to accurately measure net buying activity may hinder or prevent us from linking net buying activity to stock price movements.

The second and third columns of Table 8 show results of similar regressions after adding multiplicative variables to assess the effect of the prevalence of small trades and other firm-specific variables discussed above. Not surprisingly, based on the weak basic results presented in the first column, we find no evidence that the frequency of small trades affects the predictability of returns around earnings announcements. Thus, our results are not consistent with the alternative form of the seventh hypothesis. We find some evidence that as recent dollar trading volume—according to Bhushan (1994), a measure of trading costs—increases, the predictability of returns decreases. But again, the weakness of the basic relation between returns and $\mathrm{PSRWFE}_{\text{time-series}}$ makes any conclusions tentative at best.

The final three columns of Table 8 provide results that are completely analogous to the first three after replacing $\mathrm{PSRWFE}_{\text{time-series}}$ with $\mathrm{PSRWFE}_{\text{anlayst}}$. The first of these columns indicates that returns around earnings announcements are highly predictable when using analysts' forecasts to form a prediction of the upcoming SRW error. The coefficient of 1.337 ($t = 4.71$) implies an expected difference in top and bottom $\mathrm{PSRWFE}_{\text{analsyt}}$ deciles of 1.337%. The greater ability of analysts' forecasts to predict returns around earnings announcements implies that analysts possess information beyond that in the time-series properties of earnings that is not impounded in stock prices. The last two columns indicate that for predictions of the SRW forecast error using analysts' forecasts, the higher the fraction of total shares traded during the announcement period that are associated with trades of less than 500 shares, the greater the return predictability around the earnings announcement. This result is robust to similar specifications of small-investor trading such as the number of shares associated with small trades deflated by the number of shares outstanding and the difference between in-quarter percentile rank of the number of shares associated with small trades and in-quarter percentile rank of the number of total shares traded.

Earlier results indicate that small traders clearly respond to predictable components of the SRW forecast error that should not represent news. Yet our attempts to link small-trader activity to returns are mixed. One possibility, in addition to the lack of power mentioned above, is that while return predictability may represent stock mispricing, the magnitude of mispricing may not be determined by the relative amount of small-investor trading. Bhushan (1994) agrees with Bernard and Thomas (1990) that unsophisticated investors may cause systematic stock mispricing. But he contends that at the time of the earnings announcement, sophisticated investors who recognize the true time-series properties of earnings attempt to undo the actions of these naive investors. Bhushan contends, therefore, that the degree of mispricing is determined not by the degree of trading by unsophisticated investors, but rather by the level of transactions costs faced by sophisticated investors.

5. Conclusion

Our results indicate that different types of investors, who can be identified by trade size, behave as if they use different information sets when making their buy and sell decisions. Those investors who initiate small trades appear to base their decisions on less sophisticated information than those who initiate large trades. Specifically, we find that on average small traders ignore earnings signals based on analysts' forecasts and respond to signals of a less accurate time-series model. Large traders, on the other, hand use a more complete information set that incorporates time-series signals along with other information reflected in analysts' forecasts.

Our results substantiate the assertion of Bernard and Thomas (1990) that a nontrivial subset of investors respond to the component of seasonal random walk errors that is predictable on the basis of prior SRW errors. In other words, some investors ignore, or at least significantly underweight, the implications of current earnings innovations for future earnings levels. Bernard and Thomas hypothesize that the actions of these investors give rise to post-earnings announcement drift. We document that at least one subset of investors, those initiating trades of less than 500 shares, exhibit precisely the type of behavior alleged by Bernard and Thomas.

Prior research shows that the time-series properties of earnings can be exploited to predict both the upcoming SRW forecast error and, consistent with a significant subset of investors ignoring the information in prior SRW errors, returns around earnings announcements. We extend these results by using the information in the current analysts' forecasts to construct superior predictions of: (1) SRW forecast errors; (2) small-trader buying behavior around earnings announcements; and, (3) stock returns around earnings announcements. This strengthens the link, first discovered by Bernard and Thomas (1990), between naive expectations resembling SRW forecasts and stock returns. The greater ability of analysts' forecasts to predict returns around earnings announcements implies that analysts possess information beyond that in the time-series properties of earnings that is not impounded in stock prices.

Finally, even with a small sample that is biased towards firms whose future returns are less predictable, we find weak evidence linking the predictability of returns around earnings announcements to the preponderance of small trades. Consistent with Bhushan (1994), our evidence suggests return predictability is strongest in illiquid stocks. Overall, while we believe our paper contributes to the discussion of the effect of unsophisticated investors on market prices, we also believe this remains a fertile area for future research.

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