Who, if Anyone, Reacts to Accrual Information?*

Robert H. Battalio[a], Alina Lerman[b], Joshua Livnat[b], Richard R. Mendenhall[a, ¤]

[a] *Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556-5646, USA*
[b] *Leonard N. Stern College of Business, New York University, 40th West 4th Street, New York, NY 10012, USA*

Submitted 23 March 2009

Abstract

We confirm the value of accruals information to investors and propose a trading strategy, using earnings surprises and accruals, that outperforms prior strategies. Given the usefulness of accruals information, investors should trade on it as soon as it becomes available. While the vast majority of investors seem to ignore accruals information when it becomes public, investors initiating trades of at least 5,000 shares tend to trade in the correct direction immediately upon the 10-K/Q filing date when accruals information is released. This tendency is limited, however, to cases where earnings convey non-negative news. We provide evidence suggesting that rational behavior combined with short sales constraints may explain large traders' asymmetric response to accruals information. Those investors initiating the smallest trades appear to respond to accruals in the wrong direction. Additional tests suggest that their behavior might be explained by their attraction to attention grabbing stocks.

JEL Classification: G14

Keywords: Market efficiency; Anomalies; Accruals; Earnings.

* This paper has benefited from the helpful comments of the editor (S.P. Kothari) and an anonymous reviewer, as well as from comments made by seminar participants at Fordham University, Hofstra University, The Interdisciplinary Center in Herzelia, Israel, New York University, and the Rupin academic center in Israel. The authors gratefully acknowledge the preliminary and Point-In-Time *Compustat* quarterly data provided by Charter Oak Investment Systems Inc., which is also available through WRDS. The authors gratefully acknowledge Standard & Poor's Compustat for providing 10-K/Q SEC filing dates. The authors are also grateful for the contribution of Thomson Financial for providing forecast data available through the Institutional Brokers Estimate System. These data have been provided as part of a broad academic program to encourage earnings expectations research.

¤Corresponding author. Tel.: + 574 631 6076. Fax: +574 631 5255.
Email address: rmendenh@nd.edu.
Address: 102F Mendoza College of Business, Notre Dame, IN 46556-5646.

Other authors' email addresses: rbattali@nd.edu, alerman@stern.nyu.edu, jlivnat@stern.nyu.edu, respectively.

Abstract

We confirm the value of accruals information to investors and propose a trading strategy, using earnings surprises and accruals, that outperforms prior strategies. Given the usefulness of accruals information, investors should trade on it as soon as it becomes available. While the vast majority of investors seem to ignore accruals information when it becomes public, investors initiating trades of at least 5,000 shares tend to trade in the correct direction immediately upon the 10-K/Q filing date when accruals information is released. This tendency is limited, however, to cases where earnings convey non-negative news. We provide evidence suggesting that rational behavior combined with short sales constraints may explain large traders' asymmetric response to accruals information. Those investors initiating the smallest trades appear to respond to accruals in the wrong direction. Additional tests suggest that their behavior might be explained by their attraction to attention grabbing stocks.

1. Introduction

The primary research question of this paper is, Who, if anyone, reacts to accrual information? Specifically, we examine whether any investors respond to accrual information as soon it becomes publicly accessible, upon the filing of the firm's 10-K/Q. We begin by confirming, for our sample, prior research that finds the accrual anomaly is not subsumed by post-earnings announcement drift. We then document a strategy that leads to greater abnormal returns than post-earnings announcement drift, the accrual anomaly, or a combination of the two anomalies implemented on the 10-K/Q filing date. Our results strongly confirm the conclusions of much prior research that accruals levels contain information about future returns and are, therefore, valuable to investors. Knowledgeable, active investors should transact immediately upon receiving news of extreme accruals. We find that, on average, investors who initiate very large trades (at least 5,000 shares) act almost immediately to exploit the information in accrual levels. Those who initiate very small trades (fewer than 500 shares), on average, seem to react in the wrong direction. Both tendencies are limited, however, to cases where firms' quarterly earnings announcements either meet or beat analysts' expectations. Investors in intermediate trade-size classes do not seem to trade on accruals information during the 10-K/Q filing period. Taken as a whole, the vast majority of investors of each trade-size category act as if they are either unaware of the importance of the accruals level or for some other reason choose not to act on it when it becomes available.

The accrual anomaly is the tendency for stock prices to lag the information in accruals. Specifically, when the accruals component of a firm's earnings is high (low), future returns tend to be low (high). Sloan (1996) shows that the accruals component of earnings is less persistent than the cash flow component and that investors apparently do not fully appreciate this difference. Post-earnings announcement drift is the tendency for stock prices to lag the information in earnings announcements. While stock prices react almost immediately following an earnings surprise, cumulative abnormal returns continue to drift in the direction of the surprise for several months. Some researchers believe that the drift is caused by investors who underestimate the persistence of earnings innovations (see, e.g., Bernard and Thomas (1990) and Ball and Bartov (1996)). The two anomalies are, therefore, linked in that both seem to be caused by systematic errors on the part of investors in estimating the persistence of earnings innovations or earnings components.

Collins and Hribar (2000) show that the post-earnings announcement drift and the accrual anomaly are largely independent; a trading rule using both appears more profitable than using either alone. We replicate Collins and Hribar's tests after making two methodological refinements. Livnat and Mendenhall (2006) show that for the sub-sample of firms followed by analysts (where mispricing is less likely) post-earnings announcement drift is larger when earnings surprise is defined by analysts' earnings forecast errors than with SRW forecast errors, such as used by Collins and Hribar. We, therefore, define earnings surprise using analyst forecasts errors. Further, Collins and Hribar use assumed rather than actual 10-K/Q filing dates. Their Figure 3, a CAR plot for different proposed strategies, shows that subsequent returns are not concentrated in the period shortly following the assumed filing date. While this indicates that the assumed dates are not responsible for their conclusions, because we need precise filing dates to address our main research question, we use actual 10-K/Q filing dates. Our results confirm those of Collins and Hribar: neither anomaly subsumes the other and, therefore, investors should transact in predictable ways when accruals information is released on the 10-K/Q filing date.

Before addressing whether investors attempt to exploit the information in accruals, we propose and test a trading strategy where investors initially transact based on the earnings surprise but then unwind their positions following the filing date if the accrual signal contradicts the earnings signal. This strategy yields higher returns than others appearing in the literature.

To determine whether investors trade on accruals information, we divide investors into categories based on their trade size and correlate their buying/selling behavior on the 10-K/Q filing date with accruals levels. We find that only those investors who initiate very large trades—5,000 shares or greater—tend to transact in the correct direction upon observing the accrual signal. While this tendency is statistically significant and impacts stock prices, it is not nearly large enough to eliminate or significantly reduce the magnitude of the anomaly. The vast majority of traders in each size category behave as if they are unaware of the release of accruals information and/or the implications of accruals for future price movements. We also document that investors who initiate the smallest trades—fewer than 500 shares—tend to trade in the *wrong* direction at the time of the accrual signal. Further tests suggest that these investors may be purchasing attention grabbing stocks as in Barber and Odean (2008).

Further, we find that large and small traders' responses to accruals are restricted to cases where preliminary earnings news for the quarter is non-negative. Large traders seem to ignore the information in accruals following negative earnings surprises. We show that these investors behave rationally in not purchasing low accrual firms following negative earnings surprises, because these firms exhibit no subsequent abnormal returns. In other words, for these firms the accruals anomaly and the post-earnings announcement drift cancel each other out. We also show that large traders engage in a very high level of selling *at the time of the earnings announcement* for firms experiencing negative earnings surprises and subsequently announcing high accruals. Selling at the time of a negative earnings surprise is more than 75% greater for these firms than for those subsequently announcing low accruals. Large traders seem to be able to partially anticipate accruals levels at the time of the earnings announcement. Since selling for these firms is so great at the time of the earnings announcement, we conjecture that by the 10-K/Q filing date, these investors have either sold all of their shares and do not sell short (like the majority of mutual funds) or have reached their shorting capacity.

The rest of the paper is organized as follows. The next section reviews the relevant literature and motivates the hypotheses. The third section describes the sample and defines the variables. The fourth section presents the empirical results and the final section concludes.

2. Literature Review and Hypothesis Motivation

The hypotheses and tests of this paper may be divided into two parts. First, we replicate Collins and Hribar (2000) to confirm that firm accruals levels have information regarding future stock returns after controlling for the information in earnings surprises. This also allows us to propose and test a new trading rule. Second, after confirming the results of Collins and Hribar, we address the primary issue of this paper: Who, if anyone, reacts to accrual information? Specifically, can we find evidence that investors react to accrual information at the time it is released, i.e., on the 10-K/Q filing date? In this section we briefly discuss the accrual anomaly and the post-earnings announcement drift, discuss relevant literature, and motivate our tests.

2.1 REPLICATION OF COLLINS AND HRIBAR (2000) AND TESTS OF TRADING RULES

Sloan (1996) shows that the accrual component of annual earnings is less persistent than the cash flow component. That is, firms with high (low) levels of accruals tend to experience subsequent earnings declines (increases). He goes on to show that the stock market apparently does not fully appreciate this difference. Sloan divides sample firms into deciles on the basis of the accrual component of the most recent annual earnings (deflated by total assets) and documents that stocks in the lowest accrual decile outperform those in the highest accrual decile by about 10% per year over the 1962 to 1991 period. Many subsequent studies confirm this basic result (e.g., Collins and Hribar (2000) and Xie (2001)).

The academic literature on post-earnings announcement drift begins with Ball and Brown (1968), who find that changes in accounting earnings correlate not only with contemporaneous stock returns, but also with *future* stock returns. Many papers verifying the stock market’s apparent slow reaction to earnings surprises appeared in the accounting and finance literature in the 1970s and 1980s (e.g., Jones and Litzenberger (1970); Latané and Jones (1977, 1979); and Rendleman, Jones, and Latané (1982); Foster, Olsen, and Shevlin (1984); and Bernard and Thomas(1989)). The more recent drift studies generally find a return difference of about 4% to 6% per quarter between top- and bottom-surprise deciles (see Livnat and Mendenhall (2006) for a summary of drift magnitudes).

Collins and Hribar (2000) test whether either anomaly—accruals or post-earnings announcement drift—subsumes the other. Do they represent two distinct forms of mispricing or just one? In prior research, the accrual anomaly is tested on an annual basis and the drift on a quarterly basis. Collins and

Hribar first show that the accrual anomaly exists on a quarterly basis and then that neither anomaly subsumes the other. Using both signals, earnings surprise and accrual level, leads to larger subsequent returns than using either independently.

We replicate Collins and Hribar (2000) to show that their conclusions hold for our sample and in order to test a new trading rule. Our methods differ somewhat from theirs. First, we limit ourselves to firms followed by analysts. These stocks are typically larger and more liquid and, therefore, we believe that anomalies documented with them are less likely to be illusory. Because Livnat and Mendenhall (2006) show that, for firms followed by analysts, post-earnings announcement drift is larger when the earnings surprise is defined as the analyst forecast error instead of a time series error, we define earnings surprises using analyst forecast errors. Finally, the primary tests of this paper, that assess whether investors act on accrual information at the time it becomes available, require exact 10-K/Q filing dates. So, while Collins and Hribar use assumed dates, we use actual filing dates.

We expect to confirm the conclusions of Collins and Hribar (2000) for our sample. Consistent with their paper, we hypothesize that the accrual anomaly and post-earnings announcement drift are complementary—neither subsumes the other. Collins and Hribar show that a strategy implemented following their assumed 10-K/Q filing dates, based on both the earnings and accruals signals, outperforms strategies using either indicator separately. We propose a new trading rule that assumes investors act immediately upon seeing the earnings surprise, but then reevaluate their decision upon observing the accruals level. We hypothesize that this trading rule, because it allows investors to act in a timelier manner and to use the information in both earnings surprise and accrual levels, is more profitable than the rule proposed by Collins and Hribar.

2.2 WHO, IF ANYONE, REACTS TO ACCRUAL INFORMATION?

Our test results confirm the conclusions of Collins and Hribar (2000) that accruals levels contain information about subsequent stock returns beyond that contained in earnings surprises. This motivates us to ask, who, if anyone, reacts to accrual information?

Prior evidence is mixed on whether even relatively sophisticated market participants respond to accrual information. Bradshaw, Richardson, and Sloan (2001) provide evidence that security analysts do not properly interpret accrual information when making earnings forecasts. Collins, Gong, and Hribar (2003) show that the apparent returns to trading on accrual information are negatively correlated with the percent of the firm's shares held by institutions. Using annual data observations on institutional holdings, they also show that subsequent changes in institutional holdings are negatively correlated with accrual level. Lev and Nissim (2006) document a negative relation between annual accruals and transient institutional holding in the fourth quarter of the accrual year and the first three quarters of the next year. Finally, Ali, Chen, Tong, and Tong (2008) show that some mutual funds tend to hold stocks of firms with relatively lower levels of accruals than others and that these funds exhibit superior subsequent returns.

The papers listed above, suggesting that some investor groups may respond to accrual information, seem far from conclusive. For example, Lev and Nissim's (2006) results suggest that investors *react* to accrual information both before and for many months after it becomes available. Their evidence is limited to quarterly observations of institutional holdings, and does not allow us to infer what institutions (or other investors) do in the short window around the disclosure of accruals. Further, Ali et al (2008) find only a relatively small spread in the average accruals levels of firms held by different mutual funds. For example, the average accruals decile of firms held by those funds that are ostensibly the most cognizant of the importance of accruals is 4.42 compared to a sample average of 5.55. For each of these papers, the existence of an omitted variable that is correlated with accruals seems at least as likely an explanation.

Investors who are aware of the accrual anomaly and hope to exploit it should transact when the information first becomes available. To search for evidence of such investors, we use a well-known algorithm (see Lee and Ready (1991)) to determine how liquidity demanders trade around the 10-K/Q filing date. That is, we look to see if investors tend to buy (sell) when accruals are low (high) at the time the accrual signal becomes public.

Easley and O'Hara (1987) propose that information sets used by investors who initiate large trades may be systematically superior to those used by small traders. Further, Collins et al (2003) and Lev and Nissim (2006) suggest that institutional investors are more likely than individuals to respond and respond properly to accrual information. Lev and Nissim (2006) state that "the timeliness of institutional response to accrual information is an important issue both for assessing market efficiency and explaining the persistence of the accrual anomaly" (pp. 196-197).

Since institutional investors should, on average, initiate larger trades than individuals, we follow Battalio and Mendenhall (2005) and partition investors into several categories based on the size of the trades they initiate. We then examine how investors of each trade size respond to accrual information. Our methods are very similar to those of Battalio and Mendenhall who show that investors who initiate large trades respond to earnings announcements in a much more sophisticated manner than those who initiate smaller trades. Ex ante, we do not know what we will find. The null hypothesis is that we will find no evidence that investors in any trade-size category respond to accruals level. That is, the null hypothesis, for each trade-size category, is that the correlation between abnormal buying behavior and accruals level is zero. Given the logic and results of the above papers, we hypothesize that, if we find investors who respond to the information in accruals (i.e., investors who exhibit a significant negative correlation between abnormal buying behavior and accruals), they are most likely among those initiating larger trades.

Balsam et al (2002) suggest that investors are more likely to examine the accruals level when "there is *ex post* evidence of earnings management" (p. 988). They suggest that these firms are those that meet or just beat expectations. Given their logic, we hypothesize that we are more likely to find a negative correlation between abnormal buying behavior and accruals for firms whose earnings are equal to or very slightly larger than analysts' forecasts. In a similar vein, Leftwich and Zmijewski (1994) examine contemporaneous earnings and dividend announcements and conclude that when earnings convey positive news of any size that investors may put more weight on alternative signals of earnings persistence. It may be that, when earnings news is favorable, investors are skeptical no matter how much earnings exceed expectations. Based on their work, we hypothesize that we are more likely to find a negative correlation between abnormal buying behavior and accruals for firms whose earnings exceed analysts' forecasts—by any amount.

3. *Sample Selection and Variable Definition*

3.1 SAMPLE SELECTION

Our sample begins with all 10-K/Q filing dates identified by *Compustat* for stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and on Nasdaq between 1990 and 2005. For a firm-quarter observation to qualify for our initial sample, we require the following data: earnings per share, earnings per share for the most recent 13 quarters, relevant adjustment factors, the preliminary earnings announcement date, income before extraordinary items and discontinued operations, net cash from operations, and average total assets over the quarter (the scaling variable for accruals) of at least $1 million from *Compustat*; at least one analyst earnings forecast for the quarter on *I/B/E/S*, actual earnings per share and the preliminary earnings announcement date from *I/B/E/S*; and stock returns, firm size, and a market capitalization of at least $1 million at quarter end from *CRSP*. Since we measure the effects of the preliminary earnings surprise and the subsequent accrual information in the filing during three-day windows centered on each of these dates, we require the SEC filing date to be at least three days after the earnings announcement date. To avoid cases of late filings, we require the filing date to precede the subsequent quarter's earnings announcement date. For an earnings forecast to qualify it must be made within 90 days of the earnings announcement. We also require that the *Compustat* and *I/B/E/S* earnings announcement dates agree to within two calendar days to ensure that we have lined up *Compustat* and *I/B/E/S* data properly and to ensure we have a close earnings announcement date approximation. Finally, to separate the earnings surprise from the accrual information, we eliminate firm-quarters in which net operating cash flow is announced with the preliminary earnings. These firms are identified using the Charter Oak preliminary database that is available on WRDS.[1] These screens reduce our sample to 89,089 firm-quarters.[2]

We obtain microstructure data for our study from the NYSE's Trade and Quote (TAQ) database, which contains intraday trades and quotes for all securities listed on the NYSE, the AMEX, and the Nasdaq Stock Market. Each trade record indicates the underlying stock, the date and time the trade was reported, the venue reporting the trade, the trade size and price, and codes indicating whether the trade is subsequently cancelled or is made with special conditions. Because the TAQ database is unavailable prior to January 1, 1993, the use of trading activity 21 trading days prior to sample earnings announcements requires us to start our sample on February 1, 1993. Barber, Odean and Zhu (2006) note that the introduction of decimal trading (trading in pennies rather than in sixteenths of a dollar) coupled with the growing use of computerized trading algorithms to break up institutional trades "created a profound shift in the distribution of trade size and likely undermines our ability to identify trades initiated by individuals or institutions" (p. 8). Since decimals were introduced to equity markets in 2000, and since we use trading activity 21 days after the 10-K/Q filing date, we end our sample on November 30, 1999. After imposing each of the microstructure trading constraints, the remaining sample consists of 35,515 firm-quarters.

3.2 MICROSTRUCTRE DATA AND VARIABLES

Our analysis uses trades classified as buys or sells. Since the trade data provided by TAQ do not identify whether a trade is initiated by a buyer or seller, we use the Lee and Ready (1991) algorithm to infer whether trades are buyer- or seller-initiated. 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 below (above) the midpoint of the execution-time bid and offer are classified as sells (buys). To classify trades executed at the midpoint of the execution-time quotes, the LR algorithm examines prior trades. If the execution price of the prior trade is lower (higher) than the current trade's

[1] See Livnat and Mendenhall (2006) or Callen et al. (2006) for a description of the Charter Oak preliminary database.

[2] For 29.7% of these observations (for 21.7% of our final sample), some balance sheet components from which accruals could be estimated are disclosed with the preliminary earnings announcement. We include these observations in our sample. When we exclude these observations, no inferences are altered as we report below in the sub-section on robustness checks.

execution price, the current trade is classified as a buy (sell). If the current trade has the same price as the prior 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.[3]

To use the LR algorithm, we must find benchmark quotes for each trade in our sample. At each moment in the trading day, a stock's National Best Bid and Offer (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. We then use the NBBO prevailing when the trade is reported to the TAQ database and the LR algorithm to classify trades as buys or sells.

The typing of buys and sells necessitates the elimination of trades reported late or out of sequence since they cannot be reliably matched with execution-time NBBOs. Specifically, we eliminate trades that have a Correction Code that is not equal to zero or one and trades with a Condition Code of 'Z' or 'G'. We also eliminate trades with transaction prices more than $5.00 away from the previous price on that day and trades with no reported quantities as data errors. Additionally, 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 as buys or sells by the Lee and Ready algorithm. Finally, we only consider trades executed between 9:30 a.m. and 4:00 p.m. since the market becomes far less liquid outside of normal market hours.[4]

Between 1993 and 1996, liquidity demanding investors were guaranteed up to 1000 shares at the posted quotes in most Nasdaq-listed stocks.[5] Thus, it is unlikely that wealthy investors who have or think

---

[3]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, et al (2000) use a proprietary sample of trades that include a buy/sell indicator to test the Lee and Ready algorithm and find a success rate of 81%.

[4]See, e.g., Battalio and Mendenhall (2005) and Bessembinder and Kaufman (1997), who use data screens similar to ours.

[5]Battalio and Mendenhall (2005) provide more information on the institutional structure of the Nasdaq Stock Market between 1993 and 1996.

they have value-relevant information would place orders for less than 1000 shares. Van Ness, Van Ness and Pruitt (2000) examine quoted depths for Nasdaq-listed stocks after the implementation of the Order Handling Rules (see Barclay, et al. (1999)) and the introduction to trading in sixteenths of a dollar in 1997. Surprisingly, even when retail limit order traders are allowed to establish the NBBO, Van Ness et al find that the average quoted depth for the lowest trading-volume quartile of Nasdaq stocks is 2,328 shares. Goldstein and Kavajecz (2000) examine 100 randomly selected NYSE-listed securities before and after NYSE-listed stocks migrated from trading in eighths of a dollar to trading in sixteenths of a dollar in 1997. Prior to the change, they find that the average quoted depth for high-volume, low-priced stocks (low-volume, high-priced stocks) is 15,950 shares (2,904 shares). After the change, they find that the average quoted depth for high-volume, low-priced stocks (low-volume, high-priced stocks) is 6,488 shares (2,133 shares). Together, these statistics suggest that it is unlikely that sophisticated investors with value-relevant information would have traded fewer than 1000 shares per transaction during our sample period.

Moreover, as suggested by Easley and O'Hara (1987), there will be instances in which sophisticated investors will have information that justifies placing orders for several multiples of 1000 shares. For these reasons, we follow Battalio and Mendenhall (2005) and 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. Since quoted prices are guaranteed up to the advertised number of shares and since the average number of shares available at posted prices for less liquid stocks was less than 5,000 shares during our sample period, we expect trades in the 5,000 and more shares trade-size category to correspond to the trading interest of wealthy, sophisticated investors with access to superior information. Conversely, since investors typically could execute trades for 1000 shares or more at posted quotes, we expect that trades in the 100 to 400 shares category correspond to the trading interests of unsophisticated investors with little information.[6]

[6]Our use of share-based trade-size categories is at odds with Lee (1992), who classifies small trades as round-lot (multiples of 100 shares) trades with a dollar value of less than $10,000. As noted in the text, we use share-based trade-size categories because bid and ask prices are *explicitly* quoted in shares. Lee notes that dollar-based trade-size categories are sensitive to small price changes. For example, as noted by Hvidkjaer (2006), if the bid price is $25.00

Following Battalio and Mendenhall (2005), we use our sample of trades classified as buys and sells to construct a measure of abnormal net buying activity for each of the six trade-size categories around two events: the preliminary earnings release date (ERD) and the filing date (FD). For each category, we subtract the number of sell trades during the three trading days centered on the event date from the number of buy trades over the same period. If the event date 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 each of the two event windows, $NetEventBuy\_ERD_i$ and $NetEventBuy\_FD_i$, we compute similar statistics for the three-day trading window centered twenty trading days before the earnings announcement date ($NetPreBuy_i$) and for the three-day trading window centered twenty trading days after the filing date ($NetPostBuy_i$).[7] We then subtract the average of $NetPreBuy_i$ and $NetPostBuy_i$ and deflate by the average number of nonevent trades (Avg. # of Non-Event $Trades_i$). The Avg. # of Nonevent $Trades_i$ 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, we define the abnormal net buying activity in the *i*th trade-size category around each of the two events, $NETBUY\_ERD_i$ and $NETBUY\_FD_i$, as follows:

$$NETBUY\_EVENT_i = \frac{NetEventBuy_i - \frac{1}{2}\left(NetPreBuy_i + NetPostBuy_i\right)}{Avg.\#\ of\ Non\text{-}Event\ Trades_i} \tag{1}$$

$NETBUY\_EVENT_i$ can 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 20% of normal trading volume (both buys and sells) and event sells are at the normal nonevent level, then $NETBUY\_EVENT_i$ equals 20%. To

and the offer price is $25.125, Lee classifies a 400 share trade as small if it is at the bid, but not if it is at the ask. Hvidkjaer finds for NYSE stocks that classifying trades of less than 1,000 shares as small and trades of 2,000 shares or more as large yields results similar to those using dollar volume cutoffs. We believe that our finer distinctions and more extreme end categories provide greater power to discern differences in the behavior of sophisticated and unsophisticated investors.

[7]Battalio and Mendenhall (2005) find moving the nonevent period to 10 trading days around the announcement does not alter their results.

ensure our measure of abnormal net buying activity is reasonable, we require each event in our sample to have a minimum of ten trades per day in each of the four three-day trading windows.

3.3 ESTIMATION OF EARNINGS SURPRISE AND ACCRUALS.

We estimate the preliminary earnings surprise using both time-series and analyst forecasts, since Battalio and Mendenhall (2005) show that small traders are likely to use time-series forecasts whereas large traders tend to use analyst forecasts. Consistent with prior studies, we use rolling windows of historical data to define the time-series measure of standardized unexpected earnings (SUE). For each firm-quarter, we begin by estimating the following model:

$$E_{j,t} = \delta_{j,t} + E_{j,t-4} + \varepsilon_{j,t} \quad (2)$$

where $E_{j,t}$ is quarterly diluted Earnings Per Share (EPS) before extraordinary items for firm *j* in quarter *t*; $\delta_{j,t}$ is a drift term to allow for the firm's recent historical earnings growth; and $\varepsilon_{j,t}$ is the error term with standard deviation $STD_{j,t}$. To compute the earnings surprise for quarter *t*, we use the unrestated earnings data from quarters *t-8* through *t-1* available in the Charter Oak database and the preliminary earnings for quarter *t* from the preliminary data of Charter Oak. This ensures that the preliminary earnings and the time-series forecast that we use are based on information that was actually available to investors when earnings were announced, rather than on the restated quarterly earnings provided by *Compustat* (see Livnat and Mendenhall (2006)). Next, we define the time-series measure of earnings surprise, SUE, as:

$$SUE_{j,t} = \frac{E_{j,t} - \delta_{j,t} - E_{j,t-4}}{STD_{j,t}} \quad (3)$$

Our second measure of earnings surprise uses actual and analysts' forecasts of earnings from *I/B/E/S*. We define the standardized unexpected earnings using analysts' forecasts (SUEAF) as:

$$SUEAF_{j,t} = \frac{E_{j,t}^{ibes} - F_{j,t}}{P_{j,t}}, \quad (4)$$

where $E_{j,t}^{ibes}$ is the actual EPS reported in *I/B/E/S* and $F_{j,t}$ is the mean of the most recent quarterly forecasts of EPS made by analysts during the 90-day period prior to the disclosure of the actual earnings. The earnings surprise is then scaled by price per share for firm *j* at quarter-end.

Following Collins and Hribar (2000), we estimate accruals as net income before extraordinary items and discontinued operations for the quarter minus net operating cash flow for the quarter, scaled by average total assets during the quarter.

We group companies with fiscal quarters ending within a particular calendar quarter into quarter cohorts. For example, the first calendar quarter of 1999 includes all firm-quarters whose fiscal quarters end from January through March 1999. To allow for outliers and nonlinearities in the relations among forecast errors, we follow Bernard and Thomas (1990) and code SUE and SUEAF by within-quarter decile.[8] Following Affleck-Graves and Mendenhall (1992), we equally space the coded scores from -0.5 (lowest decile) to +0.5 (highest decile) to aid in the economic interpretation of our regression results. We use a similar procedure for accruals. Finally, we simply aggregate the top (bottom) two deciles when we analyze the top (bottom) quintiles of accruals, SUE, or SUEAF.

3.4 BUY AND HOLD ABNORMAL RETURNS.

To investigate the returns of trading on a pure post-earnings announcement drift strategy, we require daily return data from CRSP. Our abnormal buy and hold return variable, BHR, is the return generated by initiating positions two days after the preliminary earnings announcement date for quarter *t* and terminating them one day after the preliminary earnings announcement in quarter *t+1* minus the buy and hold return of the matched size and book-to-market (B/M) portfolio over the same interval. If the subsequent preliminary earnings announcement date is not available, we terminate the position 100 days after the position is initiated to avoid look-ahead bias in cases of takeovers or bankruptcies. We obtain the cut-off points to determine the size and B/M matched portfolios from Ken French's data library.[9] If a firm delists before a position is terminated, we use the delisting return from CRSP and assume the stock earns the benchmark portfolio return after the delisting. If the delisting is due to a forced delisting from an exchange and CRSP has a missing delisting return, we assume the delisting return to be -100%.

---

[8] Bernard and Thomas (1990) report that the drift is insensitive to the use of current quarter SUE values rather than prior quarter SUE values to create deciles based on earnings surprises.

[9] We obtain six size-B/M portfolios from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We use the BHR generated by initiated positions from two days after the SEC filing date for quarter *t* and terminated one day after the preliminary earnings announcement in quarter *t+1* minus the buy and hold return of the matched size and B/M portfolio over the same interval to measure the effects of quarterly accruals on prices once accruals become available (see also Livnat and Santicchia (2006)). As before, we terminate the position 100 days after the position is initiated if the subsequent preliminary earnings announcement date is not available. We use the BHR generated by initiating positions two days after the preliminary earnings announcement date and terminated one day after the SEC filing date for the same quarter to obtain the returns on a pure earnings drift strategy through the SEC filing date, and then switching to a combined earnings and accruals strategy from that date onwards.

Table 1 contains some summary statistics for our sample. It shows that the firms in our sample are larger than the typical Compustat firms, with a median market value of $442 million and a median price per share of $21.38. For our sample firms, the median time series SUE is 0.020, but the median analyst forecast SUEAF is 0.000, with accruals being negative on average, as reported in prior studies. The mean (median) excess BHR are small but positive (negative) for all three portfolio holding periods. The net buying measure is on average positive for small traders during both the preliminary earnings announcement (consistent with Lee (1992)) and the SEC filing windows. In contrast, the large traders seem to be on average net sellers during both windows, but more so during the SEC filing window.

4. Empirical Results

4.1 THE ACCRUAL ANOMALYAND POST-EARNINGS ANNOUNCEMENT DRIFT

We begin by testing the conclusions of Collins and Hribar (2000), that the accruals anomaly and post-earnings announcement drift are complementary, for our sample and methods. While we fully expect to corroborate the findings of Collins and Hribar, if the accruals anomaly is subsumed by post-earnings announcement drift for our sample, there is no reason for investors to trade upon the release of accrual information and no reason for us to test for such behavior. Further, we perform these tests to examine a new trading rule using earnings surprises and accrual levels.

Table 2 presents the hedge returns of five strategies. The holding period begins either two days following the earnings announcement date or two days following the 10-K/Q filing date and ends the day following the earnings announcement for the next quarter. Hedge returns are defined as the abnormal returns of those stocks in the buy quintile portfolio (high positive earnings forecast error and/or low accruals) minus those in the sell quintile portfolio.

As expected, the first row of Table 2 shows that strong positive (negative) earnings surprise stocks provide significantly positive (negative) subsequent abnormal returns. The hedge return for this strategy is 4.613% per quarter, which is consistent with the magnitude of the quarterly drift in prior studies. The sample size of 302 indicates that the strategy includes an average of 302 stocks long and 302 stocks short each quarter. The second row shows that if investors wait until after the filing date to transact, the hedge returns based on an earnings-surprise strategy fall to 3.453%. We include this row to put the earnings surprise strategy on an equal footing with the next two proposed strategies.

Consistent with most prior research, the third row of Table 2 shows that low (high) accrual firms exhibit significantly positive (negative) abnormal returns. The hedge return for this strategy is 2.586% for a period shorter than one quarter. Specifically, the average lag between the earnings announcement date and the filing date is 26.49 calendar days. So, this period is roughly 65 (45) calendar (trading) days compared to about 91 (63) days for one quarter. Note that applying this strategy for four quarters would result in annual returns similar to those reported by Sloan (1996). Livnat and Santiccia (2006) report a slightly greater hedge return for their sample which includes smaller and less well followed firms.

The fourth row of Table 2 presents results for a portfolio strategy proposed by Collins and Hribar (2000) that combines both earnings surprise and accrual information. To qualify, a stock must be in the extreme good-news quintile or extreme bad-news quintile for both earnings surprise and accruals. Both the buy and sell groups exhibit significant abnormal returns in the expected direction and combine for a hedge return of 6.778%, which is significantly greater than either the earnings or the accrual hedge portfolios alone.[10] While there are several important differences between our sample and methods and those of Collins and Hribar, our results confirm theirs: the accrual anomaly and post-earnings announcement drift are two distinct and complementary anomalies.[11]

In the fifth row of Table 2, we introduce a new strategy where investors initiate long (short) positions two days following the earnings announcement in stocks in the extreme positive (negative) earnings forecast error quintile. Then, when firms file their 10-K/Q, investors reassess their positions and unwind any positions for which purchased (shorted) firms do not fall into the lowest (highest) accrual quintile. As hypothesized in Section 2, this rule significantly outperforms all other tested strategies with a hedge return of 7.938% per quarter. This strategy outperforms the strategy represented by row four, because investors act immediately upon observing the earnings surprise, but continue to use the information in the accrual signal.[12] In Table 3 we replicate the tests of Table 2 for the period 1993 to 1999, the period for which we can infer whether trades are buyer- or seller-initiated.[13] The important aspects of the results from Table 2 are maintained; both the accrual anomaly and post-earnings

---

[10] The average number of stocks in the combined portfolio (54 long and 68 short) is substantially smaller than the average number in each of the independent portfolios (302 stocks long and short). Since the median number of stocks held by mutual funds in Ali et al's (2008) sample is 57.59, the combined strategies do not seem to depend on investors holding portfolios that are unusually poorly diversified.

[11] Collins and Hribar's (2000) abnormal returns are larger than ours for several reasons. First, Collins and Hribar assume that investors hold their positions for more than twice as long as we do. Second, we require each firm to be followed by at least one analyst reporting a quarterly earnings forecast to *I/B/E/S*. This additional constraint rules out many smaller and less liquid firms. It is, therefore, less likely that potential investors here would encounter either high transactions costs or an inability to trade quickly.

[12] Livnat and Mendenhall (2006) show further that combining the seasonal random walk (SRW) error as another measure of earnings surprise with the analyst forecast error leads to a larger post-earnings announcement drift. In both hedge-return tests and regressions that are untabulated, we find that all three variables—SRW errors, analyst forecast errors, and accruals—contribute significantly to predicting future returns. Not surprisingly, however, using all three variables in hedge portfolio tests like those described here leads to portfolios with far fewer stocks.

[13] As discussed in Section 3, we begin in 1993 with the beginning of the TAQ database and end prior to 2000 with the onset of decimalization.

announcement drift exist after controlling for the other. Knowledgeable investors have reason to trade on accruals information at the time the 10-K/Q is released.[14]

4.2 INVESTOR RESPONSE TO EARNINGS SURPRISE BY TRADE SIZE

In Table 4 we essentially replicate the tests of Battalio and Mendenhall (2005) for our sample. For reasons discussed in Battalio and Mendenhall (pp. 297-299), they believe their methods are most effective for Nasdaq stocks (as opposed to stocks listed on the New York or American stock exchanges) for the period prior to 1997. To make our results as generalizable as possible, however, we include both Nasdaq and exchange-listed stocks from 1993 through 1999. Table 4 indicates that, when we apply Battalio and Mendenhall's methods to our sample, the essential elements of their results remain intact.

Each column of Table 4 presents results for the net buying behavior, discussed in the prior section, of investors initiating different size trades. Recall that each net buy measure represents the difference in event buy and sell orders minus the difference in nonevent buy and sell orders deflated by the total number of nonevent trades of that trade-size category. The trade-size categories increase from left to right starting with those investors who initiate trades of less than 500 shares and ending with investors who initiate trades of 5,000 shares or more. Panel A presents correlations between the net-buy measures and SRW forecast error deciles and analyst forecast error deciles. Panel B shows the results of regressing the net-buy measures on SUE and SUEAF deciles.

The first column of Table 4 shows that the smallest traders respond more strongly to seasonal random walk forecast errors than to analyst forecast errors and the opposite is true for the largest traders. Battalio and Mendenhall's results, confirmed here, strongly suggest that those who initiate large trades, presumably institutions or wealthy individuals, respond to earnings surprises in a more sophisticated manner than do those who initiate smaller trades. Those who initiate the smallest trades, presumably individual investors, exhibit the specific type of unsophisticated behavior hypothesized by Bernard and

[14]The inferences of Tables 2 and 3 are not driven by small, illiquid stocks. As we report in the sub-section on robustness tests below, imposing more restrictive minimum values for stock price, market capitalization, and trading activity alters no inferences.

Thomas (1990) to cause post-earnings announcement drift. The important points for this paper are that Battalio and Mendenhall's methods appear effective for our sample and, since investors who initiate large trades respond in a more sophisticated manner to earnings information, they may respond in a more sophisticated manner to accruals levels.

4.3 WHO, IF ANYONE, REACTS TO ACCRUAL INFORMATION?

In this section we apply the methods of Battalio and Mendenhall (2005) to the 10-K/Q filing date to see if investors of any trade-size category react to the information in accruals when it becomes publicly available. Table 5 presents Pearson correlations between accrual levels deciles and the net buy measures as defined in Section 3. Panel A of Table 5 indicates that when we examine all qualifying observations, i.e., when we do not condition on earnings information, the correlation between accrual level and the net-buy figures is statistically indistinguishable from zero for all but the most extreme trade-size categories. The first column shows that the correlation between net buying behavior for the smallest traders (those initiating trades of less than 500 shares) and accruals is 0.020, which is, both when pooling all observations and when considering the average correlation of each calendar quarter, significantly positive at better than the 1% level. This result suggests that those initiating the smallest trades transact *in the wrong direction*, on average, at least with respect to accruals, at the time of 10-K/Q filing. This result is completely unanticipated and, therefore, does not relate to any of our ex ante hypotheses. In a later section we explore possible reasons for this result.

The far right column of Panel A shows a negative correlation between accrual level and the net buying behavior of large traders (those initiating trades of 5,000 shares of more), which suggests that these investors may, on average, interpret and act on the accrual signal properly. These results are significant at the 10% (two-sided) level and are, therefore, consistent with our hypothesis that if members of any group understand the significance of accruals levels and attempt to profit from trading on them, it should be those initiating large trades.[15] As discussed in Section 2 above, we can, ex ante, propose two (related) situations in which knowledgeable investors may be more likely to scrutinize accrual information. Balsam, et al (2002), in order to focus on firms "for which there is *ex post* evidence of earnings management" (p. 988), impose several restrictions on their data. Here we impose just one of these data restrictions: we examine cases where the firm's earnings just meet or exceed analyst forecasts. In these cases, knowledgeable investors may suspect firms of managing earnings upward from levels that fall short of analysts' forecasts to levels that meet or just exceed them.

Panel B of Table 5 shows results for those cases where average analyst forecast errors are between zero and \$0.01, inclusive. The far right column shows that the correlations between accrual levels and large-trader net buying approximately double relative to those for the full sample and are significant at the 1.6% (two-sided) level or better. This result suggests that investors who care about accruals are more likely to act on them when announced earnings meet or just beat expectations.

Leftwich and Zmijewski (1994) examine contemporaneous earnings and dividend announcements and suggest that, whenever earnings convey positive news, investors are skeptical no matter how much earnings exceed expectations. Another possibility is that investors who are savvy enough to know about the release of accrual information and its implications probably know about post-earnings announcement drift. If these investors face institutional constraints to short selling, e.g., such as the legal prohibition faced by mutual funds or contractual restrictions that sometimes appear in institutional charters, then they may act primarily when the preceding earnings news is favorable.

In Panels C and D, therefore, we partition the entire sample into whether earnings at least meet the forecast or fall short of it, respectively. Given the results in Table 4, we use SUE for bins 1-3, since small traders seem to pay greater attention to earnings surprises based on time-series forecasts, and SUEAF for bins 4-6, since large traders use analyst forecasts of earnings. Comparison of Panels C and D

[15] We require the availability of analysts' forecasts from *I/B/E/S*. When we relax this constraint, the correlations between accruals and large-trader net buying are nearly the same in magnitude but, with the increased power due to increased sample size, these correlations are significantly negative at better than the 5% (two-sided) level.

suggests that investors who trade on accruals look to them generally whenever earnings exceed expectations, not only when earnings meet or just exceed expectations. That is, Panel C shows that when, earnings meet or exceed expectations by any amount, large traders seem to behave in line with the accrual signal (p-values = 0.003 and 0.002), whereas small traders behave in a manner that is opposite of the accrual signal (p-value < 0.001). In contrast, Panel D shows that, when earnings fall short of expectations, the correlation between accruals and net buying for the extreme trade-size categories are small and insignificant. These results suggest that investors act on accrual information only after they have observed a non-negative earnings surprise. We explore possible reasons for this below in Section 4.4.[16]

Based on the results in Table 5, in Table 6 we take a closer look at the net buying behavior of investors initiating the smallest (less than 500 shares) and largest (5,000 shares or more) trades by accrual decile for those cases where the recent earnings surprise was non-negative. For small traders, the positive correlations between buying activity and accruals are borne out in the extreme deciles. For the two lowest deciles the net buying figure is -0.014, although neither is statistically significant. On the other end, small traders are significant net buyers for each of the three highest-accrual deciles. Those initiating large trades, on the other hand, are significant buyers of low accrual stocks (0.043, p-value= 0.048) and significant sellers of high accrual stocks (-0.061, p-value = 0.015).

How can we interpret these numbers? The 0.043 average abnormal buying figure for low accrual stocks corresponds to a large-trader buy-sell imbalance of 4.3% of the normal transaction level (sum of buys and sells). For example, say that a stock (or portfolio of stocks) has 50 large-trader buys and 50 large-trader sells for a total of 100 trades in a typical three-day period. If, during the three-day SEC filing period, this stock has 54 buys and 50 sells, then the figure in Table 6 would be 0.040 or 4.0%. Table 6 indicates, therefore, that for every 100 large-trader transactions that occur in an average three-day period,

[16] While these correlations may seem small, the -2.4% F-M correlation in Panel C is 42% as large as the FM correlation of 5.7% between large-trader net buying and analyst earnings forecast error reported in Table 4. Our 5.7% figure is identical to that reported in Battalio and Mendenhall's (2005) Table 3. Prior literature would certainly suggest that earnings announcements would be much more salient events than 10-K/Q filing dates.

during the three-day 10-K/Q filing period, buys outnumber sells by about four for low accrual stocks and sells outnumber buys about six for high accrual stocks.

Table 7 provides results of regression tests of the same phenomenon depicted in Tables 5 and 6. The dependent variables in Table 7 are the net buying measures for small traders (columns I and II) and large traders (columns III and IV). The explanatory variables are measures of earnings surprise, accruals, a dummy variable for earnings at or above expectations (POS), and an interaction variable between accruals and POS. The pooled results appear in Panel A and the means of quarterly regression coefficients appear in Panel B.

Results in the first (third) column test for a relationship between accruals and small- (large-) trader abnormal buying in the 10-K/Q filing window, after controlling only for small-(large-) traders' earnings expectations. Small traders appear to react in the *wrong* direction to accruals, while large investors seem to be continuing to respond to the previously announced earnings surprise and responding relatively weakly to the accrual signal (coefficient = -0.037, p=0.05).

The second (fourth) column presents results after adding the variable POS, which takes on a value of 1.00 when SUE (SUEAF) is non-negative and a value of 0.00 when SUE (SUEAF) is negative, and POS multiplied times the accrual-level decile. Now, consistent with Table 5, small-trader net buying is no longer significantly linked to accruals when earnings are below expectations, but they are associated with accruals when earnings exceed expectations. The result is stronger in Panel B for the Fama-MacBeth regressions (coefficient = 0.037, p = 0.027), than for the pooled regressions (coefficient = 0.027, p = 0.082). In contrast, the significantly negative coefficient on the multiplicative variable, accruals decile rank times POS, in the fourth column of Table 7 (coefficient = -0.094, p = 0.019), shows that large traders respond significantly to the accrual signal, but, again consistent with Table 5, only when the previously announced quarterly earnings meet or exceed analysts' forecast of earnings. Results in the second column indicate that, at the time of the 10-K/Q filing date, small investors respond opposite to the analyst forecast error for previously announced earnings. We discuss small trader behavior more fully in a later section.

The coefficient on accruals decile rank times POS for large traders is between -0.094 and -0.109. These coefficients correspond to buy-sell imbalance of 9.4% to 10.9% of the normal transaction level between the lowest accrual stocks and the highest accrual stocks. These results are consistent with the decile results presented in Table 6, where the buy-sell imbalance between the lowest and highest accrual stocks was [4.3% - (-6.1%)] 10.4% of the normal transaction level.

Generally, the results are very consistent with our hypotheses. While we were not sure we would be able to find any evidence of abnormal trading behavior at the time accruals information becomes available, we hypothesized that if we did it would most likely be for those initiating large trades (consistent with logic appearing in Easley and O'Hara (1987), Collins et al (2003), Lev and Nissim (2006), and Battalio and Mendenhall (2005)). Further, based on Balsam et al (2002) and Leftwich and Zmijewski (1994), we hypothesized that we would be most likely to find evidence of informed trading for firms whose recent earnings surprises were small and non-negative or simply non-negative, respectively. Our results are most consistent with Leftwich and Zmijewski. We were, however, surprised to find evidence that those initiating small trades transact in the *wrong* direction, at least with respect to accruals, around 10-K/Q filing dates.

4.4 WHY ONLY NON-NEGATIVE EARNINGS SURPRISE STOCKS?

Since we find the buying activity for large traders appears consistent with a rational response to accrual information only following non-negative earnings surprises, we examine those cases following negative surprises more carefully. Why don't large traders buy shares upon observing low accruals following a negative earnings surprise? Firms that announced negative earnings surprises and then accruals that ranked in the bottom quintile, exhibit essentially zero abnormal performance (CAR = 0.5%, p-value = 0.517) following the 10-K/Q filing date through the next earnings announcement. For this group of firms, the accruals anomaly and post-earnings announcement drift cancel each other out. Large traders, therefore, behave rationally by not purchasing these low-accrual stocks at the filing date.

Why don't large traders sell high accrual stocks following negative earnings surprises? At the time of the *earnings announcement*, large traders are very heavy net sellers of those negative-earnings surprise firms that would eventually announce high accruals. The abnormal buying measure for this period is 75% greater (-0.139 versus -0.079) than for negative-earnings news, low-accrual stocks. Say that for a group of stocks buys and sells are normally equal at 50 each in a three-day window. A scenario consistent with the data is that around the earnings announcement large traders initiate 50 buys and 64 sells for those firms subsequently announcing high accruals versus 50 buys and 58 sells for low-accrual stocks. The negative-earnings, high-accrual stocks do perform poorly from the 10-K/Q filing date to the next earnings announcement (-3.4%, p-value <.0001), so perhaps large traders have shorted to their capacity prior to the filing date, or they have liquidated their holdings and, like most mutual funds, they do not short at all. Asquith, Pathak, and Ritter (2005) note that, although short interest has been rising, the median NYSE-Amex firm and median Nasdaq firm each had only about 1% of its shares outstanding shorted in 2002, the last year and highest period of short interest for their sample. Clearly most investors face some form of short sales constraints, even if psychological, as evidenced by the very low level of short selling that actually takes place.

4.5 WHY DO SMALL TRADERS ACT IN THE *WRONG* DIRECTION?

To investigate why small traders trade in the wrong direction on the 10-K/Q filing date, we generate and test alternative hypotheses. First, if price movements are negatively related to accruals, small traders might perceive buying (selling) opportunities as prices decrease (increase) in light of the announcement of high (low) accruals levels. In untabulated tests, the data do not support this. Another possibility is that small traders might be exhibiting the behavior that Barber and Odean (2008) document for individual investor accounts with three different brokerage firms. Specifically, small traders here may be buying stocks that grab their attention. Recall from Table 6 that most abnormal activity for the small traders is buying rather than selling, i.e., they exhibit significant abnormal buying for each of the top three accruals deciles and do not exhibit significant abnormal selling for any decile. One measure used by

Barber and Odean of identifying stocks that grab investors' attention is short-term returns. They show that individual investors show a tendency to buy stocks that have exhibited recent, extreme, short-term (e.g., one day) returns—whether they are positive or negative. In untabulated results, we find that small trader behavior is strongly related to the absolute value of the stock return during the filing date window. When, in untabulated results, this variable is added to the regression tests of Table 7, it is positive and highly significant (p-value < 0.0001) indicating that small-trader buying significantly increases with the magnitude of stock price movements during the filing period. Adding this variable renders the coefficient on the product of POS and accruals decile insignificant for the pooled regression, but not for the Fama-MacBeth regression. While there may be other possible explanations, this evidence is generally consistent with small traders here behaving similarly to Barber and Odean's individual investors in buying stocks that grab their attention.

4.6 LARGE TRADES AND THE MAGNITUDE OF THE ACCRUAL ANOMALY

Since large investors tend to purchase low accrual stocks and sell high accrual stocks, do they affect the magnitude of the accrual anomaly? Recall that (for non-negative earnings surprise stocks) out of 100 trades in a normal period, during the filing period we find about four extra large-trader buys for low accrual stocks and six extra sells for high accrual stocks. While this shift in buying behavior is non-trivial, recall that large traders get no help in moving prices in the correct direction from investors in any other trade-size category. In fact, small traders work against them. In untabulated results, we perform statistical tests on the non-negative SUEAF subsample. When we regress the abnormal returns during and following the three-day filing period on SUE decile, SUEAF decile, accrual decile, and a decile score coded between -0.5 and +0.5 for large-trader abnormal buying, the coefficient on the abnormal-buying variable for the immediate return is 2.2% and that for the subsequent drift is -2.7% (both p-values < 0.001). In other words, large-trader buying around the filing date forces up prices and lowers subsequent returns.

Since large trades move prices and, on average, large trades tend to be buys (sells) when accruals are low (high), we might infer that the actions of large traders reduce the magnitude of the accrual anomaly. We attempt to show empirically that the *incremental* large-trader transactions associated with accruals have a significant effect on the association between accruals and returns. Again in untabulated results, to the regressions above, we add one explanatory variable: the accruals decile times the absolute value of the large-trader net buying coded decile score. We use the absolute value of net buying to capture aggregate large-buyer trading—both in the correct and incorrect direction. For both regressions, when the dependent variable is the abnormal returns during the three-day filing date window or the subsequent drift, the coefficients are in the correct direction, but are not statistically significant. The p-value for the filing date window is 0.2372 and for the drift is 0.2289.

While logic tells us that the actions of large traders reduce the size of the accrual anomaly, the effect is too weak to demonstrate statistically. This may be because too few investors—even large investors—recognize the value of accruals information and attempt to profit from it. Or our research methods may not be sufficiently precise to identify all or even most investors who act immediately on accrual information. Finally, some knowledgeable investors may act on accruals information outside our 10-K/Q filing date window, e.g., over the several days following the filing date.[17] In any event, using the best methods we can conceive, we cannot discriminate among these possibilities or draw a significant direct link between large-trader buying and the magnitude of the accrual anomaly.

4.7 ROBUSTNESS CHECKS

4.7.1 Hedge Returns and Liquidity Restrictions

To ensure that the inferences of Tables 2 and 3 are not driven by small, illiquid stocks we repeat the analyses with several liquidity restrictions. First, we replicate the hedge portfolio returns retaining only observations where price per share at quarter end was at least $5. The hedge returns for all five

[17] We examine the period where we think trading on accruals information is likely to be the most intense, i.e., where the ratio of accrual-based information trades to other types of trades is probably the highest. We believe that broadening this window would increase the noise of our tests and hinder our ability to detect abnormal trading.

strategies are slightly reduced but are still statistically significant at the 1% level. The readjusting hedge return (corresponding to row five of Table 2) is 6.580%, significantly greater than the combined strategy, which, in turn, outperforms the pure SUEAF and accrual strategies. Increasing the price per share requirement to $10 or requiring market capitalization to be at least $200 million also reduces hedge portfolio returns, but profitability of each of the five strategies remains statistically significant at the 1% level and the same conclusions apply.

4.7.2 Early Accruals Disclosure

For the results presented, we eliminate firm-quarters in which net operating cash flow is announced with the preliminary earnings. This represents 1,881 observations or roughly 5 percent of the pre-elimination sample. In addition, some firms disclose various balance sheet components in the preliminary earnings announcements, from which accruals may be estimated, i.e., Accounts Receivables, Accounts Payables and Inventories. We repeat our analysis after partitioning the sample into those that report operating cash flow or the relevant balance sheet components on the earnings release date (an additional 21% of the sample) and those that do not. Most important, for observations where accrual information is released on the earnings release date, we find no relation between accruals and trading on the 10-K/Q filing date by either small or large traders. When examining firms that do not report accruals information on the earnings release date, all hedge portfolio returns are similar to those reported and inferences are unaltered. For these observations, most trading results are similar to those reported and inferences are unaltered. Results for large-trader buying are somewhat stronger. For example, the pooled regression coefficient for the interaction variable of accruals decile rank and the indicator for non-negative earnings surprise (fourth column of Panel A of Table 7) increases to -0.114 (compared to -0.094 presented).

4.7.3 Nasdaq pre 1997

Battalio and Mendenhall (2005) argue that their trade typing procedures are more effective for Nasdaq firms prior to 1997. We replicate our analyses for this subsample of 8,492 observations. We find that the correlations between large-trader net buying and accruals that correspond to those reported in Panels A, B, and C of Table 5 more than double to -0.020, -0.046 and -0.044 (significant at 10%, 1% and 1%) respectively. The pooled regression coefficient for the interaction variable of accruals decile rank and the indicator for non-negative earnings surprise for large traders (fifth and sixth columns of Table 7) more than doubles to -0.22 and is significant at better than 5% (similar results obtain for the Fama-MacBeth regressions). All findings related to other trade size categories remain qualitatively the same.

4.7.4 Interim versus Fourth Quarter Results

Partitioning our sample into interim and fourth quarter announcements does not alter any of the primary inferences of this paper. Nonetheless, substantial differences do exist between the two groups. The fourth quarter differs from interim quarters in two fundamental ways. First, more *noise* is thrown into fourth quarter earnings than interim quarter earnings in the form of write-offs, impairments, and other unusual items (e.g., Elliott and Shaw (1988) and Francis, Hanna, and Vincent (1996)). Second, interim-quarter earnings are either unaudited or less formally audited than the fourth quarter earnings.

The main empirical differences we find between interim quarters and the fourth quarter are as follows. Strategies applied to the fourth quarter are less profitable than those applied to interim quarters. This is consistent with Rangan and Sloan (1998) who find the same for post-earnings announcement drift. The ranking of strategies by the magnitude of the abnormal returns they generate is, however, the same for both the interim quarter and fourth quarter subsamples as that reported for the complete sample. Second, accruals levels are significantly lower in the fourth quarter than in interim quarters. This is consistent with the frequent appearance of write-offs and other negative accrual elements in the fourth quarter.

Table 8 shows that the small- and large-trader tendencies are maintained for both partitions. Table 8 also shows that large traders are much less likely to buy low accrual stocks in the fourth quarter than in interim quarters (-0.013 versus 0.077). This is consistent with negative accruals such as write-offs causing low accruals to have a different meaning for investors in the fourth quarter than in interim quarters.

Further, large traders are much bigger net sellers of high-accrual stocks and their selling is much greater in magnitude than for interim quarters (-0.165 versus -0.037). This is consistent with extreme positive accruals being rarer in the fourth quarter than in interim quarters (e.g., 18.9% of high accrual observations appear in the fourth quarter versus 37.8% of low accrual observations). This may be due to the fourth quarter audit making it more difficult for managers to use accruals to engage in income increasing behavior. Finally, small-trader behavior is generally consistent for each partition, except that we do not see evidence of them selling low accrual stocks in the interim quarters.

5. Conclusion

Using a different sample and methods, we confirm Collins and Hribar's (2000) findings that earnings surprises and accruals levels are complementary signals of future return performance. Further we propose and test a new trading rule assuming investors act on the earnings surprise shortly after the earnings announcement and, after the 10-K/Q filing date, adjust their portfolios if the accruals signal contradicts the earlier earnings signal. This trading strategy significantly outperforms the others tested.

Lev and Nissim (2006) point out that "the timeliness of institutional response to accrual information is an important issue both for assessing market efficiency and explaining the persistence of the accrual anomaly" (p. 196-197). If accrual information is valuable to investors, as most of the accrual literature and our own tests suggest, then sophisticated investors should react at the time the accrual signal first becomes available. We show that on average those investors who initiate trades of 5,000 shares or more react immediately in the correct direction in response to the first release of accrual information. This tendency, however, is limited to firms who previously announced earnings that either met or exceeded analysts' forecasts. Our evidence suggests that this may be attributable to a combination of rational behavior and short sales constraints on the part of large traders. Further, investors who initiate the smallest trades, those less than 500 shares, respond in the opposite direction to the accrual information. Follow up tests suggest that these investors may be purchasing "attention grabbing" stocks. Investors in all other trade-size categories act as though accrual information is not important and/or they are unaware that it is available.

We believe this is the first direct evidence that any investors respond to the information in accrual information when it first becomes available. Our results are consistent with those of Battalio and Mendenhall (2005) in that the same group that exhibits the most sophisticated response to earnings announcements appears to also exhibit the most sophisticated response to accruals.

REFERENCES

Affleck-Graves, J., Mendenhall, R.R., 1992. The relation between the value line enigma and post-earnings-announcement drift. Journal of Financial Economics 31, 75-96.

Ali, A., Chen, X., Tong, Y., Tong, Y., 2008. Do mutual funds profit from the accruals anomaly? Journal of Accounting Research 46, 1-26.

Asquith, P., Pathak, P.A., Ritter, J.R., 2005. Short interest, institutional ownership, and stock returns. Journal of Financial Economics 28, 243-276.

Ball, R., Bartov, E., 1996. How naive is the stock market's use of earnings information? Journal of Accounting and Economics 21, 319-337.

Ball, R., Brown, P., 1968. An empirical evaluation of accounting income numbers. Journal of Accounting Research 6, 159-178.

Balsam, S., Bartov, E., Marquardt, C., 2002. Accruals management, investor sophistication, and equity valuation: evidence from 10-Q filings. Journal of Accounting Research 40, 987-1012.

Barber, B.M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21, 785-818.

Barber, B.M., Odean, T., Zhu, N., 2006. Do noise traders move markets? Zurich Meetings Paper Available at SSRN: http://ssrn.com/abstract=869827

Barclay, M.J., Christie, S.G., Harris, J.H., Schultz, P.H., 1999. The effects of market reform on the trading costs and depths of Nasdaq stocks. Journal of Finance 54, 1-34.

Battalio, R.H., Mendenhall, R.R., 2005. Earnings expectations, investor trade size, and anomalous returns around earnings announcements. Journal of Financial Economics 77, 289-319.

Bernard, V.L., Thomas, J.K., 1989. Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27(Supp), 1-48.

Bernard, V.L., Thomas, J.K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305-340.

Bessembinder, H., Kaufman, H.M., 1997. A cross-exchange comparison of execution costs and information flow for nyse-listed stocks. Journal of Financial Economics 46, 293-319.

Bradshaw, M.T., Richardson, S.A., Sloan, R.G., 2001. Do analysts and auditors use information in accruals? Journal of Accounting Research 39, 45-74.

Callen, J.L., Livnat, J., Siegel, D., 2006. The information content of SEC filings and information environment: A variance decomposition approach. The Accounting Review, Forthcoming.

Collins, D.W., Hribar, P., 2000. Earnings-based and accrual-based market anomalies: one effect or two? Journal of Accounting and Economics 29, 101-123.

Collins, D.W., Gong, G., Hribar, P., 2003. Investor sophistication and the mispricing of accruals. Review of Accounting Studies 8, 251-276.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69-90.

Elliott, J.A., Shaw, W.H., 1988. Write-offs as accounting procedures to manage perceptions. Journal of Accounting Research 26, 91-119.

Ellis, K., Michaely, R., O'Hara, M., 2000. The accuracy of trade classification rules: evidence from Nasdaq. Journal of Financial and Quantitative Analysis 35, 529-551.

Fama, E., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

Finucane, T.J., 2000. A direct test of methods for inferring trade direction from intra-day data. Journal of Financial and Quantitative Analysis 35, 553-576.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. The Accounting Review 59, 574-603.

Francis, J., Hanna, J.D., Vincent, L., 1996. Causes and effects of discretionary asset write-offs. Journal of Accounting Research 34, 117-134.

Goldstein, M. A., Kavajecz, K.A., 2000. Eighths, sixteenths, and market depth: changes in tick size and liquidity provision on the nyse. Journal of Financial Economics 56, 125-149.

Hvidkjaer, S., 2006. A trade-based analysis of momentum. Review of Financial Studies 19, 457-491.

Jones, C.P., Litzenberger, R.H., 1970. Quarterly earnings reports and intermediate stock price trends. Journal of Finance 25, 143-148.

Latané, H., Jones, C.P., 1977. Standardized unexpected earnings - a progress report. Journal of Finance 32, 1457-1465.

Latané, H., Jones, C.P., 1979. Standardized unexpected earnings - 1971-77. Journal of Finance 34, 717-724.

Lee, C.M.C., 1992. Earnings news and small traders: An intraday analysis. Journal of Accounting and Economics 15, 265-302.

Lee, C.M.C., Radhakrishna, B., 2000. Inferring investor behavior: evidence from TORQ data. Journal of Financial Markets 3, 83-111.

Lee, C.M.C., Ready, M.A., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733-746.

Leftwich, R., Zmijewski, M.E., 1994. Contemporaneous announcements of dividends and earnings. Journal of Accounting, Auditing and Finance 9, 725-762.

Lev, B., Nissim, D., 2006. The persistence of the accruals anomaly. Contemporary Accounting Research 23, 193-226.

Livnat, J., Mendenhall, R.R., 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of Accounting Research 44, 177-205.

Livnat, J., Santicchia, M., 2006. Cash flows, accruals, and future returns. Financial Analysts Journal 62, 48-61.

Odders-White, E.R., 2000. On the occurrence and consequences of inaccurate trade classification. Journal of Financial Markets 3, 259-286.

Rangan, S., Sloan, R.G., 1998. Implications of the integral approach to quarterly reporting for the post-earnings announcement drift. The Accounting Review 73, 353-371.

Rendleman, R., Jones, C.P., Latané, H.A., 1982. Empirical anomalies based on unexpected earnings and the importance of risk adjustment. Journal of Financial Economics 10, 269-287.

Sloan, R.G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71, 289-315.

Van Ness, B.F., Van Ness, R.A., Pruitt, S.W., 2000. The impact of the reduction in tick increments in major U.S. markets on spreads, depth, and volatility. Review of Quantitative Finance and Accounting 15, 153-167.

Xie, H., 2001. The mispricing of abnormal accruals. The Accounting Review 76, 357-373.

Table 1

Summary Statistics

	N	Mean	Std. Dev.	25^{th} Perc.	Median	75^{th} Perc.
Components of Earnings						
SUE (Compustat)	35,514	-0.395	5.822	-0.702	0.020	0.725
SUEAF (I/B/E/S)	35,515	-0.007	0.510	0.000	0.000	0.001
Accruals	35,515	-0.011	0.057	-0.029	-0.009	0.010
Buy and Hold Returns (%)						
ERD_t to ERD_{t+1}	35,515	0.610	30.140	-13.293	-1.364	10.701
FD_t to ERD_{t+1}	35,515	0.309	25.639	-10.924	-0.778	9.164
ERD_t to FD_t	35,515	0.178	12.221	-5.917	-0.527	5.254
Net Buying Measures						
Small Traders at ERD	35,515	0.077	0.615	-0.178	0.037	0.275
Large Traders at ERD	34,281	-0.001	1.480	-0.333	0.000	0.380
Small Traders at FD	35,515	0.013	0.465	-0.191	0.000	0.191
Large Traders at FD	34,281	-0.015	1.126	-0.294	0.000	0.317
Firm Characteristics						
MV $Equity_{t-1}$	35,515	2,909	12,013	150	442	1,478
BV $Equity_{t-1}$	35,515	800	2,425	56	160	521
Stock Price	35,515	26.36	22.04	11.88	21.38	35.00

Notes: SUE is calculated from the *Compustat* quarterly database as preliminary EPS minus expected EPS from a seasonal random walk with a drift, scaled by the standard deviation of the forecast errors of the seasonal random walk model. For the summary statistics above, one SUE outlier was removed for presentation purposes. Since all tests are performed on ranked variables, this outlier does not affect any findings. SUEAF is calculated from the *I/B/E/S* database as the actual *I/B/E/S* EPS minus the mean analyst forecast during the 90-day period before the disclosure of earnings, scaled by the price per share at the end of the quarter. Accruals equals income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter. BHR is the buy and hold return on a stock minus the average return on a matched size-B/M portfolio. ERD_t is the quarter *t* preliminary earnings release date and FD_t is the SEC filing date for quarter *t*. Net Buying Measures are adjusted net purchases for different trade size categories. For trade-size category i, 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 either the earnings announcement date or the filing date. The nonevent period is two three-day periods centered twenty trading days before the earnings announcement date and twenty trading days after the filing date. NetBuy 1 represents net buying of traders who initiate trades of less than 500 shares. NetBuy 6 represents net buying of traders who initiate trades of more than 4,900 shares. Market (Book) Value of Equity (in $million) is as of quarter end. Price is as of quarter end.

Table 2

Hedge Portfolio Average Quarterly Returns:
4th Quarter 1990 to 2nd Quarter 2005

Trading Strategy	Buy and Hold Return			Difference versus Combined	Difference versus Readjusting
	Short	Long	Hedge		
Earnings-Based: ERD_t to ERD_{t+1}					
BHR (%)	**1.942**	**2.671**	**4.613**		
N	302	302			
p-value	0.005	0.003	<0.0001		
Earnings-Based: FD_t to ERD_{t+1}					
BHR (%)	**1.529**	**1.924**	**3.453**	**3.325**	
N	302	302			
p-value	0.004	0.003	<0.0001	<0.0001	
Accruals-Based: FD_t to ERD_{t+1}					
BHR (%)	**0.827**	**1.760**	**2.586**	**4.192**	
N	302	302			
p-value	0.047	0.002	<0.0001	<0.0001	
Combined: FD_t to ERD_{t+1}					
BHR (%)	**3.531**	**3.248**	**6.778**		**1.159**
N	54	68			
p-value	<0.0001	0.002	<0.0001		<0.0001
Readjusting: ERD_t to ERD_{t+1}					
BHR (%)	**3.944**	**3.994**	**7.938**		
N					
p-value	<0.0001	0.001	<0.0001		

Notes: BHR is the buy and hold return on a stock minus the average return on a matched size-B/M portfolio. ERD_t is the quarter *t* preliminary earnings release date and FD_t is the SEC filing date for quarter *t*. Earnings-Based Trading Strategy assumes long (short) positions in the top (bottom) 20% of firms sorted according to SUEAF (earnings surprise as measured by analyst forecasts). Accruals-Based Trading Strategy assumes long (short) positions in the bottom (top) 20% of firms sorted according to Accruals (income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter). Combined Trading Strategy assumes long positions in firms that are in both the top 20% for SUEAF and the bottom 20% for accruals and short positions in firms that are in both the bottom 20% for SUEAF and the top 20% for accruals. Readjusting Trading Strategy at the earnings release date assumes long positions in the top 20% and short positions in the bottom 20% of firms sorted according to SUEAF. At the SEC filing date, the portfolio is readjusted where long (short) positions are maintained only if the firm is also in the bottom (top) 20% for accruals. Difference versus Combined Trading Strategy examines the incremental return obtained from using a combined strategy versus a pure earnings based strategy or a pure accruals strategy from the SEC filing date through the next quarterly earnings announcement. Difference versus Readjusting Trading Strategy examines the incremental return obtained from using the Readjusting Strategy versus the Combined Strategy. N is the average number of observations per quarter. Entries in boldface are statistically different from zero at the 5% level or better.

Table 3

Hedge Portfolio Average Quarterly Returns:
1st Quarter 1993 to 3rd Quarter 1999

Trading Strategy	Buy and Hold Return			Difference versus	Difference versus
	Short	Long	Hedge	Combined	Readjusting
Earnings-Based: ERD_t to ERD_{t+1}					
BHR (%)	**2.423**	**2.511**	**4.934**		
N	338	338			
p-value	0.009	0.033	<0.0001		
Earnings-Based: FD_t to ERD_{t+1}					
BHR (%)	**2.274**	**2.043**	**4.317**	**4.445**	
N	338	338			
p-value	0.002	0.041	<0.0001	<0.0001	
Accruals-Based: FD_t to ERD_{t+1}					
BHR (%)	**1.272**	**2.090**	**3.363**	**5.399**	
N	338	338			
p-value	0.035	0.021	<0.0001	<0.0001	
Combined: FD_t to ERD_{t+1}					
BHR (%)	**5.222**	**3.539**	**8.762**		**0.617**
N	63	74			
p-value	<0.0001	0.022	<0.0001		0.019
Readjusting: ERD_t to ERD_{t+1}					
BHR (%)	**5.372**	**4.008**	**9.379**		
N					
p-value	<0.0001	0.019	<0.0001		

Notes: BHR is the buy and hold return on a stock minus the average return on a matched size-B/M portfolio. ERD_t is the quarter *t* preliminary earnings release date and FD_t is the SEC filing date for quarter *t*. Earnings-Based Trading Strategy assumes long (short) positions in the top (bottom) 20% of firms sorted according to SUEAF (earnings surprise as measured by analyst forecasts). Accruals-Based Trading Strategy assumes long (short) positions in the bottom (top) 20% of firms sorted according to Accruals (income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter). Combined Trading Strategy assumes long positions in firms that are in both the top 20% for SUEAF and the bottom 20% for accruals and short positions in firms that are in both the bottom 20% for SUEAF and the top 20% for accruals. Readjusting Trading Strategy at the earnings release date assumes long positions in the top 20% and short positions in the bottom 20% of firms sorted according to SUEAF. At the SEC filing date, the portfolio is readjusted where long (short) positions are maintained only if the firm is also in the bottom (top) 20% for accruals. Difference versus Combined Trading Strategy examines the incremental return obtained from using a combined strategy versus a pure earnings based strategy or a pure accruals strategy from the SEC filing date through the next quarterly earnings announcement. Difference versus Readjusting Trading Strategy examines the incremental return obtained from using the Readjusting Strategy versus the Combined Strategy. N is the average number of observations per quarter. Entries in boldface are statistically different from zero at the 5% level or better.

Table 4

Earnings Surprise and Net Buying Behavior at Preliminary Earnings Release Date

Panel A: Pearson correlation.

	Trade Size (shares)					
	< 500 (NetBuy 1)	500 (NetBuy 2)	600 – 900 (NetBuy 3)	1,000 (NetBuy 4)	1,100-4,900 (NetBuy 5)	≥5,000 (NetBuy 6)
Pooled Correlations						
SUEAF decile rank	**0.025**	**0.019**	**0.011**	**0.042**	**0.042**	**0.053**
SUE decile rank	**0.038**	**0.020**	**0.017**	**0.031**	**0.022**	**0.028**
F-M Correlations						
SUEAF decile rank	**0.023**	**0.017**	0.010	**0.044**	**0.042**	**0.057**
SUE decile rank	**0.035**	**0.018**	**0.017**	**0.031**	**0.019**	**0.033**

Panel B: Regression.

	Trade Size (shares)					
	< 500 (NetBuy 1)	500 (NetBuy 2)	600 – 900 (NetBuy 3)	1,000 (NetBuy 4)	1,100-4,900 (NetBuy 5)	≥5,000 (NetBuy 6)
Pooled Correlations						
Intercept	**0.075**	**0.108**	0.008	**0.108**	**0.016**	-0.000
SUEAF decile rank	**0.023**	**0.048**	0.024	**0.119**	**0.088**	**0.226**
SUE decile rank	**0.056**	**0.050**	**0.033**	**0.068**	0.023	**0.062**
F-M						
Intercept	**0.075**	**0.117**	0.007	**0.106**	**0.018**	0.004
SUEAF decile rank	0.019	**0.045**	0.017	**0.121**	**0.095**	**0.237**
SUE decile rank	**0.048**	0.038	0.033	**0.056**	0.014	**0.075**

Notes: SUE is calculated from the *Compustat* quarterly database as preliminary EPS minus expected EPS from a seasonal random walk with a drift, scaled by the standard deviation of the forecast errors of the seasonal random walk model. SUEAF is calculated from the *I/B/E/S* database as the actual *I/B/E/S* EPS minus the mean analyst forecast during the 90-day period before the disclosure of earnings, scaled by the price per share at the end of the quarter. SUEAF (SUE) decile rank is the decile rank of SUEAF (SUE) scaled to fall between -0.5 and 0.5. Net Buying Measures are adjusted net purchases for different trade size categories. For trade-size category i, 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 either the earnings announcement date or the filing date. The nonevent period is two three-day periods centered twenty trading days before the earnings announcement date and twenty trading days after the filing date. F-M correlations (regression) represent the average quarterly correlation (regression) coefficients estimated following Fama and MacBeth (1973). Entries in boldface are statistically different from zero at the 5% level or better.

Table 5

Accruals and Net Buying Behavior at SEC Filing Date

Panel A. All data (average number of observations per bin is 35,250).

	Trade Size (shares)					
	< 500 (NetBuy 1)	500 (NetBuy 2)	600–900 (NetBuy 3)	1,000 (NetBuy 4)	1,100-4,900 (NetBuy 5)	≥ 5,000 (NetBuy 6)
Pooled Correlations						
Accruals decile rank	**0.019**	-0.004	0.005	0.000	0.003	-0.010
p-value	0.000	0.499	0.358	0.942	0.637	0.071
F-M Correlations						
Accruals decile rank	**0.019**	-0.008	0.005	-0.003	-0.001	-0.011
p-value	0.000	0.266	0.239	0.615	0.801	0.099

Panel B. Undeflated SUEAF of \$0.00 or \$0.01 (average number of observations per bin is 13,976).

	Trade Size (shares)					
	< 500 (NetBuy 1)	500 (NetBuy 2)	600–900 (NetBuy 3)	1,000 (NetBuy 4)	1,100-4,900 (NetBuy 5)	≥ 5,000 (NetBuy 6)
Pooled Correlations						
Accruals decile rank	**0.017**	-0.010	0.009	0.000	-0.001	**-0.021**
p-value	0.045	0.219	0.264	0.964	0.953	0.016
F-M Correlations						
Accruals decile rank	0.012	-0.014	**0.012**	-0.001	-0.002	**-0.026**
p-value	0.194	0.181	0.043	0.861	0.796	0.006

Panel C. SUE ≥ 0 for NetBuy trade-size categories 1-3 and SUEAF ≥ 0 for NetBuy trade-size categories 4-6 (average number of observations per bin is 18,088 for NetBuy 1-3 and 22,818 for NetBuy 4-6).

	Trade Size (shares)					
	< 500 (NetBuy 1)	500 (NetBuy 2)	600–900 (NetBuy 3)	1,000 (NetBuy 4)	1,100-4,900 (NetBuy 5)	≥ 5,000 (NetBuy 6)
Pooled Correlations						
Accruals decile rank	**0.029**	0.005	0.010	-0.004	-0.001	**-0.020**
p-value	0.000	0.468	0.174	0.496	0.937	0.003
F-M Correlations						
Accruals decile rank	**0.033**	0.004	**0.012**	-0.003	-0.002	**-0.024**
p-value	<0.0001	0.665	0.017	0.640	0.780	0.002

Table 5 (continued)

Panel D. SUE < 0 for NetBuy trade-size categories 1-3 and SUEAF < 0 for NetBuy trade-size categories 4-6 (average number of observations per bin is 17,340 for NetBuy 1-3 and 12,254 for NetBuy 4-6).

	Trade Size (shares)					
	< 500 (NetBuy 1)	500 (NetBuy 2)	600–900 (NetBuy 3)	1,000 (NetBuy 4)	1,100-4,900 (NetBuy 5)	≥ 5,000 (NetBuy 6)
Pooled Correlations						
Accruals decile rank	0.008	-0.013	-0.001	0.008	0.009	0.008
p-value	0.316	0.084	0.914	0.376	0.297	0.404
F-M Correlations						
Accruals decile rank	0.005	**-0.019**	-0.002	-0.001	0.007	0.007
p-value	0.503	0.023	0.808	0.884	0.500	0.562

Notes: Undeflated SUE is calculated from the *Compustat* quarterly database as preliminary EPS minus expected EPS from a seasonal random walk with a drift. Undeflated SUEAF is calculated from the *I/B/E/S* database as the actual *I/B/E/S* EPS minus the mean analyst forecast during the 90-day period before the disclosure of earnings. Accruals equals income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter. Accruals decile rank is the decile rank of accruals scaled to fall between -0.5 and 0.5. Net Buying Measures are adjusted net purchases for different trade size categories. For trade-size category i, 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 either the earnings announcement date or the filing date. The nonevent period is two three-day periods centered twenty trading days before the earnings announcement date and twenty trading days after the filing date. F-M correlations (regression) represent the average quarterly correlation (regression) coefficients estimated following Fama and MacBeth (1973).). Entries in boldface are statistically different from zero at the 5% level or better.

Table 6
Extreme Accruals (SUEAF $\geq$ 0) and Net Buying Behavior at SEC Filing Date

Trade Size	Accruals Decile 0 *(lowest)*	Accruals Decile 1	Accruals Decile 2	Accruals Decile 3	Accruals Decile 4	Accruals Decile 5	Accruals Decile 6	Accruals Decile 7	Accruals Decile 8	Accruals Decile 9 *(highest)*
< 500 shares (NetBuy 1)	-0.014	-0.014	0.014	0.004	0.005	0.006	0.009	**0.018**	**0.026**	**0.031**
p-value	0.132	0.185	0.154	0.616	0.532	0.471	0.276	0.036	0.008	0.006
≥ 5,000 shares (NetBuy 6)	**0.043**	0.001	-0.012	0.016	0.001	0.008	0.013	-0.038	-0.031	**-0.061**
p-value	0.048	0.962	0.617	0.455	0.979	0.723	0.569	0.098	0.167	0.015

Notes. Undeflated SUEAF is calculated from the I/B/E/S database as the actual I/B/E/S EPS minus the mean analyst forecast during the 90-day period before the disclosure of earnings. Accruals equals income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter. NetBuy 1 is the adjusted net purchases for trades below 500 shares and NetBuy 6 is the adjusted net purchases for trades for at least 5,000 shares. For trade-size category i, 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 filing date. The nonevent period is two three-day periods centered twenty trading days before the earnings announcement date and twenty trading days after the filing date. The average number of observations in each cell is 2,271. Entries in boldface are statistically different from zero at the 5% level or better.

Table 7
Regressions of Net Buying Behavior on Earnings and Accrual Signals

Panel A. Pooled Regression.

	NetBuy 1: Trades for less than 500 shares		NetBuy 6: Trades for at least 5,000 shares	
	I	II	III	IV
Intercept	**0.012**	0.005	**-0.015**	-0.002
	(<0.0001)	(0.331)	(0.014)	(0.895)
SUE decile rank	0.015	-0.001		
	(0.054)	(0.964)		
SUEAF decile rank			**0.057**	**0.077**
			(0.003)	(0.019)
Accruals decile rank	**0.022**	0.009	**-0.037**	0.024
	(0.004)	(0.393)	(0.050)	(0.465)
POS		0.012		-0.019
		(0.218)		(0.395)
Accruals decile rank*POS		0.027		**-0.094**
		(0.082)		(0.019)

Panel B. Fama-MacBeth Regression.

	NetBuy 1: Trades for less than 500 shares		NetBuy 6: Trades for at least 5,000 shares	
	I	II	III	IV
Intercept	0.009	0.000	-0.015	-0.001
	(0.111)	(0.975)	(0.138)	(0.975)
SUE decile rank	**0.017**	-0.003		
	(0.030)	(0.825)		
SUEAF decile rank			**0.063**	**0.086**
			(0.006)	(0.019)
Accruals decile rank	**0.027**	0.010	-0.047	0.018
	(0.001)	(0.390)	(0.065)	(0.625)
POS		0.016		-0.020
		(0.108)		(0.446)
Accruals decile rank*POS		**0.037**		**-0.109**
		(0.027)		(0.010)

Notes: SUE is calculated from the *Compustat* quarterly database as preliminary EPS minus expected EPS from a seasonal random walk with a drift, scaled by the standard deviation of the forecast errors of the seasonal random walk model. SUEAF is calculated from the *I/B/E/S* database as the actual *I/B/E/S* EPS minus the mean analyst forecast during the 90-day period before the disclosure of earnings, scaled by the price per share at the end of the quarter. Accruals equals income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter. Decile rank is the decile rank of the variable scaled to fall between -0.5 and 0.5. Net Buying Measures are adjusted net purchases for different trade size categories. For trade-size category i, 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 either the earnings announcement date or the filing date. The nonevent period is two three-day periods centered twenty trading days before the earnings announcement date and twenty trading days after the filing date. POS is an indicator variable that equals one when SUE (for NetBuy 1) or SUEAF (for NetBuy 6) are greater than or equal to zero and is equal to zero otherwise. Entries in boldface are statistically different from zero at the 5% level or better.

Table 8
Extreme Accruals (SUEAF $\geq$ 0) and Net Buying Behavior at Interim and 4th Quarter SEC Filing Dates

	Interim Quarters			Fiscal 4th Quarter		
	Accural Decile		t-test (Lowest - Highest)	Accrual Decile		t-test (Lowest - Highest)
	Lowest	Highest		Lowest	Highest	
< 500 shares (NetBuy 1)	0.000	**0.032**	**0.073**	**-0.039**	0.030	**0.034**
p-value	0.977	0.006		0.011	0.370	
N	1,280	1,991		774	463	
$\geq$ 5,000 shares (NetBuy 6)	**0.077**	-0.037	**0.002**	-0.013	**-0.165**	**0.058**
p-value	0.003	0.130		0.732	0.045	
N	1,234	1,915		749	445	

Notes. Undeflated SUEAF is calculated from the I/B/E/S database as the actual I/B/E/S EPS minus the mean analyst forecast during the 90-day period before the disclosure of earnings. Accruals equals income before extraordinary items and discontinued operations minus cash from operations, scaled by average total assets during the quarter. NetBuy 1 is the adjusted net purchases for trades below 500 shares and NetBuy 6 is the adjusted net purchases for trades for at least 5,000 shares. For trade-size category i, 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 filing date. The nonevent period is two three-day periods centered twenty trading days before the earnings announcement date and twenty trading days after the filing date. Entries in boldface are statistically different from zero at the 10% level or better.