Who, if Anyone, Reacts to Accrual Information?*

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Abstract

We confirm and extend prior research that suggests accrual levels predict future returns, even after controlling for earnings surprise. We then document abnormal buying behavior around 10-K/Q filing dates that correlates with accrual level. Specifically, we extend Collins and Hribar (2000) by showing that the accrual anomaly persists for a sample of firms followed by analysts after controlling for analyst earnings forecast errors and using exact 10-K/Q filing dates. We then show that large traders, those who initiate trades of at least 5,000 shares, tend to trade in the correct direction in response to accrual information released in SEC filings after preliminary earnings. This tendency is limited, however, to cases where earnings conveyed favorable news initially. Investors who use accrual information apparently ignore stocks whose earnings convey unfavorable news or believe that accrual level is not informative for these firms. We also provide some evidence that the smallest traders react to accrual information, but in the wrong direction.

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Abstract

We confirm and extend prior research that suggests accrual levels predict future returns, even after controlling for earnings surprise. We then document abnormal buying behavior around 10-K/Q filing dates that correlates with accrual level. Specifically, we extend Collins and Hribar (2000) by showing that the accrual anomaly persists for a sample of firms followed by analysts after controlling for analyst earnings forecast errors and using exact 10-K/Q filing dates. We then show that large traders, those who initiate trades of at least 5,000 shares, tend to trade in the correct direction in response to accrual information released in SEC filings after preliminary earnings. This tendency is limited, however, to cases where earnings conveyed favorable news initially. Investors who use accrual information apparently ignore stocks whose earnings convey unfavorable news or believe that accrual level is not informative for these firms. We also provide some evidence that the smallest traders react to accrual information, but in the wrong direction.

1. Introduction

We confirm that the accrual anomaly is not subsumed by post-earnings announcement drift, for a sample of firms followed by analysts, after making two adjustments to prior research: controlling for analyst earnings forecast errors and using exact 10-K/Q filing dates. Further, we document a strategy implemented upon observing the earnings announcement—that gives investors the option of unwinding their positions after observing the 10-K/Q—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 accrual levels contain information about future returns. Knowledgeable, active investors should, therefore, transact immediately upon receiving news of extreme accruals from the firm's 10-K/Q. We find that, on average, investors who initiate very large trades (at least 5,000 shares) act to exploit the information in accrual levels revealed by the 10-K/Q, but investors of other trade-size categories do not.

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 accrual anomaly is the tendency for stock prices to lag the information in accruals. Specifically, when the accrual component of a firm's earnings is high (low), future returns tend to be low (high). Sloan (1996) shows that the accrual component of earnings is less persistent than the cash flow component of earnings and that investors apparently do not fully appreciate this difference. 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 when earnings surprises are defined as errors from a seasonal random walk (SRW) time series model and investors transact on assumed 10-K/Q filing dates, neither of these anomalies subsumes the other. 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. Further, in the majority of cases, at least based on our sample, investors could not have received accrual information by Collins and Hribar's assumed transactions dates. We therefore confirm and extend Collins and Hribar for the subset of firms followed by analysts by defining the earnings surprise using analyst forecasts and by using actual 10-K/Q filing dates. Our results confirm those of Collins and Hribar: neither anomaly subsumes the other and, therefore, investors have reason to transact on the 10-K/Q filing date when accrual information is released.

We next examine the apparent abnormal returns of several straightforward strategies using earnings surprise and accrual level. Briefly these can be described as follows: the drift strategy implemented following the earnings announcement date; the accrual strategy implemented following the 10-K/Q SEC filing date; a combined strategy implemented following the SEC filing date; and a second combined 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. The last strategy, which does not appear elsewhere in the literature, yields the highest abnormal returns.

Our results confirm that information in the accrual level, which becomes public with the filing of the 10-K/Q, has implications for stock prices and should, therefore, be valuable to investors. Knowledgeable investors should react in predictable ways upon receiving the accrual signal. We divide investors into categories based on their trade size and correlate their buying/selling behavior with accrual levels to determine the type of investors who indeed seem to utilize the accrual signal. We find that only investors who initiate very large trades—5,000 shares or greater—tend to transact in the correct direction upon observing the accrual signal. While we find some evidence 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, most results suggest that investors in other trade-size categories behave as if they are unaware of the release of accrual information and/or the implications of accruals for future price movements.

Further, we find that large traders' response to accruals is restricted to cases where preliminary earnings news for the quarter is favorable. Since the earnings announcement becomes public prior to the accrual information in the 10-K/Q, one possible interpretation is that investors who use accrual information do not believe it is informative for firms who fail to meet earnings expectations. In other words, perhaps when earnings exceed expectations these investors look to accruals for confirmation, but when earnings fall short of expectations they accept earnings at face value. Alternatively, it could be the case that investors who use accrual information ignore altogether firms that have recently experienced negative earnings surprises, possibly because they cannot or do not want to engage in short selling.

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

In this paper, we investigate two basic issues. First, does the accrual anomaly survive post-earnings announcement drift after correcting for the information in analyst forecast errors for the subset of firms that are followed by analysts (where, as shown by prior studies, both the accrual anomaly and drift should be smaller) and when using actual 10-K/Q filing dates? Confirming that the accrual anomaly survives after making these changes is important for our second issue. If accrual levels contain information about future returns beyond that included in earnings surprises, then knowledgeable investors should react immediately to the information contained in accrual levels. This leads to our second question: Can we find evidence that investors react to the accrual information at the time it is released, i.e., at the time of the 10-K/Q filing? In this section we briefly discuss the two anomalies of interest, the accrual anomaly and post-earnings announcement drift, discuss relevant literature, and motivate our tests.

2.1 CONFIRMATION AND EXTENSION OF COLLINS AND HRIBAR (2000)

Sloan (1996) points out that many financial statement analysis textbooks discuss breaking earnings into components, especially into cash flow and accruals, in order to predict future earnings. Many of these books assert that the accrual component of earnings is more susceptible to manipulation than the cash component. Sloan uses this as motivation to investigate the relative persistence, and the stock market's awareness of the relative persistence, of the cash flow and accrual components of earnings. Sloan first 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. That is, 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 goes back much further than that of the accrual anomaly. It begins with Ball and Brown (1968), who attempt to support the utility of accounting earnings by correlating changes in earnings with contemporaneous stock price changes. Although Ball and Brown take the efficiency of the stock market as an established fact, they find that changes in accounting earnings correlate not only with contemporaneous stock returns, but also with *future* stock returns.

There is now a large literature on post-earnings announcement drift (or the SUE—standardized unexpected earnings—effect). Many papers verifying the stock market's apparent slow reaction to earnings surprises appeared in the finance literature in the 1970s and early 1980s (e.g., Jones and Litzenberger (1970); Latané and Jones (1977); and Rendleman, Jones, and Latané (1982)) and then reappeared in the accounting literature in the late 1970s and 1980's (e.g., Joy, Litzenberger, and McEnally (1977) and Foster, Olsen, and Shevlin (1984)). These papers, and most SUE studies appearing since them, use various forms of time series models to measure the information content of earnings announcements. The more recent SUE 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.

In order to confirm that the accrual anomaly contains information beyond that in the recent earnings surprise, we make two changes to Collins and Hribar's (2000) methods. First, we limit ourselves to the subset of firms that are followed by analysts. These firms are typically larger, have a greater proportion of their stock held by institutional investors, and have lower costs of trading—all of which can potentially reduce the magnitude of the earnings drift and the accrual anomaly returns. 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. So, we define the surprise as the price-deflated difference between actual *I/B/E/S* earnings and the average analyst quarterly earnings forecast from *I/B/E/S*. Collins and Hribar (2000) also assume that for each observation accrual information becomes available 17 days after the earnings announcement, i.e., they begin cumulating returns on the 18^{th} day following the earnings announcement. Our second fundamental change to Collins and Hribar's methods is to use actual 10-K/Q filing dates and begin cumulating returns (for relevant tests) two days following the SEC filing date. Although Collins and Hribar state that their results are not sensitive to this assumption (p.109), an examination of the distribution of lags between earnings announcement dates and filing dates for our sample suggests that it is important to use the actual filing dates. For our sample, only 25.98% of all observations have SEC filing dates within 17 days of the earnings announcement date. So, if the distribution of filing dates for Collins and Hribar's sample is the same as ours, their results are based on an assumption that about 74% of the time investors act on information that is not yet public.[1] Furthermore, Collins and Hribar (2000) use a holding period of two quarters after their portfolio formation date; most drift studies use a period of one quarter or 60 trading days. In our study, we confine ourselves to the period from the SEC filing through one day after the subsequent quarter's preliminary earnings announcement.

We show that the accrual and post-earnings announcement drift anomalies remain distinct after implementing these changes: a strategy combining analyst earnings forecast errors and accrual level generates larger hedge returns than strategies using either signal independently. We then propose a fourth strategy using the two signals consecutively. This strategy is in the spirit of Balsam, Bartov, and Marquardt (2002), who provide evidence that investors reassess the quality of earnings upon the filing of the 10-Q. In this strategy investors initiate a position following the earnings announcement on the basis of the analyst forecast error and then unwind their initial position following the 10-K/Q filing date if the accrual signal contradicts the preliminary earnings surprise signal. This strategy generates hedge returns that are significantly larger than those of any other strategy we test.

2.2 WHO, IF ANYONE, REACTS TO THE INFORMATION IN THE ACCRUAL SIGNAL?

Our test results confirm the conclusions of Collins and Hribar (2000) that accrual levels contain value-relevant information beyond that contained in the preliminary earnings surprise. Further, our results confirm those of Collins and Hribar that the market does not fully appreciate and react to this information:

[1] The average lag between the earnings report date and the filing date for our sample is 26.49 days and Collins and Hribar (2000) cite Easton and Zmijewski (1993) as reporting a lag of 14.7 days. We find two reasons for this discrepancy. Easton and Zmijewski's lag of 14.7 days (Table 2) is for interim-quarter 10-Qs only and does not apply to fourth-quarter 10-Ks. Easton and Zmijewski's Table 1 shows the lag for the fourth quarter is 47.5 days. Second, comparing our results from the 1990s to Easton and Zmijewski's results from earlier data, suggests that the lag between quarter end and earnings announcement dates has declined over time, but the lag between quarter end and 10-Q filing dates has not.

accrual levels are correlated with *future* stock return performance after controlling for the recent earnings surprise. This motivates us to ask, who, if anyone, reacts to the information in the accrual signal?

Prior evidence is mixed on whether even relatively sophisticated market participants respond to accrual information. Bradshaw, Richardson, and Sloan (2001) provide evidence suggesting that security analysts do not properly interpret accrual information when making earnings forecasts. Collins, Gong, and Hribar (2003) provide two pieces of evidence suggesting that institutional investors may respond to accrual information. They show that the apparent returns to trading on accrual information are negatively correlated with the percent of the firm's shares held by institutions. Collins et al, using annual data observations on institutional holdings, also show that subsequent changes in institutional holdings are negatively correlated with accrual level. Lev and Nissim (2006) state that "Given 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, we examine institutional accruals using quarterly institutional ownership data" (p. 196-197). They 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.

Correlations between accrual levels and changes in aggregate institutional holdings levels over time may suggest that institutional investors respond to accrual information, but it seems far from conclusive. For example, Lev and Nissim's (2006) results suggest that investors *react* to accrual information both before and for many months following the time the information becomes public. 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.

We would like to know whether any investors take note and act on accrual information when it first becomes available. To answer this question, 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. 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.

Our results show that, on average, investors in the largest size category do respond and respond in the correct direction at the time the accrual signal becomes public. This result is stronger when we examine a subsample of cases whose preliminary earnings news was either neutral or favorable (see Balsam et al (2002) and Brown and Caylor (2005)). Our results are consistent with the existence of a group of large investors who trade on accrual information and either accepts as legitimate unfavorable preliminary earnings news independent of the subsequently revealed accruals level, or who simply ignore negative earnings surprise firms. When preliminary earnings meet or exceed expectations, however, this same group of investors is skeptical and seems to look to the accrual signal to verify the persistence or quality of earnings. There is some evidence that, on average, investors in the smallest trade size category respond to accrual information in the *wrong* direction—but these results are not always significant at traditional levels.

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.[2] These screens reduce our sample to 89,089 firm-quarters.[3]

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

[3] 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.

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 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.[4]

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.[5]

Between 1993 and 1996, liquidity demanding investors were guaranteed up to 1000 shares at the posted quotes in most Nasdaq-listed stocks.[6] Thus, it is unlikely that wealthy investors who have or think 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

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[4]Lee and Radhakrishna (2000), Odders-White (2000), and Finucane (2000) use the NYSE's TORQ database to test the Lee and Ready algorithm and document a success rate in excess of 85%. Ellis, 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%.

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

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

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.[7]

[7]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 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.

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 ($NetPostBuy_i$).[8] 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:

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

$NETBUY\_EVENT_i$ 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 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.

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

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:

$$E_{j,t} = \delta_{j,t} + E_{j,t-4} + \varepsilon_{j,t} \tag{2}$$

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:

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

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:

$$SUEAF_{j,t} = \frac{E^{ibes}_{j,t} - F_{j,t}}{P_{j,t}}, \tag{4}$$

where $E^{ibes}_{j,t}$ 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.[9] 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.[10] 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%.

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

[9]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.

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

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.[11] 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 confirming or failing to confirm that the accrual anomaly survives when using actual 10-K/Q filing dates and controlling for post-earnings announcement drift when the earnings surprise is defined using analyst forecast errors. If the accrual anomaly is subsumed by post-earnings announcement drift, there is not necessarily any reason for knowledgeable investors to trade at the time accrual levels are revealed—upon the filing of the 10-K/Q.

Table 2 presents the hedge returns of five strategies based on earnings surprise and/or accrual information. In each case the holding period begins either two days following the preliminary earnings

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[11] As discussed in the notes to Table 1, the large SUE mean and standard deviation are attributable to one outlier. Since all tests are performed on ranked variables, the extreme SUE value associated with this outlier does not affect any findings.

release date or two days following the 10-K/Q filing date and ends the day following the earnings announcement date for the next quarter. As explained in the prior section, abnormal returns are firm buy and hold returns minus the return on a market capitalization and book-to-market matched portfolio. Hedge returns are defined as the difference in abnormal returns between those firms in the buy quintile (high positive earnings forecast error and/or low accruals) portfolio minus those in the sell quintile portfolio.

The first row of Table 2 presents results based on earnings surprise alone. As expected, 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%. This row is included only to put the earnings surprise strategy on an equal footing with the next two proposed strategies.

The third row of Table 2 provides our first results for the accrual anomaly. Obviously, accrual-based strategies cannot be implemented until the accrual information has been made public, which for our sample is after the 10-K/Q filing date (recall that we eliminate firms that report net operating cash flows in their preliminary earnings release). Consistent with most prior research, low (high) accrual firms exhibit significantly positive (negative) abnormal returns. The hedge return for this strategy is 2.586% for a period that is somewhat shorter than one quarter. Specifically, for our sample 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 the four quarters would have resulted in average annual returns that are similar to those reported by Sloan (1996). Note further that 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 provides results for a portfolio strategy that combines both earnings surprise and accrual information. To qualify for one side or the other in this hedged strategy, a firm quarter observation must be in the extreme good-news quintile or extreme bad-news quintile for both the earnings surprise and accrual signals. 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. Note that the number of firms in the combined portfolio is smaller (54 and 68 on average for the short and long portfolios as compared to 302 for each of the independent portfolios). The 6.778% hedge return on the combined portfolio compares to 11.94% which Collins and Hribar (2000) (p. 116) report for a strategy based on extreme earnings surprise and accrual quintiles for a holding period of two quarters.

There are many important differences between our sample and methods and those of Collins and Hribar that explain why their hedge returns are over 75% larger than ours. First, Collins and Hribar assume that investors hold their positions for more than twice as long as we do—two quarters instead of less than one (as discussed above).[12] We assume that investors hold their positions for no more than one quarter to avoid double counting any firm-day return (see, e.g., Marais (1989), pp. 41-42). We also require each firm to be followed by at least one analyst who has reported a quarterly earnings forecast to *I/B/E/S* in the 90 days prior to the earnings announcement. This additional sample constraint rules out many firms that are smaller, less liquid, have more idiosyncratic risk, and have less institutional following. Since, like most if not all anomalies, the accrual anomaly and post-earnings announcement drift are more pronounced for these types of firms, this is one more reason that our hedge returns should be smaller than those of Collins and Hribar.[13]

[12] Livnat and Santiccia (2006) show that the accruals hedge portfolio return almost doubles when the holding period is two quarters.

[13] For evidence regarding accruals see, e.g., Collins et al (2003), Mashruwala et al (2006), and Lev and Nissim (2006). For evidence regarding post-earnings announcement drift see, e.g., Latané and Jones (1979), Bernard and Thomas (1989), Bartov et al (2000), and Mendenhall (2004).

An upside of our additional data constraints is that they ensure our sample firms are much more liquid, on average, than firms of less constrained samples. These additional constraints, therefore, make it less likely that potential investors in sample firms would encounter either high transactions costs or an inability to trade quickly. It is less likely therefore that the returns we document would be eliminated by the barriers to trading.

Finally, as previously mentioned, we use actual 10-K/Q filing dates whereas Collins and Hribar (2000) assume investors take positions at the close of trading on the 17th day following the earnings announcement. For our sample, making the same assumption as Collins and Hribar assumes that investors act on accrual information before it becomes public about 76% of the time. This further reduces our documented abnormal returns relative to theirs.

In the fifth row of Table 2, we introduce a new strategy that uses both earnings surprise and accrual information. In this scenario investors initiate long (short) positions two days following the earnings announcement in stocks that fall 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. This case significantly outperforms all other tested strategies with a hedge return of 7.938%. 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.[14]

In Table 3 we replicate the tests of Table 2 for the period 1993 to 1999, the period for which we obtain transactions data.[15] We do this to ensure that the results documented for the 1990 to 2005 period are also valid when we limit our sample for remaining tests. The important aspects of the results from

[14] 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 much smaller sample sizes.

[15] 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.

Table 2 are maintained; both the accrual anomaly and post-earnings announcement drift exist after controlling for the other. Knowledgeable investors have reason to trade on the accrual information at the time the 10-K/Q becomes public information.[16]

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. 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 results that appear in both Panels A and B of Table 4 confirm those of Battalio and Mendenhall (2005) for our sample. 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 on the right side of Table 4. Battalio and Mendenhall's results, confirmed here, strongly suggest that those who initiate large trades, presumably institutions or wealthy individuals,

[16]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 does not alter any inferences.

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 Thomas (1990) to cause post-earnings announcement drift. That is, they respond to a specific measure of earnings surprise that is inferior to analyst forecast errors and understates the persistence of earnings innovations. The important point for this paper is that Battalio and Mendenhall's methods appear effective for our sample.

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, on average, to the information in accruals at the time it becomes public. Table 5 presents Pearson correlations between accrual levels deciles and the net buy measures as defined in Section 3. Recall that the accrual level is total accruals in the most recent quarterly earnings deflated by average total assets.

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 net-buy figures is not significantly different 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 may appear small at 0.020, both when pooling all observations and when taking the average correlation of each calendar quarter, but is significantly positive at better than the 1% level. This result suggests that those initiating the smallest trades transact *in the wrong direction*, at least with respect to accruals, at the time of 10-K/Q filing.

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 prior beliefs that at least some professional traders understand the significance of accruals.[17] 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 3% (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 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. 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

[17] 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.

SUEAF for bins 4-6, since large traders use analyst forecasts of earnings. Comparison of Panels C and D 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, larger traders seem to behave in line with the accrual signal (p-value = 0.002), whereas small traders behave in a manner that is opposite of the accrual signal (p-value = <0.0001). In contrast, Panel D shows that, when earnings fall short of expectations, the correlation between accruals and net buying for each trade-size category is small and not significantly different from zero.[18]

Panels A, B, and C of Table 6 correspond to Panels A, C, and D of Table 5, respectively, and address the same issue by looking at the mean net buying measures for the smallest and the largest traders for only the extreme accrual quintiles. The implications of these tests are the same as those of Table 5. In Panel A the entire sample results suggest that large traders react according to the accrual signal, but results are not significant at traditional levels (p-value = 0.142, two-tailed test). Small traders seem to respond in the wrong direction. Panel B shows that when earnings meet or exceed analyst forecasts (time series forecasts), the net buying of large (small) traders around the 10-K/Q filing date is significantly different between the two extreme accrual quintiles in the right (wrong) direction. In each case the difference is significant at better than the 1% level (two-tailed test). Panel C suggests that, when earnings fall short of expectations, the net buying behavior of neither large nor small traders differs significantly across the two extreme-accrual quintiles.

Tables 5 and 6 suggest that both small and large investors act on accrual information only after they have observed what they perceive to be a positive earnings surprise. The evidence is consistent with at least two related conjectures. It is possible that when earnings fall short of expectations, investors accept them at face value, but when earnings meet or exceed expectations at least a subset of investors

[18]Battalio and Mendenhall (2005) argue that their trade typing procedures are more effective for Nasdaq firms prior to 1997. As discussed in the sub-section on robustness checks below, we also find stronger results during this period.

look to accruals for confirmation. It is also possible that these investors simply ignore stocks that have experienced recent negative earnings surprises and so do not respond to the accrual signal.

Table 7 provides results of regression tests of the same phenomenon depicted in Tables 5 and 6. The dependent variables in Table 7 are net buying measures for small traders (columns 1 through 3) and large traders (columns 4 through 6). 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. Inferences from the results of the two panels are the same.

Results in the first (fourth) column tests for a relationship between small- (large) trader net buying around 10-K/Q filing dates and accruals after controlling only for small-(large-) traders' earnings expectations. Small investors appear to react in the *wrong* direction to accruals, while large investors seem to (still) be responding to the previously announced earnings surprise and relatively weakly to the accrual signal (coefficient = -0.036, p=0.059).

The second (fifth) column presents results after adding the variable POS, which takes on a value of 1.00 when SUE (SUEAF) is positive or zero and 0.00 when SUE (SUEAF) is negative, and POS multiplied times the accrual-level decile. Now small-trader net buying is no longer significantly linked to accruals when earnings are below expectations, but they are marginally significantly associated with accruals when earnings exceed expectations (coefficient = 0.030, p = 0.055), contrary to our expectations if small traders were cognizant of the accrual signal and its implications. In contrast, and consistent with Tables 5 and 6, the significantly negative coefficient on the multiplicative variable accruals decile rank times POS in the fifth column of Table 7 (coefficient = -0.098, p = 0.014) shows that large traders respond significantly to the accrual signal, but only when the previously announced quarterly earnings meet or exceed analysts' forecast of earnings.

Results in the third (sixth) column are similar to those in the previous column, but now we include SUEAF (SUE) as a control variable. The inclusion of SUE in column 6 makes little difference in the large-trader results—results continue to indicate that large investors respond to accrual information only when the previously announced analyst forecast error is non-negative. Results in the third 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. While we cannot explain this result, we think it suggests that any apparent non-zero net buying behavior on the part of small investors around the 10-K/Q filing date may be due to small investors reacting in some way to the actions of large traders. We think this is more plausible than believing that small traders are aware of the filing of the 10-K/Q and intentionally respond in the wrong direction with respect to the accrual signal or in the opposite direction of the recent analyst forecast error. Panel B of Table 7 presents corresponding average coefficients for independent quarterly regressions. Inferences are the same as for Panel A except that in each case small trader results for accrual decile times POS are more highly significant ($p = 0.024$ in Panel B versus $p = 0.055$ and 0.053 in Panel A).

The coefficient on accruals decile rank times POS for large traders is between -0.098 and -0.114. These coefficients correspond to buys (sells) increasing by 9.8% to 11.4% and sells (buys) remaining constant for a large negative (positive) accrual stock relative to a stock with zero accrual information. For example, say that two stocks normally have 50 large buys and 50 large sells in a three-day window. Both stocks' earnings exceed analyst forecasts. For one of these stocks the accrual level is in the bottom decile and for the other accruals is in the top decile. If, in each case, the accrual signal motivates 5 large traders, who would not have taken a position otherwise, to transact in the correct direction, then the coefficient would be equal to -0.100. That is, the coefficient we observe is roughly what we would observe if, during the SEC filing period, there were 55 large buys and 50 sells for the low-accrual decile stock, and 50 buys and 55 sells for the high-accrual stock.

4.4 ROBUSTNESS CHECKS

4.4.1 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 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 further reduces the hedge portfolio returns, but all five still remain statistically significant at 1% and the same conclusions about incremental returns to the Combined and Readjusting strategies apply. Similar results obtain when we require the minimum market capitalization at quarter-end to be $200 million or require at least 10 trades in the four 3-day windows applied in the net-buy analysis.

4.4.2 Balance Sheet Components Disclosure

Some firms disclose various balance sheet components in the preliminary earnings announcements, from which accruals may be estimated. We replicate both the hedge portfolio returns analysis and the net buying analysis excluding observations where Accounts Receivables, Accounts Payables and Inventories were disclosed at the preliminary earnings release date (thus excluding 29.7% of the observations in the hedge returns sample and 21.7% of the net buying sample). The hedge portfolio returns for the five strategies are similar in magnitudes to those reported in Tables 2 and 3 with the same inferences as reported in the text. For the net buying analysis we find that the pooled correlations between large-trader behavior and accruals that correspond to those reported in Panels A, B, and C of Table 5 increase to -0.011, -0.021 and -0.024 (significant at 10%, 5% 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 Panel A of Table 7) increases to

-0.118 and is significant at the 5% level or below (similar results obtain for the Fama-MacBeth regressions). The inferences for all other trade size categories remain qualitatively the same.

4.4.3 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 significant at better than 5% (similar results obtain for the Fama-MacBeth regressions). Additionally, all the findings related to other trade size categories remain qualitatively the same.

5. Conclusion

We confirm and extend the findings of Collins and Hribar (2000) who present results suggesting that post-earnings announcement drift and the accrual anomaly represent distinct forms of apparent market mispricing. We extend their work by focusing only on firms that are followed by analysts, by using analyst forecasts to capture earnings surprises, and by using exact 10-K/Q filing dates. Our results confirm those of Collins and Hribar and indicate that accrual levels have predictive ability for future stock returns beyond those in the most recent earnings surprise. We also show that readjusting the drift portfolio following the SEC filing date when the accrual signal is inconsistent with the previous earnings signal can significantly enhance returns.

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. We provide some evidence that investors who initiate the smallest trades, those less than 500 shares, actually respond to accrual information, but in the wrong direction. 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 actually 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.

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Table 1

Summary Statistics

	N	Mean	Std. Dev.	25th Perc.	Median	75th Perc.
Components of Earnings						
SUE (Compustat)	35,515	1.069×10^3	2.014×10^5	-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. One SUE outlier is responsible for the large mean and standard deviation. When it is removed, the mean SUE is -0.39. 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.

Table 3

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

Trading Strategy	Buy and Hold Return			Difference versus Combined	Difference versus Readjusting
	Short	Long	Hedge		
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.

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	**0.026**	**0.019**	**0.012**	**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	**0.024**	**0.017**	0.011	**0.045**	**0.041**	**0.058**
SUE decile rank	**0.035**	**0.019**	**0.018**	**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**	-0.002
SUEAF decile rank	**0.024**	**0.050**	0.028	**0.122**	**0.092**	**0.234**
SUE decile rank	**0.056**	**0.052**	0.032	**0.070**	0.022	**0.063**
F-M						
Intercept	**0.075**	**0.116**	0.007	**0.105**	**0.017**	0.002
SUEAF decile rank	0.020	0.045	0.022	**0.125**	**0.100**	**0.248**
SUE decile rank	**0.047**	0.038	0.032	**0.058**	0.013	**0.074**

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	0.020	-0.003	0.005	0.000	0.003	-0.009
p-value	0.000	0.562	0.304	0.945	0.548	0.080
F-M Correlations						
Accruals decile rank	0.020	-0.008	0.005	-0.002	-0.001	-0.012
p-value	0.000	0.270	0.220	0.643	0.829	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	0.018	-0.009	0.009	0.000	0.000	-0.019
p-value	0.031	0.284	0.269	0.982	0.978	0.026
F-M Correlations						
Accruals decile rank	0.013	-0.013	0.012	-0.002	-0.002	-0.024
p-value	0.197	0.206	0.057	0.861	0.837	0.011

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	0.030	0.005	0.010	-0.004	0.000	-0.020
p-value	<0.0001	0.486	0.181	0.525	0.997	0.002
F-M Correlations						
Accruals decile rank	0.034	0.003	0.012	-0.004	-0.002	-0.025
p-value	<0.0001	0.727	0.018	0.622	0.782	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	-0.012	0.001	0.009	0.010	0.009
p-value	0.266	0.120	0.945	0.291	0.247	0.332
F-M Correlations						
Accruals decile rank	0.006	-0.019	-0.001	-0.001	0.007	0.007
p-value	0.486	0.025	0.882	0.957	0.514	0.546

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).

Table 6

Net Buying Behavior for Extreme Accrual Quintiles around the SEC Filing Date

Panel A. All Data

	Highest Accrual Quintile	Lowest Accrual Quintile	t-test for Difference Between Highest & Lowest Accrual Quintile
NetBuy 1			
Mean	0.027	0.000	
p-value	<0.0001	0.977	0.001
N	6,909	7,034	
NetBuy 6			
Mean	-0.035	-0.006	
p-value	0.012	0.653	0.142
N	6,636	6,803	
t-test for Difference Between NetBuy 1 & NetBuy 6	<0.0001	0.681	

Panel B. SUE $\geq$ 0 for NetBuy trade-size category 1 and SUEAF $\geq$ 0 for NetBuy trade-size category 6.

	Highest Accrual Quintile	Lowest Accrual Quintile	t-test for Difference Between Highest & Lowest Accrual Quintile
NetBuy 1			
Mean	0.041	-0.004	
p-value	<0.0001	0.625	0.000
N	3,755	3,028	
NetBuy 6			
Mean	-0.048	0.020	
p-value	0.005	0.261	0.006
N	4,537	4,121	
t-test for Difference Between NetBuy 1 & NetBuy 6	<0.0001	0.270	

Table 6 (continued)

Panel C. SUE < 0 for NetBuy trade-size category 1 and SUEAF < 0 for NetBuy trade-size category 6.

	Highest Accrual Quintile	Lowest Accrual Quintile	t-test for Difference Between Highest & Lowest Accrual Quintile
NetBuy 1			
Mean	0.010	0.003	
p-value	0.248	0.655	0.510
N	3,154	4,006	
NetBuy 6			
Mean	-0.006	-0.046	
p-value	0.788	0.032	0.198
N	2,099	2,682	
t-test for Difference Between NetBuy 1 & NetBuy 6	0.439	0.012	

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. 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 5,000 shares or more.

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	V	VI
Intercept	0.012 (<0.0001)	0.005 (0.319)	0.006 (0.301)	-0.015 (0.010)	0.000 (0.996)	-0.001 (0.944)
SUE decile rank	0.015 (0.057)	-0.002 (0.890)	0.009 (0.579)			-0.019 (0.337)
SUEAF decile rank			-0.039 (0.0001)	0.062 (0.001)	0.088 (0.008)	0.091 (0.006)
Accruals decile rank	0.023 (0.003)	0.008 (0.442)	0.009 (0.399)	-0.036 (0.059)	0.028 (0.379)	0.030 (0.349)
POS		0.013 (0.181)	0.013 (0.184)		-0.023 (0.289)	-0.021 (0.332)
Accruals decile rank*POS		0.030 (0.055)	0.030 (0.053)		-0.098 (0.014)	-0.098 (0.013)

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	V	VI
Intercept	0.009 (0.103)	0.000 (0.993)	0.000 (0.963)	-0.015 (0.136)	-0.005 (0.805)	-0.007 (0.753)
SUE decile rank	0.017 (0.027)	-0.004 (0.763)	0.008 (0.561)			-0.024 (0.393)
SUEAF decile rank			-0.043 (0.002)	0.062 (0.008)	0.078 (0.023)	0.081 (0.020)
Accruals decile rank	0.025 (0.001)	0.007 (0.576)	0.008 (0.531)	-0.050 (0.060)	0.017 (0.650)	0.021 (0.567)
POS		0.017 (0.092)	0.017 (0.093)		-0.014 (0.563)	-0.011 (0.679)
Accruals decile rank*POS		0.040 (0.024)	0.040 (0.024)		-0.113 (0.010)	-0.114 (0.009)

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.