Who, if Anyone, Reacts to Accrual Information?*

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Abstract

We show that the vast majority of investors ignore value-relevant accruals information when it is first released, but that investors who initiate trades of at least 5,000 shares tend to transact in the proper direction. These investors trade on accruals information only when the previously-announced earnings signal is non-negative. Unconditionally, those investors initiating the smallest trades appear to respond to accruals in the wrong direction, but further investigation suggests this behavior is explained by their attraction to attention-grabbing stocks. Finally, we find that those who trade on accruals information have insufficient market power to mitigate the accruals anomaly.

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Abstract

We show that the vast majority of investors ignore value-relevant accruals information when it is first released, but that investors who initiate trades of at least 5,000 shares tend to transact in the proper direction. These investors trade on accruals information only when the previously-announced earnings signal is non-negative. Unconditionally, those investors initiating the smallest trades appear to respond to accruals in the wrong direction, but further investigation suggests this behavior is explained by their attraction to attention-grabbing stocks. Finally, we find that those who trade on accruals information have insufficient market power to mitigate the accruals anomaly.

1. Introduction

The accrual anomaly is the tendency for stock prices to lag information in firms' accruals levels. Specifically, when the accruals component of a firm's earnings is relatively high (low), future returns tend to be relatively low (high). Sloan (1996) shows that the accruals component of earnings is less persistent than the cash flow component of earnings and that investors apparently do not fully appreciate this difference. Given the importance of accruals levels in predicting future returns, knowledgeable, active investors should transact immediately upon receiving accruals information. The primary research question of this paper is, therefore, who, if anyone, reacts to accrual information when it first becomes available? Specifically, we examine whether any investors respond to accruals information upon the filing of the firm's 10-K/Q. We find circumstances under which investors who initiate very large trades (at least 5,000 shares) act almost immediately to exploit the information in accrual levels, while those who initiate very small trades (fewer than 500 shares) seem to react in the wrong direction. Investors in intermediate trade-size classes appear to completely ignore accruals information. While we document that a statistically significant fraction of one subset of investors acts immediately to take advantage of accruals information, perhaps as interesting is that 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 find that the large-trader response to accruals information is restricted to cases where the previously announced earnings news for the quarter is non-negative. In other words, large traders seem to ignore the information in accruals following negative earnings surprises. Two conditions sufficient to explain this result are short-sales restrictions and the lack of *positive* abnormal returns for any accrual group among those previously announcing negative earnings surprises. Short sales restrictions may take the form of the legal prohibition faced by mutual funds during most of our sample period or contractual restrictions that often appear in institutional charters, so the first condition is met for a large fraction of institutional investors. Further, we show that, among firms previously announcing a negative earnings surprise, no accrual group exhibits statistically or economically significant positive abnormal returns, so the second condition is also met. For long-only investors, the accrual signal is not important for those firms previously experiencing a negative earnings surprise and it is, therefore, rational for them to ignore it. While there may be other explanations, the data are clear. Accruals-based trading is detectable only for those firms whose previously announced earnings met or beat analysts' forecasts.

While investors who initiate trades greater than 5,000 shares exhibit a statistically significant propensity to respond to accruals information, this tendency is not nearly large enough to eliminate or even significantly reduce the magnitude of the anomaly. Specifically, we show that when large traders are correct on average, the immediate stock price response to accruals information is greater and the anomaly is smaller. But, on net, the aggregate actions of large traders do not increase the immediate stock price response to accruals information or reduce the magnitude of the drift. We interpret these results as indicating that, while there exists a statistically significant subset of investors initiating large trades who are cognizant of the release and importance of accruals information, this group is too small to have an economically significant impact on prices. The vast majority of investors (across all trade-size categories), who trade at the time of the 10-K/Q filing, trade for reasons unrelated to accruals levels. In other words, while we document that some investors transact immediately in an attempt to profit from accruals information—and we can identify those investors as among those initiating trades of at least 5,000 shares—their influence is insufficient to significantly affect the magnitude of the accrual anomaly. This observation, along with the finding that the traders in all other size categories exhibit no awareness of the accrual signal sheds light on why the accrual anomaly has proven to be such a persistent phenomenon.

Investors who initiate the smallest trades—fewer than 500 shares—seem to trade in the *wrong* direction at the time of the accruals signal, but we find this result is weakened substantially and rendered insignificant when controlling for two variables suggested by Barber and Odean (2008) and two additional variables that we propose. Specifically, Barber and Odean hypothesize that individual investors buy stocks that exhibit the attention-grabbing characteristics of large absolute returns and high levels of trading volume. We further hypothesize that by examining large-investor trading behavior around the filing date and small-trader buying behavior around the prior earnings announcement, we can better determine which stocks (or types of stocks) are likely to be purchased by small-traders around the filing date. As predictors of small-trader buying behavior around the 10-K/Q filing date, we find very strong support for all four variables. Inclusion of these variables renders the effect of accruals economically small and statistically insignificant. These results suggest that the unconditional positive correlation between small-trader purchases and accruals is probably driven by the attention-grabbing behavior of individual investors as documented by Barber and Odean.

This paper, therefore, contributes to the literature in a number of ways. Because it is the first to examine trading behavior immediately following 10-K/Q filing dates, we believe it represents the most convincing evidence to date that any subset of investors exhibits a significant tendency to trade specifically in response to accrual information. Further, we identify those investors as ones with the resources to trade at least 5,000 shares of a single stock at once—almost assuredly institutions—and show that they trade almost *immediately* in response to accruals. In contrast, we show that investors in all other trade-size groups behave as if accruals information is not important. We show that the tendency for large traders to react to accruals information is insufficient to eliminate or measurably reduce the accrual anomaly. Our data also clearly reveal that those investors who respond to accrual information do so only following non-negative earnings surprises. We investigate and provide plausible conditions under which this is rational. Finally, our small-trader results confirm Barber and Odean’s (2008) attention-grabbing hypothesis in a very different context using very different methods.

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

Prior evidence is mixed on whether even sophisticated market participants respond to accrual information. Bradshaw, Richardson, and Sloan (2001) and Teoh and Wong (2002) provide evidence that security analysts do not properly interpret accrual information when making earnings forecasts. Richardson (2003) finds no evidence that short sellers, normally considered relatively sophisticated investors, short the stocks of high-accrual firms.

The three papers most closely related to this one, however, provide evidence consistent with some sophisticated traders responding to accruals information. Using annual holdings data, Collins, Gong, and Hribar (2003) show that subsequent changes in the share holdings of transient institutions are negatively correlated with accruals level. Using similar data at a quarterly interval, 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 low levels of accruals and that these funds exhibit superior subsequent returns.

While each of these three papers contributes significantly to our knowledge of the accruals anomaly, we believe that none decisively demonstrates the existence of investors who trade in direct response to accruals information. Each of these papers uses a relatively long window—either one calendar quarter or year—over which to estimate investors' trading activity. They do this by taking quarterly or annual observations of institutional holdings based on SEC form 13-f filings. But a firm's accruals level is strongly correlated with several other variables including subsequent earnings innovations, value-glamour measures, and subsequent returns. In addition to making other valuable contributions, these papers show that accruals levels *are correlated with* the subsequent trades of institutions over the next 13 to 52 weeks. They do not, however, show that accruals levels necessarily *cause* these trades. In other words, each of these papers shows that accruals levels are negatively correlated with subsequent levels of institutional holding, just as accruals levels are negatively correlated with subsequent earnings levels, returns, and value measures. We believe it is impossible to isolate the effects of accruals levels, and to rule out the effects of other correlated variables, using observations on holdings levels that occur three to twelve months apart. Some of the authors of the above papers agree.

Lev and Nissim (2006) make a similar point in commenting on Collins, Gong, and Hribar (2003), who examine institutional holdings on an annual basis, when they state “it is not clear from an examination of annual changes in institutional holdings whether institutions react to the release of accruals information on a timely basis” (p. 196). Lev and Nissim point out that Collins et al. apparently agree in principle, because they state “Since we are using annual institutional holdings data, results from this section should be interpreted cautiously” (p. 275).

Lev and Nissim (2006) examine institutional holdings on a quarterly basis, but continue to use annual accruals. Their results suggest that investors *react* to accrual information in the quarter before and the three quarters after it becomes available. They perform subsequent tests that suggest the association between accruals levels and the prior quarter institutional holdings might be due to interim quarters’ accruals levels. In retrospect, it seems that Lev and Nissim may have been better served by examining quarterly accruals as well as quarterly institutional holding data. Even if they had and obtained results supporting their hypothesis, however, we would still not know whether institutional investors were *reacting to accruals levels* or were trading sometime in the following 13 weeks for some other reason that happened to be correlated with accruals. Put differently, we believe that Lev and Nissim’s criticism of Collins et al. for using annual holdings data also applies to their own analysis for using quarterly holdings.

Ali et al. (2008) rank mutual funds by the accruals levels of the firms held by those funds. They show a spread in the average accruals levels of firms held by mutual funds as well as a negative correlation between accrual level and mutual fund returns. The average accruals decile of firms held by those funds that are presumably the most cognizant of accrual’s importance is 4.42 compared to a sample average of 5.55. So, the typical stock of a fund trading on the accruals anomaly ranks not in the bottom accruals decile, but, rather, between the 4th and 5th decile. This casts some doubt on the extent to which these funds actually base their transactions on accruals levels. When funds are partitioned into deciles on the basis of the accruals levels of the firms they hold, those deciles are monotonic in at least two measures of value: book-to-market and historical sales growth (Table 3, p. 14). We know that mutual funds tend to follow *styles*, i.e., some prefer value stocks while others prefer growth stocks. Given the high correlation between value-growth indicators and accruals levels, it would be very easy to interpret a fund's preference for style as a response to accruals information. In the Ali et al. (2008) sample, a mutual fund in the bottom accruals decile one year has less than one chance in three of being in the bottom accruals decile the next year. In these results, are we observing funds reacting to accruals information or are we observing funds adjusting their holdings in light of value-growth indicators or other correlated signals?

Our conclusion is the same for each of these studies. While each contributes to our knowledge of the accruals anomaly and is suggestive that some traders may react to accruals information, an investor's motivation for trading cannot be accurately inferred from snapshots of holdings taken at least 13 weeks apart—there are simply too many other plausible explanations for the changes in holdings over time. Collins, Gong, and Hribar (2003) state "Ideally, we would test this conjecture by examining institutions' trading around earnings announcement dates or the release date of the annual report" (p. 275). This paper represents our attempt to realize the ideal proposed by Collins, Gong, and Hribar.

As suggested by Collins, Gong, and Hribar (2003), 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 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 are much more sophisticated in their response to earnings announcements than are 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.

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 during most of our sample period or contractual restrictions that sometimes appear in institutional charters, then they may act primarily when the preceding earnings news is favorable. On the other hand, if short sales constraints are not binding and/or low accrual firms exhibit economically significant positive returns following negative earnings surprises, then we should observe abnormal buying around 10-K/Q filing dates following both positive and negative earnings surprises.

In summary, if anyone trades in response to accruals information, we hypothesize it will be those investors who initiate large trades. If short-sales constraints are binding and negative-earnings surprise firms do not exhibit significant positive returns, even when accruals are low, they should only react to accruals for firms whose previously announced earnings met or beat expectations.

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 1999.[1] 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 either the net operating cash flow or balance sheet components from which accruals may be estimated are announced with the preliminary earnings. We exclude these observations from our analysis in order to focus on firm quarters where no accrual information was likely to be known until the release of the periodic filing. The firms with preliminary cash flow and balance sheet information are identified using the Charter Oak preliminary database that is available on WRDS.[2] These screens along with the microstructure trading constraints discussed below reduce our sample to 27,808 firm-quarters.

[1] We stop in 1999 due to microstructure considerations discussed below.
[2] See Livnat and Mendenhall (2006) or Callen et al. (2006) for a description of the Charter Oak preliminary database.

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.

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.[3]

[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%.

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 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

[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.

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]

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

[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 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.

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, Event(Buy-Sell)ERD_i and Event(Buy_Sell)FD_i, we compute similar statistics for the three-day trading window centered twenty trading days before the earnings announcement date – Pre(Buy-Sell)$_i$ and for the three-day trading window centered twenty trading days after the filing date Post(Buy-Sell)$_i$.[7] We then subtract the average of Pre(Buy-Sell)$_i$ and Post(Buy-Sell)$_i$ 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:

$$NETBUY\_EVENT_i = \frac{Event(Buy - Sell)_i - \frac{1}{2}\left(Pre(Buy\text{ - }Sell)_i + Post(Buy\text{ - }Sell)_i\right)}{Avg.\#\ of\ \ Non\text{ - }Event\ Trades_i} \qquad (1)$$

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%.[8] 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.

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:

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

[8] Our measure of buy-sell imbalance is very similar to that of Lee (1992).

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

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:

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

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:

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

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.[9] Following Affleck-Graves and Mendenhall (1992), we equally space the coded scores from -0.5

[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.

(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 measure the effects of quarterly accruals on returns, we use the buy and hold returns (BHR) generated by initiating positions from two days after the SEC filing date for quarter *t* and terminating one day after the preliminary earnings announcement in quarter *t+1*. (We terminate the position 100 days after the position is initiated to avoid look-ahead bias.) The BHR is defined as the stock return minus the buy and hold return of the matched size and B/M portfolio over the same interval. 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%.

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 $457 million and a median price per share of $21.75. 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 from the filing date of the periodic report through the subsequent earnings announcement are small positive (negative). The net buying measure around the SEC filing dates is on average positive for small traders (similar to Lee 1992 finding with respect to earnings announcements). In contrast, the large traders seem to be on average net sellers during the SEC filing window.

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

4. *Empirical Results*

4.1 THE ACCRUAL ANOMALYAND POST-EARNINGS ANNOUNCEMENT DRIFT

Collins and Hribar (2000) show that the accruals anomaly and post-earnings announcement drift are distinct and complementary anomalies. Since the time of their study, exact 10-K/Q filing dates have become available and those dates are essential to answering the main research question of this paper. For this reason, we replicate the Collins and Hribar study using actual filing dates rather than approximate dates. Because Livnat and Mendenhall (2006) show that post-earnings announcement drift is larger when using analyst forecast errors to proxy for earnings surprise than when using seasonal random walk (SRW) errors, we also make that change. The results appear in Table A1 and are discussed in the Appendix. The important result for this paper is that, for our sample and methods, we confirm the conclusions of Collins and Hribar (and others) that trading on the accrual signal can produce sizable abnormal returns. These results, therefore, validate the relevance of our primary research question: Who, if anyone, reacts to accrual information?

4.2 INVESTOR RESPONSE TO EARNINGS SURPRISE BY TRADE SIZE

In Table 2 we 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. (Recall that decimalization renders our methods untenable after 1999.) Table 2 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 2 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 2 shows that the smallest traders respond more strongly to SRW forecast errors than to analyst forecast errors and the opposite is observed for the largest traders in the last column. 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 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. In subsequent tests we control for the reaction to the earnings surprise by including the analyst forecast error in the analysis of large trader behavior and the SRW forecast error in the analysis of small trader behavior.

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 3 presents Pearson correlations between accrual levels deciles and the net buy measures as defined in Section 3. Panel A of Table 3 indicates that when we examine all qualifying observations, i.e., when we do not condition on earnings information, the correlation between the 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 about 0.015 and statistically significant both when pooling observations and when considering the average correlation of each calendar quarter. 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. The pooled 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.[11] As discussed in Section 2 above, we can propose a situation in which knowledgeable investors may be more likely to act on accrual information. Short sales constraints combined with a lack of positive abnormal returns for all accrual groups following negative earnings surprises would imply that investors trading on accruals would do so only when the prior earnings surprise is positive.

In Panels B and C of Table 3, we partition the entire sample into whether earnings at least meet the earnings forecast or fall short of it, respectively. Given the results in Table 2, 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. The far right column shows that the correlations between accrual levels and large trader net buying more than double relative to those for the full sample and are significant at better than the 1% (two-sided) level. This result suggests that investors who care about accruals are more likely to act on them when announced earnings meet or beat expectations. Similarly, comparison of Panels B and C illustrates that investors who trade on accruals look to them only when the earnings surprise is non-negative. That is, Panel B shows that when earnings meet or exceed expectations, large traders seem to behave in line with the accrual signal (p-values equal

[11] 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 both significantly negative at better than the 5% (two-sided) level.

to 0.002), whereas small traders behave in a manner that is opposite of the accrual signal (p-values less than or equal to 0.005). In contrast, Panel C shows that, when earnings fall short of expectations, the correlations 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 the failure to respond to the accrual signal in the case of negative earnings below in Section 4.4.[12]

To contrast the trading behavior in greater detail, in Table 4 we take a closer look at the net buying behavior of investors initiating the smallest (less than 500 shares) and the largest (5,000 shares or more) trades by accrual quintile. We examine the cases where the recent earnings surprise was non-negative separately from the cases where it was negative in accordance with the findings in Table 3. Examining the non-negative earnings surprise firms in Panel A we see that for small traders, the positive correlations between buying activity and accruals are borne out in the extreme quintiles. In the lowest quintile the net buying figure is -0.020, statistically significant at the 5% level. On the other end, small traders are significant net buyers for the highest-accrual quintile. On the other hand, for those initiating large trades, there is a significantly greater net buying imbalance for low-accrual stocks (0.025) than for high accrual stocks (-0.044). As expected, given the results in Table 3, we do not see clear patterns in average net buying across accrual quintiles for cases where the earnings surprise was negative (Panel B of Table 4). There the small traders are generally always net buyers while large traders are always net sellers.

How can we interpret these numbers? The -0.044 average abnormal net buying figure for high accrual stocks corresponds to a large trader buy-sell imbalance of -4.4% 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

[12] While even the correlations in Panel B may seem small, the -2.7% F-M correlation is nearly half (48%) as large as the FM correlation of 5.7% between large-trader net buying and analyst earnings forecast error reported in Table 2. (Our 5.7% figure is identical to that reported in Battalio and Mendenhall’s (2005) Table 3.) Further, while prior literature would certainly suggest that earnings announcements are much more salient events than 10-K/Q filing dates, as we report in below in Section 4.7.1, when we examine only Nasdaq firms and use Battalio and Mendenhall’s sample period—where they maintain these techniques should be most effective—the correlation increases in magnitude from -2.7% to -4.7%.

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 50 buys and 55 sells, then the figure in Table 4 would be 0.050 or 5.0%. Table 4 indicates, therefore, that for every 100 large trader transactions that occur in an average three-day period, during the three-day 10-K/Q filing period, sells outnumber buys by between four and five for high accrual stocks and buys outnumber sells a little over two for low accrual stocks.

Table 5 provides results of regression tests of the same phenomenon depicted in Tables 3 and 4. The dependent variables in Table 5 are the net buying measures for small traders (columns I and II) and large traders (columns III and IV). 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. At the 10-K/Q filing date, both small traders and large traders appear to continue to be reacting to measures of previously announced earnings surprise. There is also evidence that small traders react in the *wrong* direction to accruals, while large investors respond correctly to the accrual signal (respectively, coefficient = 0.020, p=0.024 and coefficient = -0.045, p=0.043).

The second (fourth) column presents results after adding the variable POS, which takes on a value of 1 when SUE (SUEAF) is non-negative and a value of 0 when SUE (SUEAF) is negative, and POS multiplied times the accrual-level decile. Now, consistent with Table 3, 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 = 0.042, p = 0.034), than for the pooled regressions (coefficient = 0.033, p = 0.064). In contrast, the significantly negative coefficient on the multiplicative variable, accruals decile rank times POS, in the fourth column of Table 5 (coefficient = -0.112, p = 0.015 for pooled and -0.133, p=0.003 for F-M), shows that large traders respond significantly to the accrual signal, but, again consistent with Table 3, only when the previously announced quarterly earnings meet or exceed analysts' forecast of earnings.

For large traders, the sum of the coefficients on the accruals decile rank variable and the accruals rank times POS variable, give values of 0.084 (0.112 – 0.028) and 0.104 (0.133 – 0.029), in the pooled and Fama-MacBeth results, respectively. These results represent differences in buy-sell imbalances between top and bottom accruals decile firms of 8.4% and 10.4%, relative to the normal transaction level. These values, based on the regression using accrual deciles, are even larger than the 6.9% [2.5% - (-4.4%)] difference in buy-sell imbalance obtained from a direct comparison of the extreme accrual quintile means above.[13]

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, if short sales constraints are binding and negative earnings surprise stocks do not exhibit positive abnormal returns even conditional on accruals, we hypothesized that we would be more likely to find evidence of informed trading for firms whose recent earnings surprises were non-negative. In the following sections we further explore this finding, as well as the surprising evidence that those initiating small trades appear to transact in the *wrong* direction with respect to the accruals signal around 10-K/Q filing dates.

4.4 LARGE TRADER BEHAVIOR FOR NEGATIVE EARNINGS SURPRISE STOCKS

Since we find that the buying activity for large traders appears consistent with a rational response to accrual information only following non-negative earnings surprises, it is natural to ask: Why don't large traders buy (sell) shares upon observing low (high) accruals following a negative earnings surprise?

The following represents one possible answer. 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 and post-earnings announcement drift

[13] Below in Section 4.7.1, we present results suggesting that the findings presented here may significantly understate the amount of immediate accruals-based trading by large invetors.

essentially cancels out the effect of announcing low accruals following a negative earnings surprise, then they may act primarily when the preceding earnings news is favorable. Two conditions sufficient to explain the observed results are, therefore, short sales constraints and a lack of positive returns for negative earnings surprise, low-accrual stocks.

Do institutional investors face short-sales constraints? The vast majority of investors studied at annual and quarterly intervals by Collins et al. (2003), Lev and Nissim (2006), and Ali et al. (2008) are mutual funds and, as Saar (2001) explains, mutual funds assume almost no short positions: "Most mutual funds do not sell short as a matter of policy because it involves the risk of unlimited losses if the stock price goes up, and the charters of many mutual funds explicitly restrict the usage of short sales [see Smith (1985)]. Sharpe (1991) notes that some of this aversion is due to the implicit threat of suit for violation of fiduciary standards. The regulatory environment also discourages short sales. The SEC limits the amount of short sales a mutual fund can undertake [see Investment Company Act Release 7221 (1972)], and there are additional regulatory constraints on short selling (the up-tick rule) and on profit from short selling (the "short-short rule"). The end result is that institutions are looking for stocks to hold and not stocks to sell short." Consistent with Saar's comments, 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 takes place for stocks in general. Is it reasonable to believe that in an unconstrained world, for every 100 investors sufficiently optimistic to hold a stock, only one is pessimistic enough to short it? The comments and results of Sharpe (1991), Saar (2001), and Asquith et al. (2005) indicate that short-sales restrictions are binding for a large fraction of institutional investors. In other words, the first of the two conditions sufficient to explain the large-trader results is likely met for many accruals-based traders.

If accruals-based traders tend to be long-only investors and conditioning on accruals does not lead to positive abnormal returns for any group of negative earnings surprise firms, then accruals-based traders would rationally ignore the accruals signal for these firms. Table 6 once again divides the sample on the basis of the sign of the previously announced earnings surprise. The first row shows that, among firms whose previously announced earnings met or beat analysts' forecasts, the accrual signal is an important discriminator of post-10-K/Q filing-date returns. Since these returns are positive, the accruals signal is very important for long-only investors. The second row shows the results of the same tests for negative surprise firms. Note that, among these firms, no accrual group exhibits statistically or economically significant positive abnormal returns. For long-only investors, the accrual signal is not important for those firms previously experiencing a negative earnings surprise and it is rational for them to ignore it. The second of the two conditions is clearly met. It is worth noting, that these results corroborate those of Richardson (2003) who finds no evidence that short sellers respond to the information in accruals.

Obviously some investors employ long-short strategies, but Asquith et al. (2005) show they represent only a small percentage of total trading. Further, they may break up their trades as in Barclay and Warner (1993). If those long-short traders represent a small fraction of the accruals-based traders and/or break up their trades so that they are spread throughout the other size-categories, it is unlikely that we would detect them. In any event, the data are clear: an economically significant and statistically detectable fraction of large investors act properly on accruals information at the time it is released, they are detectable only following non-negative earnings surprises, and they seem to represent only a small fraction of the overall trading at the time of the 10-K/Q release.

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

The first column of Table 7 replicates the second column of Table 5, which shows the tendency for small traders to trade in the *wrong* direction with respect to accruals, particularly when the earnings surprise was positive (p-value = 0.064 pooled, 0.034 Fama-MacBeth). Given that none of the intermediate trade-size groups seem to respond at all to accruals levels, we find it implausible that small traders are even cognizant of accruals levels, let alone trade on them (even if in the wrong direction). To investigate why small traders appear to 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 exhibit the behavior that Barber and Odean (2008) document for individual investors at three different brokerage firms. They show that individual investors display a tendency to buy stocks that appear in the media, have exhibited large abnormal trading volume, or have exhibited recent, extreme short-term (e.g., one day) returns—whether positive or negative. We hypothesize that the small traders in our sample may be buying stocks that grab their attention rather than stocks that announce high accruals. In the second column of Table 7, we add four variables that we believe should be positively associated with a stock's attention-grabbing potential. Two of Barber and Odean's (2008) variables, absolute returns and trading volume, are readily available and we include them. The first, Abs FD Return, is the decile rank of absolute raw 3 day return around the filing date. The second, Abn Volume decile rank, is the average trading volume in the three days around the FD divided by the average trading volume in the days -40 through -2 before the earnings announcement.

We introduce two additional explanatory variables. The first is the absolute value of abnormal net buys of large traders at the filing date. We include this variable because large investors trade for many reasons including events that could grab the attention of small traders. Since each measure of a stock's tendency to grab the attention of small traders is imperfect, we add this variable in the hope that it might capture some of the attention-grabbing potential missed by the others. Finally, small investors may be drawn to some stocks for reasons that are difficult to capture with standard capital market variables (e.g. hot stocks, stocks in the media, CEO-star stocks, etc.). In other words, some stocks may be more visible or attractive to small traders for reasons that are unobservable to the researcher. A variable that should proxy for these unobservable factors is abnormal small-trader buying at the time of the recent earnings announcement. If small traders purchased the stock at the time of the earnings announcement, it must be the kind of stock that small investors are willing to hold and the type that might be more likely to grab their attention at other points in time. Since earnings announcements are associated with particularly high levels of individual investor market participation (Taylor 2010), they should represent good periods over which to observe whether small traders are predisposed to buy a certain stock. For these reasons, our final explanatory variable is abnormal small-trader buying at the time of the recent earnings announcement. The second column of Table 7 shows results after we add the explanatory variables discussed above. Note that each of the four is very highly significant in the expected direction. These results corroborate those of Barber and Odean (2008) in a very different context and lend empirical support for the two additional proposed variables. More important for this paper, however, is that the coefficient on accruals is reduced by nearly 50% and is not significant at traditional levels for either the pooled or the F-M regression. We conclude the initial indications that small investors trade in the wrong direction in response to accruals levels are spurious and that those results are caused by the tendency of small investors to be drawn to attention-grabbing stocks—as documented by Barber and Odean for individual investors.

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, it is natural to ask whether they affect the magnitude of the accrual anomaly. Column I (III) in Table 8 contains results of regressing the abnormal returns during (following) the three-day filing period on SUEAF decile, accrual decile, a decile score for large trader net buying at the filing date, and the interaction between the large trader net buying and the accruals decile. The coefficient on the net buying variable for the immediate return in the three day window around the filing date is 2.2% and that for the subsequent drift is -3.0% (with p-values of < 0.0001). In other words, large trader net buying around the filing date forces prices up immediately and lowers the subsequent return. The coefficient on the interaction term of scaled decile ranks multiplied by -1 (to represent an increase in the variable as an increase in the correct net buying behavior with respect to accrual signals) is positive but small for the immediate return regression and positive but not significant for the drift regression. On net, the aggregate actions of large traders do not appear to significantly impact 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. From prior results we know that far from 100 percent of large traders react to the accrual signal in an appropriate manner and we want to test whether they affect the magnitude of the immediate response to accruals and the magnitude of the accruals anomaly when they are, in fact, correct. The variable Correct is equal to 1 when the large trader net buying behavior is positive (negative) when the accruals are below (above) the median and 0 elsewhere. The coefficient on Correct is positive for both regressions suggesting that regardless of the accrual signal correct net buying behavior is associated with higher immediate and subsequent returns. The interaction of Correct and the accrual decile rank score is negative and significant for the immediate reaction and positive and significant for the drift. This indicates that for correct large trader buys and sells more reaction to the accrual signal is occurs immediately and less occurs in the future. Specifically, the interaction term for the drift is 0.053, only slightly smaller in magnitude than the coefficient on the accruals of -0.061. From this we hypothesize that if large traders were always correct, the magnitude of the accruals anomaly would be significantly smaller (the sum of the two is less than -1%). The results are similar in the F-M regressions.

While the actions of large traders should reduce the size of the accrual anomaly, the aggregate 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. Some knowledgeable investors may also act on accruals information outside our 10-K/Q filing date window, e.g., over the several days following the filing date.[14] Although our other results clearly demonstrate that there exists a statistically significant subset of investors who initiate large trades and are cognizant of the release and importance of accruals information, this group is too small to have an economically significant impact on prices. Recall that large traders also get no help in moving prices in the correct direction from investors in any other trade-size categories. Conditional on these results, it is not surprising that the accrual anomaly is not traded away. The results clearly show that relatively few investors trade on accruals information. Why this is true remains an open question.

[14] 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.

4.7 ROBUSTNESS CHECKS

4.7.1 Nasdaq pre 1997

Battalio and Mendenhall (2005) argue that their trade typing procedures are more effective for Nasdaq firms prior to 1997. Under the joint hypothesis that Battalio and Mendenhall are correct and our prior tests actually capture large-investor trades in response to accrual information, we should find stronger results for the pre-1997 Nasdaq subsample. We replicate our analyses for this subsample of 6,660 observations. We find that the correlations between large trader net buying and accruals that correspond to those reported in Panels A and B of Table 3 approximately double to -0.020 and -0.047 (significant at 10% and 1%), respectively, while the correlation for negative earnings surprise in Panel C remains insignificant (p-value of 0.349). The pooled regression coefficient for the interaction variable of accruals decile rank and the indicator for non-negative earnings surprise for large traders (fourth column of Table 5) more than doubles to -0.247 and is significant at 1% (similar results hold for the Fama-MacBeth regressions). If Battalio and Mendenhall are correct that their methods are more effective for Nasdaq stocks prior to 1997, the approximate doubling of relevant correlations and coefficients we attain when examining that subsample of observations, suggests that the results in this paper are understated due to the limitations of our methods of categorizing trades by transaction size.

4.7.2 Interim versus Fourth Quarter Results

The fourth quarter differs from interim quarters in two fundamental ways. First, fourth quarter earnings include more *noise* 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. While substantial differences do exist between results obtained when partitioning by interim versus the fourth quarter, care should be taken in interpreting the results due to the relatively small sample sizes used in some of these tests.

The main empirical differences we find between interim quarters and the fourth quarter is that accruals levels are 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 9 shows that the small- and large trader tendencies are maintained for both partitions (we focus on non-negative SUEAF firms since the earlier analysis indicates that we observe most of the reaction to the accruals signal among them). Table 9 also shows that large traders are much less likely to buy low accrual stocks in the fourth quarter than in interim quarters (0.010 versus 0.033). 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 (-0.148 versus -0.021). This is consistent with extreme positive accruals being rarer in the fourth quarter than in interim quarters (e.g., 18% of high accrual observations appear in the fourth quarter versus 35% 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 statistically significant difference in their trading of high and low accrual stocks in the interim quarters. Replicating Table 7 on the subsample of 4^{th} fiscal quarters we observe, as before, that the reaction to accruals signal is subsumed by attention grabbing behavior (not tabulated).

5. Conclusion

Previous research documents the persistence of the accrual anomaly, the negative correlation between firms' accrual levels and subsequent abnormal returns, over several decades. This association suggests that most investors did not fully appreciate the importance of accruals levels for future operating performance (e.g., Sloan 1996). 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. Given that prior research indicates investors who initiate large trades act in a much more sophisticated manner around earnings announcements than those initiating small or medium size trades, we hypothesize that large traders might, on average, react to accruals information at the time of the 10-K/Q filing date, when it first becomes available. We find evidence of this type of behavior for those investors who initiate trades of 5,000 shares or more, but only when the prior earnings forecast error is non-negative. One simple set of conditions sufficient to explain this result is short sales restrictions combined with a lack of positive abnormal returns following negative earnings surprises independent of accrual level. We show that the latter condition is met and that the former condition is plausible for at least a significant portion of institutional investors.

Initially, we obtained results suggesting that investors who initiate the smallest trades, those less than 500 shares, respond in the opposite direction to the accrual information. Follow up tests strongly suggest that, consistent with Barber and Odean (2008), these investors are attracted to "attention grabbing" stocks and are not acting in response to accruals.

We believe this paper represents the first direct evidence that any subset of investors responds to the information in accrual information when it first becomes available. Prior tests rely on differences in share holdings measured at least 13 weeks apart, which, we argue, cannot isolate the effects of accruals levels from the other potential explanations. 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.

Finally, although when large traders act correctly, they tend to reduce the accrual anomaly, we do not find evidence that their behavior in aggregate has a significant effect. The limited extent to which large traders act on accruals combined with the fact that less sophisticated traders do not respond at all, contributes to the puzzling persistence of the accrual anomaly.

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Table 1
Summary Statistics

	N	Mean	Std. Dev.	25th Perc.	Median	75th Perc.
Components of Earnings						
SUE (Compustat)	27,807	-0.380	6.088	-0.678	0.020	0.729
SUEAF (I/B/E/S)	27,808	-0.007	0.545	0.000	0.000	0.001
Accruals	27,808	-0.010	0.055	-0.028	-0.009	0.009
Buy and Hold Returns (%)						
FD_t to ERD_{t+1}	27,808	0.239	25.255	-10.415	-0.739	8.709
Net Buying Imbalance						
Small Traders at FD	27,808	0.012	0.464	-0.192	0.000	0.192
Large Traders at FD	26,768	-0.018	1.131	-0.313	0.000	0.322
Firm Characteristics						
MV $Equity_{t-1}$	27,808	3,051	11,706	152	457	1,583
BV $Equity_{t-1}$	27,808	870	2,586	58	169	566
Stock Price	27,808	26.74	22.82	12.13	21.75	35.19

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 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
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	**0.028**	**0.022**	**0.013**	**0.045**	**0.047**	**0.055**
SUE decile rank	**0.037**	**0.019**	**0.018**	**0.034**	**0.025**	**0.027**
F-M Correlations						
SUEAF decile rank	**0.029**	**0.025**	**0.014**	**0.049**	**0.047**	**0.057**
SUE decile rank	**0.037**	**0.021**	**0.019**	**0.035**	**0.024**	**0.031**

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						
Intercept	**0.073**	**0.108**	0.008	**0.103**	**0.017**	0.005
SUEAF decile rank	**0.028**	**0.064**	0.031	**0.141**	**0.105**	**0.241**
SUE decile rank	**0.052**	**0.049**	**0.040**	**0.077**	0.024	0.055
F-M						
Intercept	**0.073**	**0.115**	0.008	**0.099**	**0.020**	0.010
SUEAF decile rank	0.026	**0.068**	0.025	**0.144**	**0.113**	**0.237**
SUE decile rank	**0.049**	0.038	**0.041**	**0.067**	0.019	0.070

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 the earnings announcement 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 3
Accruals and Net Buying Behavior at SEC Filing Date

Panel A. All data (average number of observations per bin is 27,586).

	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	0.015	-0.003	0.001	-0.002	-0.003	-0.011
p-value	*0.013*	*0.655*	*0.843*	*0.693*	*0.673*	*0.063*
F-M Correlations						
Accruals decile rank	0.014	-0.008	0.001	-0.005	-0.008	-0.013
p-value	*0.004*	*0.272*	*0.780*	*0.427*	*0.300*	*0.107*

Panel B. 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 14,171 for NetBuy 1-3 and 17,760 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	0.024	0.007	0.003	-0.010	-0.004	-0.024
p-value	*0.005*	*0.407*	*0.735*	*0.188*	*0.607*	*0.002*
F-M Correlations						
Accruals decile rank	0.029	0.004	0.007	-0.007	-0.005	-0.027
p-value	*0.000*	*0.635*	*0.304*	*0.375*	*0.588*	*0.002*

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 13,566 for NetBuy 1-3 and 9,675 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	0.003	-0.013	-0.001	0.011	0.001	0.008
p-value	*0.728*	*0.131*	*0.944*	*0.292*	*0.939*	*0.421*
F-M Correlations						
Accruals decile rank	-0.002	-0.021	-0.003	0.002	-0.005	0.006
p-value	*0.861*	*0.013*	*0.743*	*0.839*	*0.701*	*0.600*

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. 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 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 represent the average quarterly correlation coefficients estimated following Fama and MacBeth (1973).

Table 4
Accruals and Net Buying Behavior at SEC Filing Date

Panel A. SUEAF≥0.

	Accruals Quintile					
	1 (lowest)	2	3	4	5 (highest)	*t-test (1 vs 5)*
<500 (NetBuy 1)	-0.020	0.012	0.007	0.016	0.021	*0.001*
p-value	*0.021*	*0.094*	*0.313*	*0.016*	*0.012*	
≥5,000 (NetBuy 6)	0.025	0.015	0.008	-0.024	-0.044	*0.018*
p-value	*0.246*	*0.401*	*0.695*	*0.162*	*0.028*	
t-test (NB1 vs NB6)	*0.050*	*0.871*	*0.967*	*0.028*	*0.002*	

Panel B. SUEAF<0.

	Accruals Quintile					
	1 (lowest)	2	3	4	5 (highest)	*t-test (1 vs 5)*
<500 (NetBuy 1)	0.027	0.006	0.023	0.021	0.019	*0.617*
p-value	*0.011*	*0.580*	*0.062*	*0.043*	*0.104*	
≥5,000 (NetBuy 6)	-0.052	-0.057	-0.034	-0.045	-0.024	*0.462*
p-value	*0.049*	*0.041*	*0.170*	*0.066*	*0.377*	
t-test (NB1 vs NB6)	*0.005*	*0.032*	*0.037*	*0.012*	*0.139*	

Notes: 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. 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 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.

Table 5
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	-0.018	-0.017
	<.0001	*0.461*	*0.008*	*0.332*
SUE decile rank	0.019	0.001		
	0.033	*0.957*		
SUEAF decile rank			0.076	0.074
			0.001	*0.047*
Accruals decile rank	0.020	0.004	-0.045	0.028
	0.024	*0.743*	*0.043*	*0.459*
POS		0.014		-0.001
		0.215		*0.968*
Accruals decile rank*POS		0.033		-0.112
		0.064		*0.015*
N	27,808	27,808	26,768	26,768
R2	0.03%	0.04%	0.05%	0.06%

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	-0.017	-0.012
	0.122	*0.980*	*0.134*	*0.644*
SUE decile rank	0.021	0.000		
	0.017	*0.988*		
SUEAF decile rank			0.079	0.082
			0.005	*0.055*
Accruals decile rank	0.021	0.001	-0.051	0.029
	0.006	*0.907*	*0.090*	*0.472*
POS		0.016		-0.005
		0.083		*0.881*
Accruals decile rank*POS		0.042		-0.133
		0.034		*0.003*

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 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. P-values are italicized and shown beneath the coefficients.

Table 6

Buy and Hold Abnormal Returns

	Accruals Quintile					
	1 (lowest)	2	3	4	5 (highest)	*t-test (1 vs 5)*
Firms whose Earnings Meet or Beat Analysts' Forecasts						
BHR: FD_t to ERD_{t+1}	0.033	0.013	0.017	0.004	0.002	*<.0001*
p-value	*<.0001*	*<.0001*	*<.0001*	*0.336*	*0.582*	
Firms whose Earnings Fall Short of Analysts' Forecasts						
BHR: FD_t to ERD_{t+1}	0.005	-0.020	-0.018	-0.021	-0.036	*0.000*
p-value	*0.585*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	

Notes: Analysts' forecasts are calculated from the *I/B/E/S* database as 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. The BHR is defined as the stock return minus the buy and hold return of the matched size and B/M portfolio over the same interval. FD_t is the filing date of the firm's 10-K or 10-Q. ERD_{t+1} is one day after the following quarter's earnings announcement.

Table 7
Small Trader Reaction

Panel A. Pooled Regression.

	NetBuy 1 at FD I	NetBuy 1 at FD II
Intercept	0.005	0.005
	0.461	*0.407*
SUE decile rank	0.001	-0.016
	0.957	*0.330*
Accruals decile rank	0.004	0.004
	0.743	*0.747*
POS	0.014	0.012
	0.215	*0.252*
Accruals decile rank*POS	0.033	0.017
	0.064	*0.323*
Abs FD Return decile rank		0.043
		<.0001
Abn Volume decile rank		0.109
		<.0001
Abs NetBuy6 at FD decile rank		0.035
		<.0001
NetBuy1 at ERD decile rank		0.338
		<.0001
N	27,808	26,677
R2	0.04%	6.39%

Panel B. Fama-MacBeth Regression.

	NetBuy 1 at FD I	NetBuy 1 at FD II
Intercept	0.000	0.002
	0.980	*0.803*
SUE decile rank	0.000	-0.011
	0.988	*0.427*
Accruals decile rank	0.001	-0.001
	0.907	*0.954*
POS	0.016	0.013
	0.083	*0.140*
Accruals decile rank*POS	0.042	0.027
	0.034	*0.164*
Abs FD Return decile rank		0.044
		0.002
Abn Volume decile rank		0.104
		<.0001
Abs NetBuy6 at FD decile rank		0.031
		0.018
NetBuy1 at ERD decile rank		0.346
		<.0001

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. 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 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 is greater than or equal to zero and is equal to zero otherwise. Abs FD Return is the absolute value of the raw return of the stock in the three day window around the filing date. Abn Volume is the average trading volume in the three days around the filing date divided by the average trading volume in days -40 through -2 before the earnings announcement minus 1. Abs NetBuy 6 is the absolute value of NetBuy 6 at the filing date. Decile rank is the decile rank of the variable scaled to fall between -0.5 and 0.5. For the interaction variables the decile ranks of the multiplied variables are from 1to 10 (not scaled). P-values are italicized and shown beneath the coefficients.

Table 8
Mitigation of the Anomaly by Large Trader Trading

Panel A. Pooled Regression.

	Abn 3 day Return at FD(t)		Drift: FD(t) to ERD(t+1)	
	I	II	III	IV
Intercept	0.000	-0.001	0.003	-0.001
	0.773	*0.172*	*0.099*	*0.579*
SUEAF decile rank	0.001	0.001	0.051	0.050
	0.438	*0.307*	*<.0001*	*<.0001*
Accruals decile rank	-0.001	0.016	-0.036	-0.061
	0.531	*<.0001*	*<.0001*	*<.0001*
NetBuy6 decile rank	0.022		-0.030	
	<.0001		*<.0001*	
NetBuy6 d.r.*Accruals d.r.	0.008		0.012	
	0.008		*0.437*	
Correct		0.002		0.008
		0.013		*0.016*
Correct*Accruals d.r.		-0.033		0.053
		<.0001		*<.0001*
N	26,678	26,450	26,768	26,541
R2	1.92%	1.09%	0.69%	0.65%

Panel B. Fama-MacBeth Regression.

	Abn 3 day Return at FD(t)		Drift: FD(t) to ERD(t+1)	
	I	II	III	IV
Intercept	0.000	-0.001	0.004	0.000
	0.611	*0.114*	*0.409*	*0.937*
SUEAF decile rank	0.001	0.001	0.050	0.050
	0.384	*0.301*	*<.0001*	*<.0001*
Accruals decile rank	-0.001	0.017	-0.036	-0.064
	0.320	*<.0001*	*<.0001*	*<.0001*
NetBuy6 decile rank	0.022		-0.027	
	<.0001		*<.0001*	
NetBuy6 d.r.*Accruals d.r.	0.009		0.011	
	0.036		*0.422*	
Correct		0.002		0.008
		0.036		*0.066*
Correct*Accruals d.r.		-0.036		0.056
		<.0001		*<.0001*

Notes: 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. 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 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. BHR is the buy and hold return on a stock minus the average return on a matched size-B/M portfolio. Decile rank is the decile rank of the variable scaled to fall between -0.5 and 0.5. The interaction variable is the multiplication of these adjusted scaled deciles ranks and is further multiplied by -1 for ease of interpretation. Correct is equal to 1 when the large trader net buying behavior is positive (negative) when the accruals are below (above) the median and 0 elsewhere.

Table 9

Extreme Accruals and Net Buying Behavior at Interim and 4th Quarter SEC Filing Dates for Firms Meeting or Beating Analyst Estimates (SUEAF $\geq$ 0)

	Interim Quarters			Fiscal 4th Quarter		
	Accrual Decile			Accrual Decile		
	Lowest	Highest	*t-test*	Lowest	Highest	*t-test*
Accruals	-0.066	0.053	*<.0001*	-0.085	0.053	*<.0001*
p-value	*<.0001*	*<.0001*		*<.0001*	*<.0001*	
N	2,055	2,918		1,123	647	
< 500 shares (NetBuy 1)	0.000	0.017	*0.235*	-0.057	0.039	*0.0002*
p-value	*0.975*	*0.048*		*<.0001*	*0.117*	
N	2,055	2,918		1,123	647	
$\geq$ 5,000 shares (NetBuy 6)	0.033	-0.021	*0.086*	0.010	-0.148	*0.028*
p-value	*0.186*	*0.281*		*0.805*	*0.022*	
N	1,989	2,805		1,084	614	

Notes: 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.

Appendix

We test the conclusions of Collins and Hribar (2000), that the accruals anomaly and post-earnings announcement drift are complementary, for our sample and methods. Table A1 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 A1 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%. This is included for comparison with the next two proposed strategies. The third row of Table A1 confirms the existence of the accruals anomaly for our sample. The hedge return is 2.586% for a period of roughly nine weeks. Applying this strategy for four quarters would result in annual returns similar to those reported by Sloan (1996).

The fourth row of Table A1 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. The hedge return of this strategy is 6.778%, which is significantly greater than either the earnings or the accrual hedge portfolios alone. 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.[15]

In untabulated results, we replicate the tests of Table A1 for the period 1993 to 1999, the period for which we can infer whether trades are buyer- or seller-initiated. The important aspects of the results from Table A1 are maintained; both the accrual anomaly and post-earnings announcement drift exist after controlling for the other. Additional robustness checks imposing restrictive minimum values for share price, size, and trading activity confirm the reported results. Knowledgeable investors have reason to trade on accruals information at the time the 10-K/Q is released.

[15] 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.

Table A1

Hedge Portfolio Average Quarterly Returns:
4th Quarter 1993 to 2nd Quarter 2009

Trading Strategy	Buy and Hold Return			Difference versus Combined
	Short	Long	Hedge	
Earnings-Based: ERD_t to ERD_{t+1}				
BHR (%)	**1.882**	**1.143**	**3.025**	
N	309	310		
p-value	0.004	0.037	<0.0001	
Earnings-Based: FD_t to ERD_{t+1}				
BHR (%)	**1.095**	0.069	**1.784**	**4.504**
N	309	310		
p-value	0.037	0.124	<0.0001	<0.0001
Accruals-Based: FD_t to ERD_{t+1}				
BHR (%)	**1.811**	**1.353**	**3.164**	**3.124**
N	310	309		
p-value	0.001	0.002	<0.0001	<0.0001
Combined: FD_t to ERD_{t+1}				
BHR (%)	**3.302**	**2.986**	**6.288**	
N	57	63		
p-value	<0.0001	0.006	<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. 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. N is the average number of observations per quarter. Entries in boldface are statistically different from zero at the 5% level or better.