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The Role of Analysts' Cash Flow Forecasts in the Decline of the Accruals Anomaly

by

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Abstract:

The accrual anomaly, demonstrated by Sloan (1996), generated significant excess returns to a strategy long in firms with low accruals and short in firms with high accruals consistently for over four decades until 2002. Since then, the accruals anomaly has apparently disappeared. In this paper, I argue that one factor responsible for the decline in returns to accruals based strategies is the increasing incidence of cash flow forecasts from analysts. I argue that as the markets get more information about likely future accruals, they are less likely to misprice them. Consistent with this, I find that the negative relationship between accruals and future returns is significantly weaker in the presence of cash flow forecasts. Further, the mitigating effect of cash flow forecasts on the relationship between accruals and future returns is greater when cash flow forecasts have more information relative to earnings forecasts and when cash flow forecasts are accurate. The explanation is incremental to alternative explanations based on the improved quality of accruals in recent times and greater interest in accruals strategies by hedge funds. The results highlight the potentially critical role that analysts' cash flow forecasts play in the valuation of stocks.

1. Introduction

The accruals anomaly, documented by Sloan (1996), has been among the most actively scrutinized topics in accounting research over the past decade. Sloan (1996) shows that a strategy long in firms with the most negative accruals and short in firms with the most positive accruals consistently generates economically significant hedge returns. Sloan attributes the returns to misperception regarding the persistence of the cash flow component and the accrual component of earnings. Specifically, the market systematically over-estimates the persistence of accruals which have a tendency to reverse and under-estimates the persistence of cash flows.

The idea that one can create trading rules on something as basic as the difference between earnings and cash flows is quite damning to the notion of efficient markets. Not surprisingly, the research examining the accruals anomaly is divided on whether the anomaly is real or illusory. Khan (2008) argues that the misspecification of risk drives the apparent anomaly and that the anomaly disappears in a well specified inter-temporal CAPM model. On the other hand, Hirshleifer, Hou and Teoh (2006) show, in cross-sectional and time series asset pricing tests, that the accrual characteristic rather than an accrual factor predicts returns, consistent with a behavioral explanation for the accrual anomaly. Desai, Rajgopal and Venkatachalam (2004) argue that the accruals anomaly is not an independent effect but the value-glamour stock phenomenon in disguise.

Prior research has also questioned why the accrual anomaly persisted for years after the publication of Sloan (1996), who showed that the accruals strategy returned an average hedge return of 10.4% that was positive in 28 out of the 30 years between 1962 and 1991. Lev and Nissim (2006) and Mashruwalla, Shevlin and Rajgopal (2006) both show that the phenomenon continued to be robust until 2001. Mashruwalla, Rajgopal and Shevlin (2006) argue that transaction costs and the level of idiosyncratic risk reduce the attractiveness the accruals strategy to potential arbitrageurs. Lev and Nissim (2006) argue that the small size and illiquidity of firms in extreme accrual deciles precludes many institutional investors from investing in these stocks

Against this backdrop, it is quite surprising to observe that an effect as robust as the accrual anomaly appeared to be has apparently disappeared in the period since 2002 (Figure 1). In this paper, I argue that the increasing incidence of cash flow forecasts by analysts has contributed to the decline in the accruals anomaly. If the accrual anomaly is driven by the mispricing of accruals, then better information about expected future accruals should weaken such mispricing. When analysts forecast cash flows in addition to earnings, they implicitly forecast accruals. If they correct for expected reversals in accruals in their forecasts, then this should mitigate the mispricing of accruals.

Traditionally, analysts have focused their attention on the prediction of earnings, (specifically EPS). Recently, analysts have also started to issue forecasts of cash flow per share (CPS). The incidence of cash flow forecasts was extremely rare until 2001, when barely 10% of all firms had cash flow forecasts. This proportion has increased dramatically since 2002, to the point that by 2007, almost 45% of all firms have cash flow forecasts in 2007 and 53% of analysts who issue any kind of forecast issue cash flow forecasts (1281 out of 2412, Table 2). Further, 93% of firms had at least one other firm in the same industry (3 digit SIC code) with a cash flow forecast, indicating the increased availability of peer firm accrual information even for firms without cash flow forecasts.

The increased availability of cash flow forecasts has lead to their scrutiny by academic research. DeFond and Hung (2003) show that firms with cash flow forecasts have larger accruals, higher earnings volatility, greater capital intensity, poorer financial health and greater accounting choice heterogeneity relative to their industry peers. Givoly, Hayn and Lehavy (2009) however, caution that cash flow forecast are often mere mechanical adjustments to earnings forecasts and tend to be unreliable. Countering this, Call, Chen and Tong (2009) note that the role of cash flow forecasts is to assist in the forecasting of earnings and indeed find that earnings forecasts are more likely to be accurate when accompanied by cash flow forecasts. I draw on the research on cash flow forecast to develop my hypotheses.

I first hypothesize that the mispricing of accruals should be less prevalent in firms which have a cash flow forecast. Supporting this, I find that the negative relationship between accruals and future returns is significantly weaker for firms with cash flow forecasts. I next hypothesize that the mitigating effect of cash flow forecasts should be stronger for firms where the cash flow forecasts contain more information relative to earnings forecasts. Consistent with this, I find that the mispricing is less severe when the cash flow forecasts have more information in them relative to earnings forecasts. Finally, I hypothesize and find that the mitigating effect of cash flow forecasts should be strongest when cash flow forecast are more accurate. These results are consistent with cash flow forecasts making it less likely that accruals get mispriced.

There are other potential explanations for the decline in the accruals anomaly. Bhojraj, Sengupta and Zhang (2009) suggest that the passage of SOX in 2002 and FAS 146 related to restructurings in 2003 improved the quality of accruals information, which led to reduced mispricing. I find that the quality of accruals has improved since 2002 as the accrual component of earnings appears to have become more persistent. However, the increase in the persistence of accruals is associated with the incidence of cash flow forecasts. Further, the results are robust to the exclusion of firms with restructuring charges.

Green, Hand and Soliman (2009) on the other hand suggest that the decline in returns to accruals based strategies is driven by greater investments by large quantitative hedge funds advised by senior accounting academics. They link increased trading turnover in extreme accrual stocks to the level of assets managed by hedge funds. However, the increase in turnover is not unique to firms with extreme accruals. Further, the increase in turnover appears to be driven by a large number of small trades, inconsistent with greater investment by large institutions. Finally, the association between increased turnover and assets managed by hedge funds disappears after controlling for the extent of cash flow forecasts.

The results in this paper hence support a behavioral explanation for the existence of the accrual anomaly in the first place. As investors have access to better information about expected cash flows, and by inference, accruals, they are less likely to make incorrect inferences about the differential persistence of the cash flow component of earnings and the accrual component of earnings. This also highlights the critical role that financial analysts play in capital markets.

There are some caveats which are essential to mention. Firstly, the period where the accrual anomaly has presumably disappeared is short. Reappearance of returns to an accruals strategy would negate the explanation offered, especially if cash flow forecasts continue to be available. Second, even if the accrual anomaly did indeed disappear, it was probably the result of many simultaneous changes in the information environment of the capital markets. This paper suggests that one such change was the information provided by cash flow forecasts.

The rest of the paper is organized as follows. Section 2 draws on related research on the accruals anomaly and cash flow forecasts to develop hypotheses. Section 3 describes the data and presents preliminary evidence confirming the decline in the accrual anomaly. Section 4 presents the empirical results testing the hypotheses. Section 5 considers alternative explanations for the decline in the accrual anomaly. Section 6 concludes.

2. *Related Research and Hypothesis Development*

2.1 RELATED RESEARCH

2.1.1 The Accruals Anomaly

The accrual anomaly was first outlined in Sloan (1996) who argued that investors are unable to distinguish between the cash component of earning which is more persistent and the accrual component of earnings which has a greater tendency on reverse. Hence, investors are systematically positively surprised by the future earnings of firms with negative accruals and negatively surprised by the future earnings of firms with positive accruals. Sloan (1996) shows that an investment strategy that goes long in the lowest accrual firms and short in the highest accrual firms generates excess returns that are economically significant and persistent across time. The basic result in Sloan (1996) has been refined by many papers that have used more sophisticated and decomposed definitions of accruals. For instance, Richardson et al (2006) show that the mispricing of accruals is greater for accruals that are less reliable (such as non-current accruals) and lesser for accruals that are more reliable (such as change in working capital and financing accruals).

There is vast and largely unsettled literature examining whether the accrual anomaly is indeed an anomaly or whether it represents the returns to omitted risk factors. Khan (2008) argues that the returns to the accrual anomaly disappear in a well specified intertemporal CAPM model. Hirshleifer, Hou and Teoh (2006) however argue that the accrual anomaly results from mispricing as asset pricing tests indicate that the accrual characteristic is associated with the excess returns as opposed to any accrual based factor. Desai, Rajgopal and Venkatachalam (2004) do not address the issue of whether the accrual anomaly is caused by risk or mispricing, but rather focus on whether the accrual anomaly is an independent effect. They conclude that the accrual anomaly is a manifestation of the value/glamour or book-to-market effect demonstrated in Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994).

Prior research has also examined how a trading rule with returns as high as the accrual anomaly appeared to generate persisted for as long as it did after the publication of Sloan (1996). Lev and Nissim (2006) examine the characteristics of firms in the extreme deciles of the accrual distribution. They find that these firms are likely to be very small, have low profitability and high levels of risk. They argue that institutional investors shy away from investing in such stocks. Further, they argue that individual investors face too high information processing as well as transaction costs to profit from an accruals-based strategy. Lev and Nissim (2006) conclude that "the accruals anomaly persists and will probably endure." Mashruwalla, Rajgopal and Shevlin (2006) show that the accrual anomaly is concentrated in firms with high idiosyncratic volatility, low price and low-volume stocks making it risky and expensive for risk-averse arbitrageurs to take positions in stocks with extreme accruals.

Prior research has also examined whether sophisticated intermediaries were able to understand the accrual anomaly. Bradshaw, Richardson and Sloan (2001) test whether analysts are able to factor in the differential time series properties of the cash flow component and accrual component of earnings. They find that analysts' forecasts do not incorporate the expected decline in earnings associated with high accruals, i.e. analysts are also subject to the accrual anomaly.

2.1.2 Cash Flow Forecasts

The issuance of cash flow forecasts by analysts is a rlatively recent phenomenon with cash flow forecasts first appearing in the I/B/E/S database in 1993. Call, Chen and Tong (2009) document that the proportion of U.S. firms in the I/B/E/S database with at least one cash flow forecast issued by analysts increased from 4% in 1993 to 54% in 2005. Further, the emergence of cash flow forecasts has improved the information environment for the underlying firms. DeFond and Hung (2003) show that firms for whom analysts issue both cash flow and earnings forecasts have larger accruals, higher earnings volatility, greater capital intensity, poorer financial health and greater accounting choice heterogeneity relative to their industry peers. These factors increase the potential utility of having cash flow forecasts in addition to earnings forecasts.

Defond and Hung (2003) analyze the textual contents of analysts' reports that contain cash flow forecasts and conclude that these forecasts are not merely mechanical adjustments of earnings forecasts for items such as interest, tax and depreciation, but involve sophisticated models to predict accruals such as working capital and deferred taxes. Givoly, Hayn and Lehavy (2009) however conclude that cash flow forecasts are less accurate and of lower quality that earnings forecasts. However, they do not test whether the provision of cash flow forecasts improves the quality of earnings forecasts provided by analysts, something that Call, Chen and Tong (2009) document.

The research on cash flow forecasts also provides evidence on the underlying mechanism for the accrual anomaly as described by Sloan (1996). Both Defond and Hung (2003) and Call (2008) show that investors place a greater weight on the cash flow component of earnings and a lesser weight on the accrual component of earnings for firms with cash flow forecasts.

Finally, Levi (2007) finds that the accruals are more likely to be fully impounded in prices when firms disclose accrual information in their preliminary earnings announcements. This suggests that when investor demand for accrual information is met through additional disclosure, the mispricing associated with accruals is mitigated. This suggests that analysts' cash flow forecasts may play a similar role.

2.2 HYPOTHESIS DEVELOPMENT

2.2.1 The Accruals Anomaly and the Incidence of Cash Flow Forecasts

The prior research on cash flow forecasts indicates that the presence of cash flow forecasts improves the accuracy of analysts' forecasts and makes it less likely that investors overweight the accrual component and underweight the cash component of earnings. Prior research has shown a negative relationship between accruals and future returns. I hypothesize that the incidence of cash flow forecasts will reduce the accrual anomaly by weakening this negative relationship. Stated formally,

> H1: The relationship between the accrual component of earnings and future returns will be less negative for firms with cash flow forecasts.

2.2.2 The Accruals Anomaly and the Incremental Information in Cash Flow Forecasts

The impact of analysts' cash flow forecasts on the reduction of the accruals anomaly is likely to be greater when there is more information in the cash flow forecast relative to the earnings forecast. If analysts are merely making adjustments for routine items such as interest, depreciation and amortization, then the information is less likely to impact the mispricing of accruals. On the other hand, if analysts' cash flow forecasts have information that is sufficiently different from earnings forecasts, then such information is more likely to be useful in the appropriate pricing of accruals. I hypothesize that the accrual anomaly will be weaker for firms where the information in cash flow forecasts relative to earnings forecasts is greater. Stated formally,

> H2: The relationship between the accrual component of earnings and future returns will be less negative for firms with more informative cash flow forecasts.

2.2.3 The Accruals Anomaly and the Accuracy of Cash Flow Forecasts

The ability of cash flow forecasts to lessen the accrual anomaly will of course depend on the accuracy of the cash flow forecasts. When cash flow forecasts are more accurate, then investors are less likely to face any accrual related surprises as any reversals have potentially been incorporated in the forecasts. I hence hypothesize a weakening of the accrual anomaly in the presence of more accurate cash flow forecasts. Stated formally,

H3: The relationship between the accrual component of earnings and future returns will be less negative for firms with more accurate cash flow forecasts.

3. Preliminary Evidence on the Decline in the Accruals Anomaly

3.1 DATA SOURCES AND DEFINITIONS OF ACCRUALS VARIABLES

I collect financial information from COMPUSTAT, stock return information from CRSP and information about cash flow forecasts and earnings forecasts from IBES. All firms for which financial information and stock returns are available are used in the analysis, with the exception of financial services firms (SIC Code between 6000 and 6999). The time period analyzed starts in 1993, the year in which cash flow forecasts appeared for the first time, and ends in 2007, to ensure that stock returns for the next fiscal year can be calculated. The full sample analyzed consists of 63,843 firm-years corresponding to 9360 distinct firms.

To determine whether a firm had cash flow forecast anytime in a given fiscal year, I search for forecasts of one-year-ahead cash flow per share (CPS). I focus on annual cash flow forecasts for two reasons. Firstly, annual cash flow forecasts are much more prevalent, especially in the early part of the sample. Secondly, all the analysis in this paper is at the annual level.

Consistent with Richardson et al (2005), I use the following definitions for the measurement of accruals. Total accruals, TACC, is defined as below.

TACC = ΔWC+ΔNCO+ΔFIN where:

(i) ΔWC, the change in net working capital is defined as WC_t - WC_{t-1}. WC is calculated as Current Operating Assets (COA) - Current Operating Liabilities (COL), and COA = Current Assets (Compustat #4) - Cash and Short Term Investments (STI) (Compustat #1), and COL = Current Liabilities (Compustat #5) - Debt in Current Liabilities (Compustat #34).

(ii) ΔNCO, the change in net non-current operating assets is defined as NCO_t – NCO_{t-1}. NCO is calculated as Non-Current Operating Assets (NCOA) - Non-Current Operating Liabilities (NCOL), and NCOA = Total Assets (Compustat #6) - Current Assets (Compustat #4) - Investments and Advances (Compustat #32), and NCOL = Total Liabilities (Compustat #181) - Current Liabilities (Compustat #5) - Long-Term Debt (Compustat #9).

(iii) ΔFIN, the change in net financial assets is defined as FIN_t – FIN_{t-1} and FIN = Financial Assets (FINA) - Financial Liabilities (FINL). FINA = Short Term Investments (STI) (Compustat #193) + Long Term Investments (LTI) (Compustat #32), and FINL = Long Term Debt (Compustat #9) + Debt in Current Liabilities (Compustat #34) + Preferred Stock (Compustat #130).

Consistent with prior research, each component of earnings is deflated by average total assets. In addition, I define return on assets (ROA) as operating income after depreciation (Compustat #178) deflated by average total assets. Consistent with Richardson et al (2005), each component of earnings is winsorized at +1 and -1. to reduce the influence of outliers.

In the analysis to follow, I use two measures of accruals. First, I use the total accrual measure (TACC) as used in Sloan (1996). Second, I break down TACC into two components - change in net operating assets (ΔNOA) and change on financial assets (ΔFIN). Note that the change in net operating assets (ΔNOA) is the sum of the change in net working capital (ΔWC) and the change in net non-current operating assets (ΔNCO).

Firm level returns are computed as the buy-and-hold returns for the 12 month period starting four months after fiscal year end to ensure that the most recent financials have been released. The returns are size-adjusted by subtracting the returns in the same period for the same capitalization decile as the firm, as available on CRSP. Firm delistings are adjusted for using the methodology suggested by Shumway (1997) [1].

3.2 DESCRIPTIVE STATISTICS AND CORRELATIONS

Table 1 presents the sample descriptive statistics and correlations. Panel A of Table 1 presents the sample descriptive statistics. The mean ROA for the sample is close to zero, while the median ROA is 6.5%. The mean of total accruals (TACC 0.078) equals the mean change in net operating assets (ΔNOA 0.078) plus the mean change in financial assets (ΔFIN -0.011). The mean size-adjusted one-year-ahead return is -1.2%. CFF has a mean of 0.145, indicating that 14.5% of all firm-year have a cash flow forecast. The sample firms had mean total assets of \$1457 million and mean market capitalization of \$1837 million.

Panel B presents the correlation matrix. Consistent with Sloan (1996), total accruals (TACC) is negatively correlated with future returns ($RETS_{t+1}$). Further, consistent with Richardson et al (2005), the correlation of ΔNOA with future returns is more negative. Finally, the indicator variable CFF is positively correlated with profitability (ROA), firm size (ASST and MCAP) and stock return performance ($RETS_{t+1}$). In tests that follow, I attempt to control for

[1] Shumway (1997) suggests using the CRSP delisting return where available. If not available, he uses -30% if the delisting is for performance reasons and 0 otherwise.

sampling bias by running tests within the subsample of firms that have at least one cash flow forecast over the time period.

3.3 PRELIMINARY EVIDENCE ON CASH FLOW FORECASTS AND THE ACCRUAL ANOMALY

Table 2 presents evidence on the increasing incidence of cash flow forecasts over time. In 1993, only 26 firms out of 4231 had cash flow forecasts, while over 2000 firms had EPS forecasts. The number of cash flow forecasts increases gradually upto and exponentially since then. In 2001, only 297 firms had cash flow forecasts, representing only 7% of all firms and 13% of firms with analyst following (i.e. EPS forecasts). By 2002, this number had risen to 1011 firms, which represents 26% of all firms and 45% of followed firms. In the years that followed, the proportion of firms with cash flow forecasts has risen to more than 40% of all firms. Moreover, over half the firms that have EPS forecasts also have CPS forecasts.

Table 2 also presents the returns to the accruals trading strategy. In each year, firms are sorted into quintiles based on either total accruals (TACC) or change in net operating assets (ΔNOA). The hedge returns are the difference in the average size-adjusted returns for the firms in the lowest accrual quintile (long) and firms in the highest accrual quintile (short). As the results indicate, the hedge returns are consistently positive until 2002. Further, consistent with Richardson et al (2005), the returns to the strategy based on ΔNOA are generally greater. Strikingly, the returns to the accruals trading strategy have essentially disappeared since 2003.

Figure 1 graphically presents the increasing incidence of cash flow forecasts and the decline in the accrual anomaly. As the cash flow forecasts have become more prominent since 2002, the accrual anomaly has dissipated. In the analysis to follow, I test whether there is an association between the increase in cash flow forecasts and the decline in the accrual anomaly.

4. Results

4.1 THE WEAKENING OF THE ACCRUALS ANOMALY OVER TIME

I first analyze whether the accrual anomaly is getting weaker over time. Consistent with Richardson et al (2005), I run the following regressions

$$RETS_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \varepsilon \quad (1)$$

and

$$RETS_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \varepsilon \quad (2)$$

where $RETS_{t+1}$ is the one-year-ahead size adjusted return, ROA_t is return on assets and $TACC_t$ is total accruals, ΔNOA is change in net operating assets and ΔFIN is change in financial assets (see section 3.2 for detailed descriptions). If the accrual anomaly is indeed present in the time period, I expect the coefficient β_2 on TACC in model (1) and the coefficient δ_2 on ΔNOA in model (2) to be significantly negative.

I run the specification both as pooled regressions as well as annual Fama and MacBeth (1973) regressions. The t-statistics for the pooled regressions control for clustering by firm. The annual regressions correct for auto-correlation in the coefficients across time, using the correction in Bernard (1995). The results are presented in Table 3.

The first set of columns present the regressions run on the entire time period from 1993 to 2007. The regressions confirm the existence of the accrual anomaly as both measures of accruals (TACC as well as ΔNOA) are strongly negatively correlated with future returns. Also, consistent with Richardson et al (2005), the coefficient on ΔNOA is significantly more negative than the coefficient on total accruals (TACC) or the coefficient on financing accruals (ΔFIN).

I next partition the sample into any early period (1993-2002) and a later period (2003-2007). The later period corresponds to the time when cash flow forecasts became increasingly prevalent. As the results indicate, the negative relationship between accruals and future returns is extremely strong in the early period, but declines substantially in the later period. To illustrate, the mean coefficient on TACC in the annual regressions declines from -0.1452 in the early period to a barely significant -0.0442 in the later period. Similar declines are seen for the pooled regression as well as the specification that uses ΔNOA. The regressions confirm the preliminary evidence in Table 2 and Figure 1 that the accrual anomaly has indeed declined across the entire cross-section of stocks.

4.2 THE ACCRUALS ANOMALY AND INCIDENCE OF CASH FLOW FORECASTS

I now test whether the decline in the accruals anomaly can be linked to the increasing incidence of cash flow forecasts. I modify the earlier regression specification by introducing an interaction with an indicator variable CFF that equals 1 for a firm-year with a cash flow forecast and 0 otherwise. The modified regressions are hence

$$RETS_{t+1} = \alpha_0 + \alpha_1*CFF + \beta_1* ROA_t + \beta_{11}* ROA_t*CFF + \beta_2* TACC_t + \beta_{22}* TACC_t*CFF + \varepsilon \quad (3)$$

and

$$RETS_{t+1} = \gamma_0 + \gamma_1*CFF + \beta_1* ROA_t + \beta_{11}* ROA_t*CFF + \beta_2* \Delta NOA_t + \beta_{22}* \Delta NOA_t*CFF + \delta_3* \Delta FIN_t + \delta_{33}* \Delta FIN_t*CFF + \varepsilon \quad (4)$$

If cash flow forecasts reduce the mispricing of accruals, I expect the incremental relationship between future returns and accruals to be less negative in the presence of cash flow forecasts. In other words, I expect the coefficients β_{22} on TACC*CFF in model (3) and the coefficient δ_{22} on ΔNOA*CFF in model (4) to be significantly positive. As before, I run the regressions using both pooled and annual specifications.

Table 4 presents the results from the regressions in equations (3) and (4). The first set of columns present the results for the entire sample for both pooled regressions as well as annual regressions. The results support hypothesis 1, that the presence of cash flow forecasts reduces the mispricing of accruals. For the pooled regression, the coefficient β_2 on TACC is -0.1578, while the incremental coefficient β_{22} on TACC*CFF is 0.0738 (t-stat 2.03), indicating that the negative relationship between accruals and future returns is approximately halved in the presence of cash flow forecasts. Similarly, the coefficient δ_2 on ΔNOA is -0.2573, while the incremental coefficient δ_{22} on ΔNOA*CFF is 0.1338 (t-stat 3.29). The results are also significant for the annual Fama-MacBeth regressions.

One issue that can affect the interpretation of the results from these regressions is the fact the effects may simply reflect the results of sampling bias or selection. In other words, the weaker "accrual anomaly" in the presence of cash flow forecasts may simply reflect the fact that these firms might be less subject to accrual mispricing than other firms, independent of whether they have cash flow forecasts or not. To control for this, the regressions are rerun for the subset of firms for which at least one cash flow forecast exists over the sample period being analyzed. These regressions are presented in the next set of columns in Table 4. Clearly, the accrual effect is weaker in this subset of firms, as the coefficient β_2 on TACC and δ_2 on ΔNOA are smaller in magnitude at -0.1107 and -0.1995 respectively for the pooled regressions. However, the incremental effect for cash flow forecasts continues to be positive and significant. The incremental coefficient β_{22} on TACC*CFF is 0.0471 (t-stat 1.74), while the incremental coefficient δ_{22} on ΔNOA*CFF is 0.0760 (t-stat 1.83). The results from the annual regressions are insignificant for TACC*CFF, but continue to be significant for ΔNOA*CFF.

The results from Table 4 broadly support Hypothesis 1 that the negative relationship between accruals and future returns is weaker in the presence of cash flow forecasts. In the following section, I test whether the relationship is influenced by the information in cash flow forecasts.

4.3 THE ACCRUALS ANOMALY AND INFORMATION IN CASH FLOW FORECASTS

If cash flow forecasts mitigate the mispricing of accruals, then the effect should be larger when there is more new information in analysts' cash flow forecasts. I define the information content of forecasts as the extent to which cash flow forecasts differ from earnings forecasts. This captures the extent of the forecasted accrual. I define INFO as

$$INFO_t = |CPS\_EST_{t+1} - EPS\_EST_{t+1}|/PRICE_t \quad (5)$$

where CPS_EST_{t+1} is the mean consensus one-year ahead annual cash flow per share estimate, measured four months after prior fiscal year end, EPS_EST_{t+1} is the corresponding EPS estimate and PRICE is the price per share at the time of the forecast.

In order to test this next hypothesis, I modify the regressions in equations (3) and (4) by interacting TACC and ΔNOA with INFO. The modified regressions are hence

$$RETS_{t+1} = \alpha_0 + \alpha_1*INFO + \beta_1* ROA_t + \beta_{11}*ROA_t*INFO + \beta_2*TACC_t + \beta_{22}*TACC_t*INFO + \varepsilon \quad (6)$$

and

$$RETS_{t+1} = \gamma_0 + \gamma_1*INFO + \delta_1* ROA_t + \delta_{11}* ROA_t*INFO + \delta_2* \Delta NOA_t + \delta_{22}* \Delta NOA_t*INFO + \delta_3* \Delta FIN_t + \delta_{33}* \Delta FIN_t*INFO + \varepsilon \quad (7)$$

I expect the incremental relationship between future returns and accruals to be less negative for more informative cash flow forecasts. In other words, I expect the coefficients β_{22} on TACC*INFO in equation (6) and the coefficient δ_{22} on ΔNOA*CFF in model (7) to be significantly positive. As before, I run the regressions using both pooled and annual specifications.

Table 5 presents the results from the regressions in equations (6) and (7). The first set of columns present the results for the entire sample for both pooled regressions as well as annual regressions. INFO is set to zero for firms without cash flow forecasts. The results generally support hypothesis 2, that more informative cash flow forecasts are associated with a reduction in the negative relationship between accruals and future returns. For the pooled regressions, the incremental coefficient β_{22} on TACC*INFO is 0.6067 (t-stat 2.62), while the incremental coefficient δ_{22} on ΔNOA*CFF is 0.6508 (t-stat 2.75). For the annual regressions, the incremental coefficient β_{22} on TACC*INFO is positive but insignificant (0.3083, t-stat 0.79), but the incremental coefficient δ_{22} on ΔNOA*CFF continues to be significant (0.5664, t-stat 1.92).

The next set of columns present the results for the subsample with cash flow forecasts. For these firms, INFO can be explicitly calculated. The number of observations declines to 9210. However, within the sample of firm-years with cash flow forecasts, there is strong support for Hypothesis 2. The incremental coefficients β_{22} on TACC*INFO and δ_{22} on ΔNOA*CFF are significant and positive in both pooled and annual regressions. Hence, the results from this section support the hypothesis that the "mispricing" of accruals is reduced when analysts' cash flow forecast are more informative. I next test whether the effect of cash flow forecasts on the pricing of accruals is greater when accruals are more accurate.

4.4 THE ACCRUALS ANOMALY AND ACCURACY OF CASH FLOW FORECASTS

If cash flow forecasts mitigate the mispricing of accruals, then the effect should be larger when the cash flow forecast is more accurate. I measure the accuracy of the forecast as the reciprocal of the unsigned forecast error in the cash flow forecast. I define ACCU as

$$ACCU_{t+1} = 1/(|CPS\_ACT_{t+1} - CPS\_EST_{t+1}|/PRICE_{t+1}) \quad (8)$$

where CPS_EST_{t+1} is the mean consensus one-year ahead annual cash flow per share estimate, measured four months after prior fiscal year end, CPS_EST_{t+1} is the actual realized cash flow per share and PRICE is the price per share at the time of the forecast. Note that $ACCU_{t+1}$ is an ex-post measure; in the tests to follow, I use both ex-post forecast accuracy as well as prior period forecast accuracy for the analysis. I modify the regressions in equations (3) and (4) by interacting TACC and ΔNOA with INFO. The modified regressions are hence

$$RETS_{t+1}=\alpha_0 +\alpha_1*ACCU +\beta_1*ROA_t +\beta_{11}*ROA_t*ACCU +\beta_2*TACC_t +\beta_{22}*TACC_t*ACCU +\varepsilon \quad (9)$$

and

$$RETS_{t+1}= \gamma_0 + \gamma_1*ACCU + \delta_1* ROA_t + \delta_{11}* ROA_t*ACCU +\delta_2* \Delta NOA_t + \delta_{22}* \Delta NOA_t*ACCU$$
$$+\delta_3* \Delta FIN_t + \delta_{33}* \Delta FIN_t*ACCU + \varepsilon \quad (10)$$

I expect the incremental relationship between future returns and accruals to be less negative for more accurate cash flow forecasts. In other words, I expect the coefficients β_{22} on TACC*ACCU in equation (9) and the coefficient δ_{22} on ΔNOA*CFF in model (10) to be significantly positive. As before, I run the regressions using both pooled and annual specifications.

Panel A of Table 6 presents the results from the regressions in equations (9) and (10) using ex-post realized forecast accuracy. The first set of columns present the results for the entire sample for both pooled regressions as well as annual regressions. ACCU is set to zero for firms without cash flow forecasts. The results support hypothesis 3, that more accurate cash flow forecasts are associated with a reduction in the negative relationship between accruals and future returns. For the pooled regressions, the incremental coefficient β_{22} on TACC*ACCU is 0.0207 (t-stat 2.28), while the incremental coefficient δ_{22} on ΔNOA*ACCU is 0.0387 (t-stat 3.68). The coefficients are similar for the annual regressions and continue to be significant. The next set of columns present the results for the subsample with cash flow forecasts where ACCU can be explicitly calculated. The number of observations declines to 8706, but the incremental coefficients β_{22} on TACC*ACCU and δ_{22} on ΔNOA*CFF continue to be significant and positive in both pooled and annual regressions.

Panel B of Table 6 repeats the analysis using realized forecast accuracy from the prior period to calculate ACCU. The results continue to be significant for all specifications. One can interpret these results as suggesting that the stock market pays greater attention to cash flow forecasts that are likely to be accurate. Overall, the results from Panels A and B of Table 6 strongly support Hypothesis 3 that the "mispricing" of accruals is reduced when analysts' cash flow forecast are more informative.

The results thus far show strong support for the hypotheses regarding the impact of cash flow forecasts on the pricing of accruals. The negative relationship between accruals and future returns is weaker in the presence of cash flow forecasts. Further, this relationship weakens further when cash flow forecast have more accrual information in them and when cash flow forecasts are likely to be accurate. This suggests that the information in cash flow forecasts has helped the stock markets better understand the accrual component of earnings. In the following section, I test alternate explanations for why the accrual anomaly may have weakened.

5. Alternative Explanations for the Decline in the Accrual Anomaly

This paper argues that the dramatic increase in cash flow forecasts and consequently in the amount of information regarding future accruals contributed to the weakening of the anomaly. However, the period associated with the increase in cash flow forecasts also witnessed a number of changes that may have affected the nature of accruals and the likelihood that they would be mispriced.

Bhojraj, Sengupta and Zhang (2009) argue that the passage of SOX improved the quality of accruals, as firms were less willing to carry out accrual based manipulation of earnings. Further, the passage of FAS 146 reduced the ability of firms to manipulate restructuring charges, which they argue contributed to the success of accruals based strategies in prior periods. Green, Hand and Soliman (2009) propose a different explanation for the “demise” of the accrual anomaly. They suggest that the presence of a number of leading accounting academics in the quantitative investment management and hedge fund industries lead to a greater investment in accruals based strategies which eliminated excess returns over time.

Given the number of changes that occurred simultaneously, it is impossible to perfectly differentiate between these alternate explanations. It is quite likely that all of these effects had an impact on the accruals anomaly and caused it to disappear. In this section, I conduct additional analyses to test whether the cash flow forecast based explanation is incremental to these alternative explanations.

5.1 THE CHANGING NATURE OF ACCRUALS OVER TIME

Bhojraj, Sengupta and Zhang (2009) suggest that one reason why the accrual anomaly has lessened is that accruals have become more persistent and less likely to be manipulated in recent years due to two reasons – greater costs to earnings management after the passage of SOX in 2002 and less ability to manipulate restructuring costs after FAS 146 in 2003. Figure 2 graphs the variability of earnings and accruals over the sample period and indicates that the variability of earnings and accruals has indeed sharply declined in recent years after increasing in the late 1990s. Figures 3-A and 3-B, which graph the mean of the 10th and 90th percentiles of earnings and accruals over the sample period, indicate that the extreme accruals have indeed become less extreme over time.

I begin by attempting to empirically confirm the increased persistence of the accrual component of earnings. Consistent with Richardson et al (2005), I regress future earnings on current earnings and the accrual component of earnings. I run the following regressions.

$$ROA_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \varepsilon \quad (11)$$

and

$$ROA_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \varepsilon \quad (12)$$

where ROA_{t+1} is one-year-ahead return on assets (operating income after depreciation (Compustat #178) deflated by average total assets) and all other variables are defined as before. The results are presented in Table 7.

The first set of columns presents the results of the regression for the entire period. Consistent with prior research, the accrual component of earnings has lower persistence. For the pooled regressions, the incremental coefficient β_2 on TACC is -0.0478 (t-stat -23.42), while the incremental coefficient δ_2 on DNOA is -0.0637 (t-stat -25.89). Average coefficients from the annual regressions are also similar. I next partition the sample into the early period (1993-2002) and later period (2003-2007) and rerun the regressions in both subsamples. As the results indicate, the persistence of accruals appears to have increased in later periods. To illustrate, the incremental coefficient β_2 on TACC was -0.0527 in the earlier period but is only -0.0274 in the later period; i.e. the gap in the persistence between the cash and accruals components of earnings has narrowed.[2] Results are similar for the annual regressions and for the persistence of ΔNOA. These results suggest that accruals have become more persistent with time, consistent with the Bhojraj, Sengupta and Zhang (2009) explanation.

[2] The coefficient on total accruals in the pooled regressions has increased from 0.7572 (0.8099-0.0527) to 0.8489 (0.8763-0.0274) indicating a dramatic increase in the persistence of the accrual component of earnings.

However, it is also possible that accruals have become more persistent because of the greater scrutiny placed on them owing to the availability of cash flow forecasts. Recent research by Collins and McInnis (2009) suggests that one factor that may have contributed to the improved quality of accruals in recent times is the greater availability of cash flow forecasts.

To better understand why accruals have become more persistent, I examine whether the tendency of accruals to reverse has changed, and whether this change is associated with the presence of cash flow forecasts. I first test whether future accruals are indeed negatively associated with current accruals. I control for the determinants of accruals used in the earnings management literature – level of property plant and equipment (Jones 1991), sales growth adjusted for growth in receivables (Dechow, Sloan and Sweeney 1995) and firm performance as measured by ROA (Kothari, Leone and Wasley 2004). I run the following regression.

$$TACC_t = \alpha_0 + \beta_1*TACC_{t-1} + \beta_2*\Delta REV_t + \beta_3*PPE_t + \beta_4*ROA_t + \varepsilon \quad (13)$$

where $TACC_t$ and $TACC_{t-1}$ are current and lagged total accruals scaled by average assets, ΔREV is change in revenues (Compustat Data#12) less change in receivables (Compustat Data #2) scaled by average assets, PPE is total gross PPE (Compustat Data #7) scaled by average assets and ROA is return on assets, defined earlier.

I next test whether the presence of cash flow forecasts affects the intertemporal relationship between accruals. I modify the above regression by interacting $TACC_{t-1}$ with the indicator variable that equals 1 for firm-years with cash flow forecasts. The model is hence

$$TACC_t = \alpha_0 + \alpha_1*CFF + \beta_1*TACC_{t-1} + \beta_{11}*TACC_{t-1}*CFF + \beta_2*\Delta REV_t + \beta_3*PPE_t + \beta_4*ROA_t + \varepsilon \quad (14)$$

If accruals tend to reverse, I expect the coefficient β_1 on $TACC_{t-1}$ to be negative. If cash flow forecasts make it less likely that accruals reverse, then I expect the incremental coefficient

β_{11}*$TACC_{t-1}$ to be positive. As earlier, the regressions are run both in pooled specifications as well as annual regressions. The results are presented in Panel A of Table 8.

The first set of columns present the results for the entire sample. The first regression runs a pooled specification of the model in equation (12). The coefficient β_1 on $TACC_{t-1}$ is -0.0671 (tstat -17.12), consistent with reversals in accruals. When the regression is run with interactions for cash flow forecasts, the coefficient β_2 on $TACC_{t-1}$*CFF is 0.1292 (tstat 8.50). This indicates that the reversal in accruals essentially disappears for observations with cash flow forecasts. Results from the annual regressions are similar. The next set of columns repeats the analysis for the subsample of firms with at least one cash flow forecast. The reversal associated with accruals is weaker but generally significant across the specifications. However, the incremental coefficient on TACC*CFF continues to be significantly positive.

To summarize, the evidence suggests that accruals have become more persistent and less likely to reverse over time. Further, the increased persistence of accruals is associated with the incidence of cash flow forecasts. This corroborates the recent results in Collins and McInnis (2009) and provides an alternate explanation for why accruals have become more persistent from that provided in Bhojraj, Sengupta and Zhang (2009).[3]

5.2 CHANGES IN THE ACCOUNTING STANDARD FOR RESTRUCTURING

Dechow and Ge (2006) show that a substantial portion of the accrual anomaly can be attributed to the stock market not understanding the transitory nature of special items.

[3] I also conduct additional tests examining the association between proxies of earnings quality and cash flow forecasts. I find that firms that had cash flow forecasts had lower absolute discretionary accruals (as measured by the cross-sectional industry level performance-adjusted modified Jones model) once they had cash flow forecasts than in periods before cash flow forecasts. I also find that the onset of cash flow forecasts is associated with lower variance in the residuals from the modified Dechow-Dichev (2002) model that regresses working capital accruals on past, current and future cash flows, controlling for sales growth and PPE as suggested by McNichols (2002). These results are consistent with the quality of firms' accruals improving after cash flow forecasts are available.

Restructuring charges are the most common and significant portion of special items. Firms that take excessive restructuring charges depress current performance in order to improve future performance. Such firms would likely be in the extreme low deciles of accruals. If the markets are unable to anticipate the likely mechanical future revival, these firms are likely to have large positive excess returns in the future. Bhojraj, Sengupta and Zhang (2009) state that "The inability to efficiently price restructuring firms during this period largely drives the accruals anomaly for firms with low accruals." They also note that FAS 146 improved the quality of restructuring information available in recent years by clamping down on excessive restructuring charges. They show that the mispricing of special items in general and restructuring charges in particular has reduced after the passage of the new standard.

To ensure that the results are not driven by changes in the nature of restructuring charges and special items, I conduct two sensitivity analyses. First, I eliminate all observations in the bottom decile of special items and repeat the analysis. The pattern in the returns to the accruals anomaly is essentially unchanged. The results from Table 2 indicate that for the entire sample, the time series average of the returns to the accrual strategy is 16.1% in the early period (1993-2002) and declines to -2% in the recent period (2003-2007). The hedge returns for the sample after eliminating the bottom decile of special items is 15.9% for the early period and -1.3% for the later period. All the regression results are also essentially unchanged. Second, I eliminate those observations with non-zero restructuring information on COMPUSTAT (5718 firm-years in 2001-2007). Again, the results are essentially unaltered. Hence, the core result that the increasing incidence of cash flow forecasts has helped mitigate the mispricing of accruals is incremental to any improvement in the nature of accruals related to improved accounting for restructuring items.

5.3 GREATER INSTITUTIONAL INTEREST IN ACCRUALS BASED STRATEGIES

Green, Hand and Soliman (2009) conjecture that the driving factor for the decline in the accrual anomaly is the greater willingness of hedge funds to invest in accruals based strategies. They claim that the movement of prominent accounting academics to quantitatively oriented funds like Barclays Global Investors (BGI) increased the flow of funds into accrual based strategies and arbitraged away any excess returns. The evidence they provide comes from a two-stage time series regression. In the first stage, they regress trading turnover for firms in extreme accrual portfolios on the assets under management for hedge funds and control variables for changes in trading liquidity and transaction costs. They find that the increase in turnover is positively associated with assets managed by hedge funds. In the next stage, they regress returns from the accrual anomaly on the fitted value of share turnover and find a negative association. They interpret this as a reduction in the anomaly with greater institutional investment.

Green, Hand and Soliman (2009) assume that the most important source of increased turnover is the greater involvement of institutional investors. If increased turnover is driven by greater institutional investment, one should observe a greater proportion of large trades and an increase in average trade size. On the other hand, if trading turnover increases because of greater interest by smaller retail investors, one should observe a greater proportion of small trades, and a decrease in average trade size. An alternative conjecture, if one observes the latter, is that smaller investors, who were earlier susceptible to the mispricing of accruals, are less likely to be fooled given the additional accrual information now available in cash flow forecasts.

To differentiate between these two explanations, I collect information about trade size from the NYSE TAQ database, which provides information on every trade on the NYSE, AMEX and NASDAQ exchanges from 1993 onwards. For each stock, I first calculate the average trade size in number of shares, average trade size in dollars, number of trades and monthly trading turnover for each trading month. I then calculate the time series average of these three metrics for each firm, using the same time period used for compounding the returns in prior analyses.

Table 9 presents the average trading characteristics for the entire sample over the time period.[4] Panel A presents the characteristics for the entire sample. While trading turnover and number of shares trades appear to have increased across time, this increase is driven primarily by the frequency in trading. The actual size per trade has decreased from 1926 shares ($24,950) in 1993 to 354 ($3863) in 2007. There can be two potential explanations for these trends. First, the extent of retail investor participation may have increased across time. Second, institutional investors may indulge in stealth trading by splitting up large trades into smaller trades.

Panel B of Table 9 presents the mean trade size in dollars and mean monthly trading turnover for the sample partitioned into quintiles based on accruals. Consistent with Green, Hand and Soliman (2009), the turnover of stocks in the extreme quintiles has increased. For instance, firms with the lowest accruals had an increase in share turnover from 7.8% in 1993 to 20.4% in 2007. However, similar trends are seen in all quintiles. Further, the mean trade size for firms with extreme accruals continues to decline. In the 2003 to 2007 period where the accruals anomaly stopped generating returns, firms in the lowest accrual quintile saw the mean trade size decline from 692 shares ($5032) in 2003 to 434 shares ($2387) in 2007. The typical cutoff used to identify institutional trades is 500 shares or $5000 (Lee and Radhakrishna 2000, Malmendier and Shanthikumar 2007), though recent research recommends using different cutoffs for smaller firms (Hvidkjaer 2008). Still, the small size of the mean (not median) trade suggest that the increase in turnover stems not from institutional traders but from smaller investors.

[4] I was able to successfully obtain TAQ data for 55,718 out of 63843 firms, with the proportion of firms with available data exceeding 95% in recent years.

I next investigate whether the increase in trading turnover is associated with an increase in institutions trading on the anomaly or with increased trading associated with the availability of cash flow forecasts. I begin with the first stage regression used in Green, Hand and Soliman (2009) who regress trading turnover for firms with extreme accruals on proxies for hedge fund activity, transaction costs and idiosyncratic risk. I add a proxy pertaining to the availability of cash flow forecasts. I run the following time-series regression on portfolios of extreme accrual stocks (quintiles 1 and 5).

$$LTURN = \alpha_0 + \beta_1{*}LAUM + \beta_2{*}IDIO + \beta_3{*}LPRC + \beta_4{*}CFF + \varepsilon \quad (15)$$

where LTURN is the value-weighted average of mean log of monthly turnover (Shares Traded/ Shares Outstanding), LAUM is the log of assets under management by hedge funds[5], IDIO is the value-weighted average of firm-level idiosyncratic risk[6] and LPRC is the value-weighted average of the mean month-end log of stock price. IDIO is a proxy for arbitrage risk, while LPRC is a proxy for transaction costs. CFF is the proportion of firms that have cash flow forecasts in the year of analysis. I run this regression separately for low accrual and high accrual firms.

Panel C of Table 9 presents the results of the regression. The first two columns present the regression excluding CFF. Consistent with Green, Hand and Soliman (2009), the increase in share turnover is strongly associated with the level of assets managed by hedge funds (LAUM). The next two columns add CFF which measures the availability of cash flow forecasts for the respective quintiles. As the results indicate, CFF is strongly significant, while LAUM ceases to be significant. This indicates that the increase in trading turnover is more likely to be associated with the increase in accruals related information from cash flow forecasts rather than increased trading by hedge funds.

[5] From Green, Hand and Soliman (2009) who get the information from Barclayshedge.com

[6] Idiosyncratic risk is measured as the standard deviation of the residual of firm-level regressions of returns on the CRSP value weighted index over the same period as that for the one-year-ahead returns

6. Conclusions

Sloan (1996) shows that a strategy of investing in firms with low accruals and shorting firms with high accruals generates significant and consistent excess returns across time. The simplicity of Sloan's strategy and the magnitude of the excess returns it generates has been the focus of much research. Some researchers argue that the excess returns are illusory and disappear with appropriate risk adjustments (Khan 2008), while others argue that it reflects the markets mispricing of accruals (Hirshleifer, Hou and Teoh 2006). Recent research has also examined why the returns to the accruals anomaly were not been arbitraged away (Lev and Nissim 2006, Mashruwalla, Rajgopal and Shevlin 2006).

Against this backdrop, it is stunning to observe the decline of the accruals anomaly in the past half decade. A strategy that consistently generated economically significant returns over almost four decades has recently generated zero or negative returns. What could explain the disappearance of a once robust effect? In this paper, I suggest one potential explanation for this decline – the increasing incidence of cash flow forecasts. In the recent past, analysts have increasingly provided forecasts of cash flows in addition to earnings, implicitly forecasting future accruals. The number of firms with cash flow forecasts increased exponentially since 2002, the same time the accrual anomaly stopped generating returns. I hypothesize that the diminished returns to an accruals based strategy is related to the reduced mispricing of accruals as markets get more information about likely future accruals from cash flow forecasts.

I find that the negative relationship between future returns and accruals is mitigated in the presence of cash flow forecasts. The negative relationship between accruals and future returns is essentially halved for firms with cash flow forecasts. I further find that this relationship is weaker for those forecasts that have a greater divergence from earnings forecasts and hence have more accruals information. Finally, the mispricing of accruals is weaker when forecasts that are either ex-post more accurate or ex-ante more likely to be accurate. This provides strong empirical support that the decline in the returns to the accruals anomaly is strongly associated with the greater availability of cash flow forecasts.

There are other potential explanations for the decline in the accruals anomaly. Bhojraj, Sengupta and Zhang (2009) suggest that the weakening of the accruals anomaly is related to the passage of SOX in 2002 which increased the costs of accruals based earnings management, and the passage of FAS 146 in 2003, which reduced firms' ability to manipulate restructuring expenses. Green, Hand and Soliman (2009) on the other hand suggest that the driver of the decline is greater investment in accruals based strategies by large quantitative hedge funds that were advised by senior accounting academics. While it is likely that each of these explanations played a partial role in the decline of returns to an accruals based strategy, I test whether the explanation centered on cash flow forecasts is incremental to the above two explanations.

I find that the while the quality of accruals has improved since 2002, the persistence of accruals increases with the incidence of cash flow forecasts. The results are also robust to the exclusion of firms with restructuring charges. Further, tests examining the trading characteristics of firms indicate that the increase in trading turnover is not unique to firms with extreme accruals and is unlikely to be driven by greater investment by large institutions. Finally, the association between increased turnover and assets managed by hedge funds disappears after controlling for the extent of cash flow forecasts.

To conclude, the decline of the accruals anomaly is strongly associated with the greater availability of information about expected future accruals from cash flow forecasts. This supports the behavioral explanation offered by Sloan (1996) for the existence of the anomaly.

As more and better information is available about future accruals from analysts who potentially factor in the differential persistence of accruals in their forecasts, the market is less likely to misprice accruals.

It is essential to mention some caveats regarding the association between the decline in the accruals anomaly and increase in cash flow forecasts. Firstly, the period where cash flow forecasts have become prevalent and the accrual anomaly has presumably disappeared is short. If returns to an accruals strategy do reappear despite the continued availability of cash flow forecasts, this would negate the explanation offered. Secondly, even if the accrual anomaly did indeed disappear, it was probably the result of many simultaneous changes in the information environment of the capital markets. This paper suggests that one such change was the information provided by cash flow forecasts. Third, the different explanations offered for the weakening of the accruals anomaly are probably interrelated. It is plausible that analysts started to issue cash flow forecasts once they were reassured that firms accruals were less likely to be subject to manipulation, post SOX and FAS 146. Also, institutions might have been more willing to trade in stocks with extreme accruals once they had access to cash flow forecasts.

The results of this paper also contribute to recent research examining the usefulness of analysts' cash flow forecasts to capital markets. While Givoly, Hayn and Lehavy (2009) question the utility of cash flow forecasts, Call, Chen and Tong (2009) show that analysts make better earnings forecasts when they also issue cash flow forecasts. The finding in this paper that cash flow forecasts played a role in reducing the mispricing of accruals suggests that they do provide incrementally value relevant information to capital markets. An interesting extension of this result would be to examine the persistence of the accruals anomaly in international settings where cash flow forecasts are not widespread.

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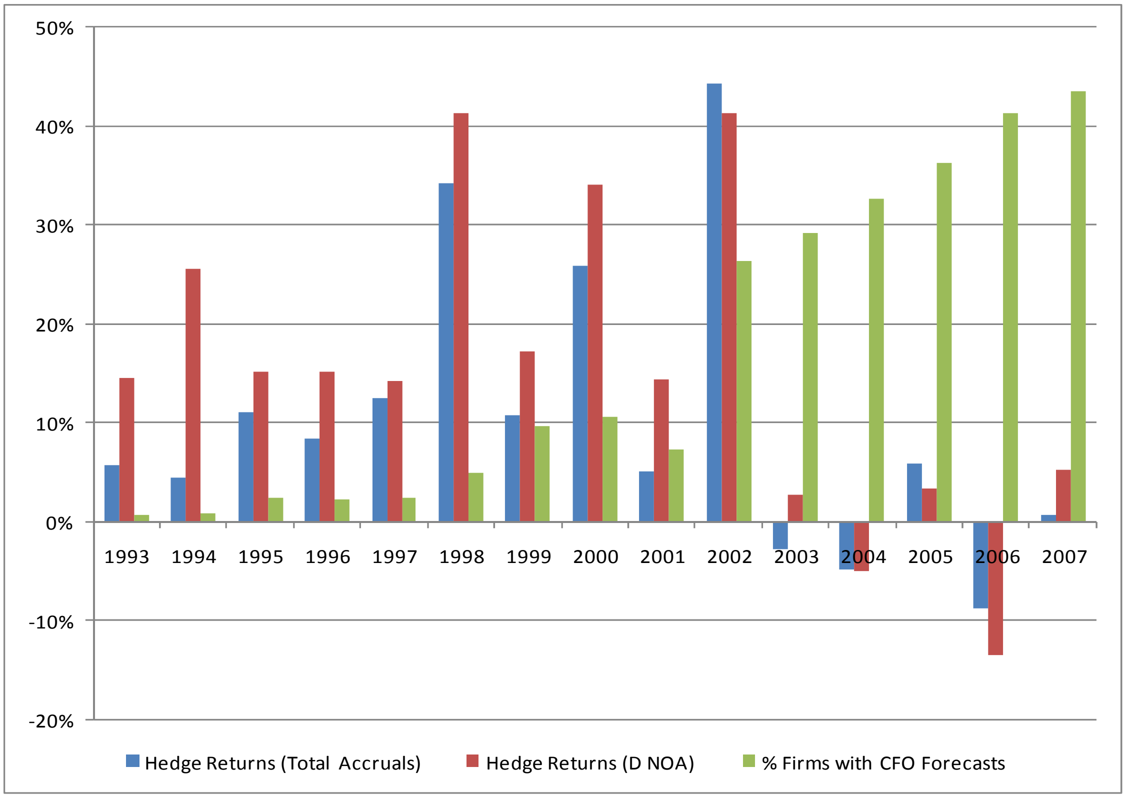

Figure 1: The Accrual Anomaly and Incidence of Cash Flow Forecasts across Time

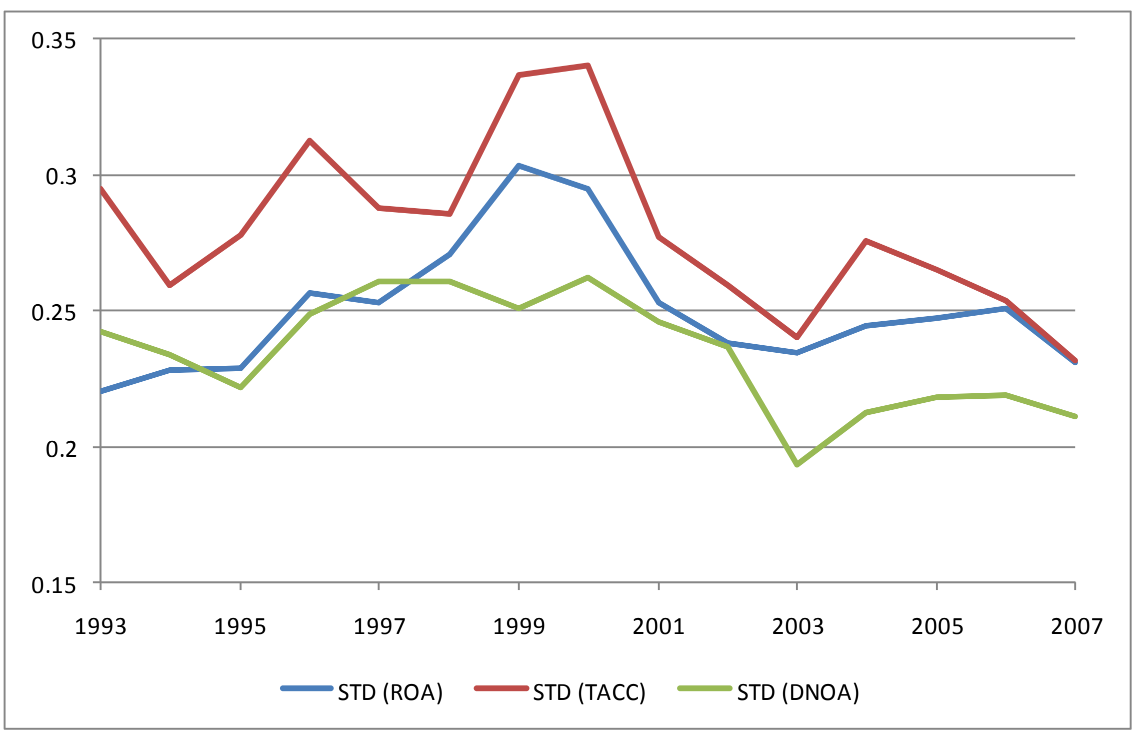

Figure 2: Cross-sectional Variability of Earnings and Accruals across Time

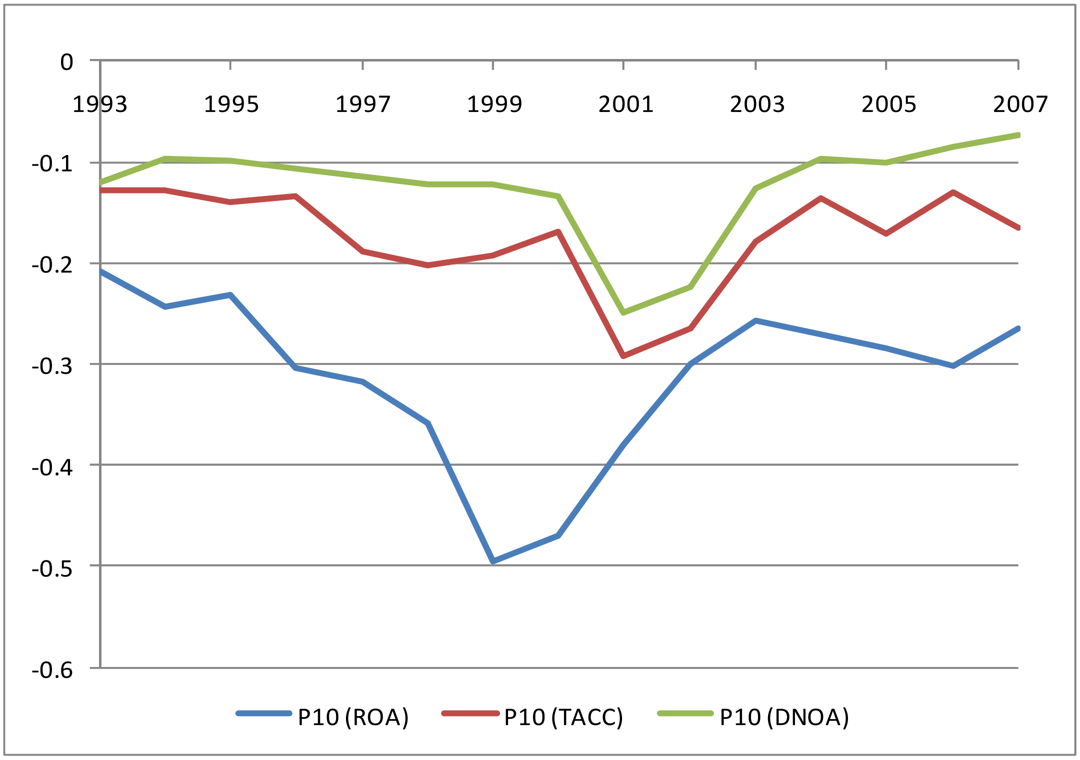

Figure 3-A: 10th Percentile of Earnings and Accruals across Time

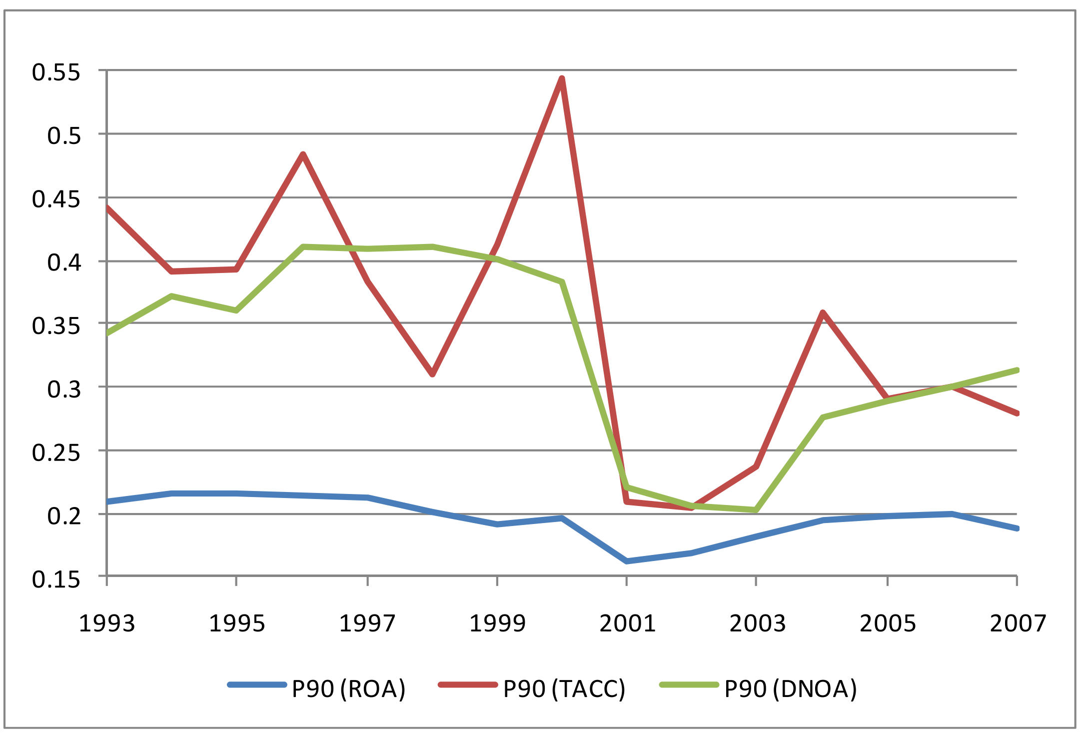

Figure 3-B: 90th Percentile of Earnings and Accruals across Time

TABLE 1: Sample Descriptive Statistics and Correlations

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. ROA_t is return on assets defined as operating income after depreciation (Compustat # 178) scaled by average total assets (Compustat #6). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See pages 9-10 for detailed definitions. $RETS_{t+1}$ is size-adjusted one-year ahead buy and hold return where returns are compounded starting 4 months after prior fiscal year end and returns are size-adjusted by subtracting the value weighted average returns for the same size decile in the same period. CFF is an indicator variable that equals 1 for firm-years with an analyst cash flow forecast and 0 for other firm-years. $ASST_t$ is total assets (Compustat #6) and MCAP is market capitalization (Shares outstanding (Compustat #25) * Stock price (Compustat #199)).

Panel A: Sample Descriptive Statistics

Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl
ROA_t	-0.003	0.254	-0.041	0.065	0.127
$TACC_t$	0.066	0.274	-0.034	0.039	0.139
ΔNOA_t	0.078	0.241	-0.029	0.043	0.156
ΔFIN_t	-0.011	0.252	-0.086	0.000	0.056
$RETS_{t+1}$	-0.012	0.644	-0.398	-0.099	0.211
ROA_{t+1}	-0.002	0.244	-0.041	0.063	0.124
CFF	0.145	0.352	0.000	0.000	0.000
$ASST_t$	1457	6988	36	132	590
$MCAP_t$	1837	10874	35	147	663

Panel B: Correlation Matrix

Figures above/below diagonal are Pearson/Spearman rank-order correlations

	ROA_t	$TACC_t$	ΔNOA_t	ΔFIN_t	$RETS_{t+1}$	ROA_{t+1}	CFF	$ASST_t$	$MCAP_t$
ROA_t		0.197	0.157	0.063	0.068	0.839	0.135	0.080	0.092
$TACC_t$	0.319		0.555	0.631	-0.049	0.108	0.009	-0.016	0.008
ΔNOA_t	0.250	0.598		-0.320	-0.072	0.079	0.015	-0.007	-0.001
ΔFIN_t	0.088	0.382	-0.372		0.013	0.038	-0.006	0.012	-0.008
$RETS_{t+1}$	0.134	-0.040	-0.073	0.033		0.173	0.026	0.008	0.002
ROA_{t+1}	0.811	0.189	0.128	0.080	0.297		0.136	0.083	0.092
CFF	0.133	0.023	0.017	-0.005	0.086	0.138		0.240	0.195
$ASST_t$	0.356	0.008	0.036	-0.029	0.140	0.343	0.433		0.723
$MCAP_t$	0.367	0.157	0.106	0.053	0.092	0.332	0.443	0.837	

TABLE 2: Cash Flow Forecasts and the Accrual Anomaly across Time

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. ROA_t is return on assets defined as operating income after depreciation. Hedge Returns are calculated each fiscal year based on either total accruals (TACC) or change in net operating assets (Δ NOA) as the difference between average size-adjusted one-year-ahead buy-and-hold returns for the lowest quintile and the highest quintile of the accrual measure. TACC is total accruals and ΔNOA is change in net operating assets, both scaled by average assets. See pages 9-10 for detailed definitions.

YEAR	N	# of CFO Forecasts	# of EPS Forecasts	CFO Firms as % of All Firms	CFO Firms as % of Followed Firms	Hedge Returns (TACC)	Hedge Returns (Δ NOA)
1993	4231	26	2007	1%	1%	6%	14%
1994	4423	36	2192	1%	2%	4%	26%
1995	4682	115	2448	2%	5%	11%	15%
1996	5342	119	2756	2%	4%	8%	15%
1997	5322	123	2881	2%	4%	12%	14%
1998	4902	240	2738	5%	9%	34%	41%
1999	4972	478	2789	10%	17%	11%	17%
2000	4533	479	2530	11%	19%	26%	34%
2001	4080	297	2279	7%	13%	5%	14%
2002	3841	1011	2229	26%	45%	44%	41%
2003	3803	1111	2392	29%	46%	-3%	3%
2004	3827	1248	2507	33%	50%	-5%	-5%
2005	3732	1352	2596	36%	52%	6%	3%
2006	3210	1324	2539	41%	52%	-9%	-13%
2007	2943	1281	2412	44%	53%	1%	5%

TABLE 3 Weakening of the Accrual Anomaly across Time

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETS_{t+1}$, which is the size-adjusted one-year ahead buy and hold return where returns are compounded starting 4 months after prior fiscal year end and returns are size-adjusted by subtracting the value weighted average returns for the same size decile in the same period. ROA_t is return on assets defined as operating income after depreciation (Compustat # 178) scaled by average total assets (Compustat #6). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See pages 9-10 for detailed definitions. The two regression models are

$RETS_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \varepsilon$. and

$RETS_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \varepsilon$

t-statistics for pooled regressions control for clustering by firm. Coefficients for annual regressions are averaged as in Fama and MacBeth (1973). t-statistics for annual regressions are from the distribution of annual coefficients, controlling for autocorrelation as in Bernard (1995).

	Entire Sample				Early Period (1993-2002)				Later Period (2003-2007)			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	-0.00147	0.0071	-0.0002	0.0079	-0.0047	0.0064	-0.0019	0.0094	0.0062	0.0075	0.0033	0.0049
	(-0.56)	(2.66)	(-0.02)	(1.15)	(-1.43)	(1.89)	(-0.37)	(2.23)	(1.67)	(1.99)	(0.23)	(0.29)
ROA	0.2055	0.2131	0.1750	0.1790	0.2045	0.2114	0.1592	0.1646	0.2057	0.2085	0.2067	0.2079
	(20.20)	(20.87)	(2.87)	(2.91)	(16.12)	(16.72)	(1.61)	(2.45)	(13.49)	(13.62)	(3.97)	(3.99)
TACC	**-0.1527**		**-0.1115**		**-0.1845**		**-0.1452**		**-0.0359**		**-0.0442**	
	(-16.14)		**(-4.60)**		**(-15.95)**		**(-6.86)**		**(-2.38)**		**(-2.20)**	
ΔNOA		**-0.2458**		**-0.1886**		**-0.2943**		**-0.2531**		**-0.0559**		**-0.0598**
		(-21.75)		**(-3.72)**		**(-21.44)**		**(-7.93)**		**(-3.02)**		**(-1.45)**
ΔFIN		-0.0546		-0.0228		-0.0622		-0.0191		-0.0228		-0.0303
		(-5.11)		(-1.15)		(-4.75)		(-0.98)		(-1.35)		(-1.14)
N	63843	63843	63843	63843	46328	46328	46328	46328	17514	17514	17514	
Adj. R^2	0.87%	1.20%	2.21%	2.62%	0.91%	1.36%	2.62%	3.10%	1.02%	1.03%	1.39%	1.66%

TABLE 4: The Accrual Anomaly and Incidence of Cash Flow Forecasts

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETS_{t+1,}$ which is the size-adjusted one-year ahead buy and hold return where returns are compounded starting 4 months after prior fiscal year end and returns are size-adjusted by subtracting the value weighted average returns for the same size decile in the same period. ROA_t is return on assets defined as operating income after depreciation (Compustat # 178) scaled by average total assets (Compustat #6). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See pages 9-10 for detailed definitions. CFF is an indicator variable that equals 1 for firm-years with an analyst cash flow forecast and 0 for other firm-years The two regression models are

$RETS_{t+1} = \alpha_0 + \alpha_1{*}CFF + \beta_1{*}ROA_t + \beta_{11}{*}\ ROA_t{*}CFF + \beta_2{*}\ TACC_t + \beta_{22}{*}\ TACC_t{*}CFF + \varepsilon$ and

$RETS_{t+1} = \gamma_0 + \gamma_1{*}CFF + \beta_1{*}ROA_t + \beta_{11}{*}ROA_t{*}CFF + \beta_2{*}\Delta NOA_t + \beta_{22}{*}\Delta NOA_t{*}CFF + \delta_3{*}\Delta FIN_t + \delta_{33}{*}\Delta FIN_t{*}CFF + \varepsilon$

t-statistics for pooled regressions control for clustering by firm. Coefficients for annual regressions are averaged as in Fama and MacBeth (1973). t-statistics for annual regressions are from the distribution of annual coefficients, controlling for autocorrelation as in Bernard (1995).

	Entire Sample				Subsample of firms with at least 1 cash flow forecasts			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	-0.0054 (-1.90)	0.0037 (1.29)	-0.0012 (-0.15)	0.0066 (0.97)	0.1041 (20.87)	0.1128 (21.9)	0.1013 (4.94)	0.1096 (4.95)
CFF	0.0267 (3.17)	0.0213 (2.48)	-0.0313 (-0.83)	-0.0227 (-0.64)	-0.0828 (-9.64)	-0.0878 (-9.97)	-0.1332 (-3.42)	-0.1252 (-3.52)
ROA	0.2020 (19.20)	0.2098 (19.98)	0.1734 (2.85)	0.1769 (2.89)	-0.0792 (-3.41)	-0.0707 (-3.04)	-0.0909 (-1.00)	-0.0828 (-0.90)
ROA*CFF	-0.0354 (-0.73)	-0.0365 (-0.75)	0.0402 (0.91)	0.0014 (0.04)	0.2458 (5.12)	0.2439 (5.08)	0.3042 (4.84)	0.261 (4.53)
TACC	-0.1574 (-16.03)		-0.1113 (-4.82)		-0.1107 (-5.72)		-0.0593 (-1.38)	
TACC*CFF	**0.0738** **(2.03)**		**0.1083** **(1.71)**		**0.0471** **(1.74)**		**0.0572** **(1.08)**	
ΔNOA		-0.2573 (-21.74)		-0.1941 (-4.36)		-0.1995 (-8.58)		-0.1490 (-3.47)
ΔNOA*CFF		**0.1338** **(3.29)**		**0.1280** **(1.98)**		**0.0760** **(1.83)**		**0.0836** **(1.66)**
ΔFIN		-0.0543 (-4.90)		-0.0184 (-0.83)		-0.0343 (-1.59)		0.0255 (0.52)
ΔFIN*CFF		0.0236 (0.56)		0.1546 (1.71)		0.0036 (0.08)		0.1118 (1.41)
N	63843	63843	63843	63843	23855	23855	23855	23855
Adj. R^2	0.90%	1.24%	2.38%	2.79%	0.78%	0.99%	2.44%	2.95%

TABLE 5: The Accrual Anomaly and Information in Cash Flow Forecasts

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETS_{t+1,}$ which is the size-adjusted one-year ahead buy and hold return where returns are compounded starting 4 months after prior fiscal year end and returns are size-adjusted by subtracting the value weighted average returns for the same size decile in the same period. ROA_t is return on assets defined as operating income after depreciation (Compustat # 178) scaled by average total assets (Compustat #6). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See pages 9-10 for detailed definitions. INFO, which measures the accrual information in cash flow forecasts is defined as $INFO_t = |CPS\_EST_{t+1} - EPS\_EST_{t+1}|/PRICE_t$ where CPS_EST_{t+1} is the mean consensus one-year ahead annual cash flow per share estimate, measured four months after prior fiscal year end, EPS_EST_{t+1} is the corresponding EPS estimate and PRICE is the price per share at the time of the forecast. For the regressions for the entire sample, INFO is set to zero when there are no cash flow forecasts. The two regression models are

$RETS_{t+1} = \alpha_0 + \alpha_1 * INFO + \beta_1 * ROA_t + \beta_{11} * ROA_t * INFO + \beta_2 * TACC_t + \beta_{22} * TACC_t * INFO + \varepsilon$ and

$RETS_{t+1} = \gamma_0 + \gamma_1 * INFO + \beta_1 * ROA_t + \beta_{11} * ROA_t * INFO + \beta_2 * \Delta NOA_t + \beta_{22} * \Delta NOA_t * INFO + \delta_3 * \Delta FIN_t + \delta_{33} * \Delta FIN_t * INFO + \varepsilon$

t-statistics for pooled regressions control for clustering by firm. Coefficients for annual regressions are averaged as in Fama and MacBeth (1973). t-statistics for annual regressions are from the distribution of annual coefficients, controlling for autocorrelation as in Bernard (1995).

	Entire Sample (INFO= 0 when no cash flow forecasts)				Subsample with cash flow forecasts			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	-0.0047 (-1.76)	0.0039 (1.44)	-0.0027 (-0.43)	0.0051 (0.97)	0.0005 (0.09)	0.0045 (0.73)	-0.0342 (-0.91)	-0.0242 (-0.71)
INFO	0.2728 (6.59)	0.2923 (7.01)	-0.0608 (-0.29)	-0.0410 (-0.18)	0.2476 (7.88)	0.2642 (8.39)	0.1270 (0.64)	0.1510 (0.74)
ROA	0.2017 (19.71)	0.2095 (20.50)	0.1706 (2.78)	0.1747 (2.83)	0.169 (4.77)	0.1769 (4.99)	0.1932 (1.92)	0.1649 (1.74)
ROA*INFO	0.3885 (1.04)	0.2662 (0.71)	1.6883 (1.63)	1.6060 (1.47)	0.488 (1.77)	0.2803 (1.01)	1.5944 (2.54)	1.5278 (2.51)
TACC	-0.1535 (-16.15)	-0.2466 (-21.65)	-0.1141 (-5.21)		-0.0908 (-3.57)		-0.0549 (-0.94)	
TACC*INFO	**0.6067** **(2.62)**		**0.3083** **(0.79)**		**0.415** **(2.44)**		**0.4367** **(1.70)**	
ΔNOA				-0.1934 (-4.33)		-0.1128 (-3.89)		-0.0649 (-0.97)
ΔNOA*INFO		**0.6508** **(2.75)**		**0.5664** **(1.92)**		**0.3059** **(1.77)**		**0.4909** **(1.81)**
ΔFIN		-0.0561 (-5.22)		-0.0237 (-1.15)		-0.0742 (-2.44)		0.0367 (0.45)
ΔFIN*INFO		1.0247 (3.25)		-0.8849 (-0.59)		1.1452 (4.91)		0.7065 (1.41)
N	63843	63843	63843	63843	9210	9210	9210	9210
Adj. R^2	0.94%	1.28%	2.54%	2.95%	1.03%	1.36%	5.24%	6.96%

TABLE 6: The Accrual Anomaly and Accuracy of Cash Flow Forecasts

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETS_{t+1}$, which is the size-adjusted one-year ahead buy and hold return where returns are compounded starting 4 months after prior fiscal year end and returns are size-adjusted by subtracting the value weighted average returns for the same size decile in the same period. ROA_t is return on assets defined as operating income after depreciation (Compustat # 178) scaled by average total assets (Compustat #6). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See pages 9-10 for detailed definitions. Forecast accuracy is measured as $ACCU_{t+1} = 1/(|CPS\_ACT_{t+1} - CPS\_EST_{t+1}|/PRICE_{t+1})$ where CPS_EST_{t+1} is the mean consensus one-year ahead annual cash flow per share estimate, measured four months after prior fiscal year end, CPS_EST_{t+1} is the actual realized cash flow per share and PRICE is the price per share at the time of the forecast. Panel A uses ex-post realized forecast accuracy ($ACCU_{t+1}$) while Panel B uses lagged realized forecast accuracy ($ACCU_t$). For the regressions for the entire sample, ACCU is set to zero when there are no cash flow forecasts or realizations available. The two regression models are

$RETS_{t+1} = \alpha_0 + \alpha_1{*}ACCU + \beta_1{*}ROA_t + \beta_{11}{*}\ ROA_t{*}ACCU + \beta_2{*}\ TACC_t + \beta_{22}{*}\ TACC_t{*}ACCU + \varepsilon$ and

$RETS_{t+1} = \gamma_0 + \gamma_1{*}ACCU + \beta_1{*}ROA_t + \beta_{11}{*}ROA_t{*}ACCU + \beta_2{*}\Delta NOA_t + \beta_{22}{*}\Delta NOA_t{*}ACCU + \delta_3{*}\Delta FIN_t + \delta_{33}{*}\Delta FIN_t{*}ACCU + \varepsilon$

t-statistics for pooled regressions control for clustering by firm. Coefficients for annual regressions are averaged as in Fama and MacBeth (1973). t-statistics for annual regressions are from the distribution of annual coefficients, controlling for autocorrelation as in Bernard (1995).

Panel A: Ex-Post Forecast Accuracy

	Entire Sample (ACCU = 0 when no cash flow forecasts)				Subsample with cash flow forecasts			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	-0.003	0.0062	0.0008	0.0087	0.0714	0.0817	-0.0017	0.0243
	(-1.06)	(2.17)	(0.09)	(1.16)	(4.29)	(4.81)	(-0.03)	(0.39)
ACCU	0.0037	0.002	-0.0103	-0.0086	-0.0137	-0.0155	-0.0062	-0.0107
	(1.61)	(0.86)	(-1)	(-0.89)	(-3.12)	(-3.46)	(-0.6)	(-1.1)
ROA	0.2063	0.2142	0.1783	0.1822	0.4346	0.4688	0.394	0.3515
	(19.72)	(20.51)	(2.94)	(2.98)	(4.29)	(4.61)	(2.01)	(1.83)
ROA*ACCU	-0.0195	-0.0199	0.0049	-0.0064	-0.0657	-0.0721	-0.0383	-0.029
	(-1.49)	(-1.52)	(0.26)	(-0.36)	(-2.51)	(-2.75)	(-0.69)	(-0.53)
TACC	-0.158		-0.1116		-0.2831		-0.1530	
	(-16.19)		(-4.82)		(-3.82)		(-2.45)	
TACC*ACCU	**0.0207**		**0.0355**		**0.0500**		**0.0336**	
	(2.28)		**(1.87)**		**(2.78)**		**(1.69)**	
ΔNOA		-0.2577		-0.1941		-0.3796		-0.1961
		(-21.96)		(-4.23)		(-4.66)		(-2.19)
ΔNOA*ACCU		**0.0387**		**0.0410**		**0.0669**		**0.0402**
		(3.68)		**(2.33)**		**(3.27)**		**(1.74)**
ΔFIN		-0.0544		-0.0195		-0.1223		0.1179
		(-4.95)		(-0.91)		(-1.42)		(0.62)
ΔFIN*ACCU		0.0046		0.0425		0.0216		-0.0308
		(0.44)		(1.71)		(1.04)		(-0.71)
N	63843	63843	63843	63843	8706	8706	8706	8706
Adj. R^2	0.88%	1.23%	2.35%	2.76%	0.71%	0.85%	4.59%	6.56%

Panel B: Prior Forecast Accuracy

	Entire Sample (ACCU = 0 when no cash flow forecasts)				Subsample with cash flow forecasts			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	-0.0049 (-1.86)	0.0037 (1.38)	-0.0018 (-0.22)	0.0061 (0.86)	0.0665 (3.78)	0.072 (3.96)	0.0691 (1.29)	0.0692 (1.31)
ACCU	0.0029 (1.42)	0.002 (0.96)	-0.0011 (-0.09)	-0.0009 (-0.07)	-0.012 (-2.6)	-0.0124 (-2.59)	-0.0204 (-2.38)	-0.0205 (-2.2)
ROA	0.2035 (20.81)	0.2117 (21.68)	0.1597 (2.44)	0.1623 (2.46)	0.1965 (1.66)	0.1822 (1.54)	0.0139 (0.07)	-0.0163 (-0.06)
ROA*ACCU	-0.0118 (-0.97)	-0.0139 (-1.14)	-0.0392 (-0.91)	-0.0363 (-0.81)	-0.0096 (-0.32)	-0.0066 (-0.22)	0.0132 (0.3)	0.0246 (0.40)
TACC	-0.146 (-16.02)		-0.1068 (-4.12)		-0.4447 (-4.42)		-0.4685 (-5.03)	
TACC*ACCU	**0.0211 (2.12)**		**0.0097 (0.71)**		**0.0754 (3.11)**		**0.0956 (2.31)**	
ΔNOA		-0.2398 (-21.81)		-0.1824 (-3.52)		-0.4633 (-4.47)		-0.5100 (-4.30)
ΔNOA*ACCU		**0.0252 (2.37)**		**0.0229 (1.21)**		**0.073 (2.88)**		**0.1057 (1.88)**
ΔFIN		-0.0513 (-5.00)		-0.0224 (-1.29)		-0.3439 (-2.79)		-0.7237 (-2.11)
ΔFIN*ACCU		0.0032 (0.27)		-0.0154 (-0.42)		0.0655 (2.21)		0.1601 (1.57)
N	63843	63843	63843	63843	7163	7163	7163	7163
Adj. R^2	0.87%	1.22%	2.31%	2.66%	0.52%	0.61%	4.59%	6.56%

TABLE 7: Increased Persistence in the Accrual Component of Earnings across Time

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $ROA_{t+1,}$ which is the one-year ahead Return on Assets. ROA_t is current return on assets defined as operating income after depreciation (Compustat # 178) scaled by average total assets (Compustat #6). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See pages 9-10 for detailed definitions.
The two regression models are

$ROA_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \varepsilon$. and

$ROA_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \varepsilon$

t-statistics for pooled regressions control for clustering by firm. Coefficients for annual regressions are averaged as in Fama and MacBeth (1973). t-statistics for annual regressions are from the distribution of annual coefficients, controlling for autocorrelation as in Bernard (1995).

	Entire Sample				Early Period (1993-2002)				Later Period (2003-2007)			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	-0.0005 (-0.96)	0.001 (1.68)	-0.0009 (-0.26)	0.0004 (0.10)	-0.0015 (-2.20)	0.0003 (0.37)	-0.0013 (-0.43)	0.0003 (0.11)	0.0012 (1.32)	0.0021 (2.20)	-0.0002 (-0.01)	0.0005 (0.04)
ROA	0.8266 (374.85)	0.8278 (375.78)	0.837 (49.57)	0.838 (49.00)	0.8099 (304.46)	0.8108 (305.48)	0.8141 (97.63)	0.815 (95.66)	0.8763 (230.63)	0.8781 (230.06)	0.8828 (68.27)	0.884 (67.18)
TACC	**-0.0478 (-23.42)**		**-0.0426 (-6.17)**		**-0.0527 (-21.79)**		**-0.051 (-17.96)**		**-0.0274 (-7.32)**		**-0.0256 (-5.38)**	
ΔNOA		**-0.0637 (-25.89)**		**-0.0577 (-6.81)**		**-0.0696 (-24.04)**		**-0.0688 (-17.25)**		**-0.0400 (-8.66)**		**-0.0355 (-7.55)**
ΔFIN		-0.0306 (-13.33)		-0.025 (-4.18)		-0.0335 (-12.31)		-0.0297 (-7.00)		-0.0166 (-3.98)		-0.0157 (-2.60)
N	59354	59354	59354	59354	43202	43202	43202	43202	16152	16152	16152	16152
Adj. R^2	70.65%	70.72%	71.66%	71.75%	68.56%	68.65%	68.79%	68.90%	77.05%	77.08%	77.41%	77.44%

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TABLE 8: Cash Flow Forecasts and the properties of Accruals

Sample consists of 63,843 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $TACC_t$, which is total accruals scaled by average assets. $TACC_{t-1}$ is lagged total accruals. See pages 9-10 for detailed definitions. CFF is an indicator variable that equals 1 for firm-years with an analyst cash flow forecast and 0 for other firm-years. ΔREV is the change in revenues (Compustat #12) less the change in receivables (Compustat #4) scaled by lagged assets. PPE is gross PP&E (Compustat #7) scaled by lagged assets. The two regression models are

$TACC_t = \alpha_0 + \beta_1 * TACC_{t-1} + \beta_2 * \Delta REV_t + \beta_3 * PPE_t + \beta_4 * ROA_t + \varepsilon$ and

$TACC_t = \alpha_0 + \alpha_1 * CFF + \beta_1 * TACC_{t-1} + \beta_{11} * TACC_{t-1} * CFF + \beta_2 * \Delta REV_t + \beta_3 * PPE_t + \beta_4 * ROA_t + \varepsilon$

t-statistics for pooled regressions control for clustering by firm. Coefficients for annual regressions are averaged as in Fama and MacBeth (1973). t-statistics for annual regressions are from the distribution of annual coefficients, controlling for autocorrelation as in Bernard (1995).

	Entire Sample				Subsample with cash flow forecasts			
	Pooled	Pooled	Annual	Annual	Pooled	Pooled	Annual	Annual
Intercept	0.049	0.0503	0.0482	0.051	0.0433	0.0506	0.0436	0.0549
	(26.54)	(26.96)	(4.93)	(5.26)	(16.49)	(18.29)	(4.07)	(5.20)
CFF		-0.0159		-0.0044		-0.0264		-0.0213
		(-4.95)		(-0.34)		(-8.38)		(-1.17)
$TACC_{t-1}$	-0.0671	-0.0761	-0.0556	-0.0685	-0.039	-0.0669	-0.0161	-0.0593
	(-17.12)	(-18.74)	(-1.97)	(-2.37)	(-6.31)	(-9.56)	(-1.07)	(-2.25)
$TACC_{t-1}$ *CFF		**0.1292**		**0.0988**		**0.1222**		**0.0962**
		(8.50)		**(3.01)**		**(8.45)**		**(2.45)**
ΔREV	0.207	0.2065	0.1867	0.1851	0.2194	0.2163	0.1977	0.1924
	(59.37)	(59.21)	(12.74)	(12.37)	(40.8)	(40.14)	(17.84)	(17.05)
PPE	-0.0317	-0.0311	-0.0295	-0.0294	-0.0148	-0.0135	-0.014	-0.0117
	(-12.07)	(-11.8)	(-2.27)	(-2.18)	(-4.55)	(-4.16)	(-1.07)	(-0.88)
ROA	0.1695	0.1712	0.1800	0.1842	0.1317	0.1362	0.1378	0.1498
	(36.06)	(36.22)	(5.05)	(5.45)	(15.37)	(15.89)	(3.60)	(4.01)
N	48438	48438	48438	48438	19950	19950	19950	19950
Adj. R^2	11.48%	11.62%	12.74%	12.98%	10.69%	11.15%	13.02%	13.92%

TABLE 9: Trading Turnover, Institutional Investment and Cash Flow Forecasts

Sample consists of 55,718 non-financial firms in the time period 1993-2007 with financial information on COMPUSTAT, stock returns on CRSP and trading information on the TAQ database. Panel A presents the mean trading characteristics for the entire sample by year. Monthly Trading turnover is the number of shares traded scaled by shares outstanding. Statistics are averaged or cumulated by firm on a monthly basis and then averaged for the year over a 12 month period beginning 4 months after fiscal year end. Panel B presents trading characteristics by quintiles on the basis of total accruals, TACC, defined on pages 9-10. Panel C presents the results from the following time series regression run for the two extreme accrual quintiles (quintiles 1 and 5).

$LTURN = \alpha_0 + \beta_1*LAUM + \beta_2*IDIO + \beta_3*LPRC + \beta_4*CFF + \varepsilon$

where LTURN is the value-weighted average of mean log of monthly turnover (Shares Traded/ Shares Outstanding), LAUM is the log of assets under management by hedge funds (from Barclayshedge.com as per Green, Hand and Soliman (2009)), IDIO is the value-weighted average of firm-level idiosyncratic risk measured as the standard deviation of the residual of firm-level regressions of returns on the CRSP value weighted index over the same period as that for the one-year-ahead returns, and LPRC is the value-weighted average of the mean month-end log of stock price.

Panel A: Trading Characteristics for Entire Sample

Year	N	Mean Trade Size (# of shares)	Mean Trade Size ($)	Monthly Number of Trades	Monthly Trading Volume (# of shares)	Monthly Trading Turnover
1993	3212	1926	24950	1105	2057698	8.0%
1994	3435	1837	26626	1560	2670742	10.4%
1995	3693	1824	27250	1871	3167033	11.5%
1996	4278	1665	26567	2367	3580855	12.8%
1997	4414	1510	21644	3500	4434880	11.9%
1998	4174	1252	19975	6543	6370784	15.2%
1999	4280	1154	17534	10040	8974149	15.2%
2000	3980	1040	12155	11555	10491453	12.1%
2001	3683	861	7786	14418	11420484	10.9%
2002	3529	657	8216	21199	13545030	16.0%
2003	3575	574	8271	26013	13992574	17.0%
2004	3665	512	7728	32262	15604762	17.7%
2005	3671	407	6333	47606	18074469	19.3%
2006	3187	333	6020	82149	22901020	22.1%
2007	2942	354	3863	128690	28738012	22.0%

Panel B: Trading Characteristics Partitioned by Accrual Quintile

	Accrual Quintile 1			Accrual Quintile 2,3 and 4			Accrual Quintile 5		
	Mean Trade Size		Trading Turnover	Mean Trade Size		Trading Turnover	Mean Trade Size		Trading Turnover
	#	$		#	$		#	$	
1993	2257	18014	7.8%	1749	26968	6.7%	2159	25486	12.3%
1994	2086	16842	12.2%	1716	29409	8.0%	1980	27255	16.3%
1995	2209	17843	12.2%	1705	29966	9.1%	1819	27991	18.4%
1996	1855	18109	14.9%	1563	29525	10.6%	1805	25337	17.6%
1997	1642	13766	13.8%	1450	24227	10.1%	1568	21241	16.0%
1998	1277	13483	22.3%	1266	22061	11.3%	1184	19973	20.0%
1999	1187	11691	20.2%	1188	19597	11.4%	1012	16699	22.6%
2000	1186	7394	11.4%	973	14401	10.2%	1109	9796	19.1%
2001	1163	3623	9.8%	793	8943	9.7%	784	8155	15.5%
2002	896	4709	19.2%	602	9203	13.6%	604	8445	20.6%
2003	692	5032	20.4%	524	9571	14.6%	610	7477	21.1%
2004	680	5212	19.7%	461	9110	15.4%	504	5979	22.4%
2005	511	4206	21.7%	367	7193	17.4%	426	5842	22.7%
2006	437	4102	22.6%	299	6978	20.7%	332	5053	25.7%
2007	434	2387	20.4%	292	4115	21.6%	461	4583	25.0%

Panel C: Regression for Determinants of Share Turnover

Model LTURN = $\alpha_0 + \beta_1$*LAUM + β_2*IDIO + β_3*LPRC + β_4*CFF + ε

	Accrual Quintile 1	Accrual Quintile 5	Accrual Quintile 1	Accrual Quintile 5
Intercept	0.02591	0.1097	-0.1356	-0.0278
	(0.21)	(0.55)	(-1.44)	(-0.18)
LAUM	0.0182	0.0129	-0.0038	-0.0048
	(5.47)	(2.36)	(-0.59)	(-0.70)
LIDIO	1.0153	1.5262	6.3444	4.3137
	(0.88)	(0.88)	(3.86)	(2.79)
LPRC	0.0035	-0.0093	0.0161	0.0060
	(0.11)	(-0.16)	(0.72)	(0.14)
CFF			0.2240	0.1937
			(3.69)	(3.23)
N	15	15	15	15
Adj. R^2	70.0%	23.6%	86.0%	58.8%