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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 accruals anomaly, demonstrated by Sloan (1996), generated significant excess returns 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 this decline is the increasing incidence of analysts' cash flow forecasts which has provided markets with forecasts of future accruals. The negative relationship between accruals and future returns is significantly weaker in the presence of cash flow forecasts. This anomalous relationship becomes weaker with the initiation of cash flow forecasts and stronger with the termination of cash flow forecasts. Further, the mitigating effect of cash flow forecasts is greater for forecasts that are ex-ante more likely to be accurate or ex-post most accurate. The explanation is incremental to explanations based on the improved quality of accruals, reduced manipulation of special items and restructuring charges and the greater investment in accruals strategies by hedge funds. The results highlight the increasing importance of analysts' cash flow forecasts in the appropriate 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. While Khan (2008) argues that the accruals anomaly disappears in a well specified inter-temporal CAPM model, Hirshleifer, Hou and Teoh (2011) show that the accrual characteristic rather than an accrual factor predicts returns, consistent with mispricing.

Prior research has also questioned why the accruals 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. Recently, Lev and Nissim (2006) and Mashruwalla, Rajgopal, and Shevlin (2006) confirm that the anomaly continued to be robust for the next decade. Both these papers argue that the anomaly persists because potential arbitrageurs are deterred by the costs of arbitrage (Mashruwalla, Rajgopal and Shevlin 2006) or by the small size and illiquidity of firms in extreme accrual deciles which precludes many institutional investors from investing (Lev and Nissim 2006).

Against this backdrop, it is quite surprising to observe that an effect as robust as the accruals anomaly appeared to be has significantly weakened in the period since 2002 (Figure 1).

In this paper, I argue that the increasing incidence of cash flow forecasts by analysts is one factor that has contributed to the decline in the accruals anomaly. If the accruals 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 incremental information in cash flow forecasts can help mitigate the mispricing of accruals.

Traditionally, analysts have focused their attention on the prediction of earnings (EPS). Recently, analysts have also started to issue forecasts of cash flow per share (CPS). Cash flow forecasts were rare until 2001, when less than 10% of all firms had cash flow forecasts as reported on I/B/E/S. This proportion has increased dramatically since 2002, to the point that by 2009, almost 42% of all firms have cash flow forecasts in 2007 and 55% of analysts who issue any kind of forecast issue cash flow forecasts (1443 out of 2645, Table 2).

The increased incidence 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) question the quality of cash flow forecasts and caution that such forecasts are often mere mechanical adjustments to earnings forecasts. 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. Further, I find that the mitigating effect of cash flow forecasts on the pricing of accruals is greatest in the latter period of my sample (2002-2009), which corresponds to the time period when the accruals anomaly declined. I next hypothesize and find that accruals are less likely to be mispriced when cash flow forecasts are initiated for the first time and more likely to be mispriced when cash flow forecasts are no longer available for a firm. Finally, I hypothesize and find that the mitigating effect of cash flow forecasts is stronger when cash flow forecasts are more accurate.

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 while the persistence of accruals has improved since 2002, this increased persistence is associated with the incidence of cash flow forecasts. Further, all 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 the accruals anomaly 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 association between increased turnover and assets managed by hedge funds weakens after controlling for the extent of cash flow forecasts. The cash flow forecast based explanation is hence incremental to other explanations for the decline in the accruals anomaly.

There are some caveats which are essential to mention. The period where the accruals 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.

Indeed, the accruals anomaly appeared to generate significant returns in the year 2008, although this might also be related to the financial crisis. Further, even if the accruals anomaly has indeed disappeared, it is 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. Finally, the cash flow forecast based explanation only partially explains the decline in the mispricing of accruals as a decline in mispricing is also seen for firms without 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 accruals anomaly. Section 4 presents the empirical results testing the hypotheses. Section 5 considers alternative explanations for the decline in the accruals anomaly. Section 6 concludes.

2. Related Research and Hypothesis Development

2.1 RELATED RESEARCH

2.1.1 The Accruals Anomaly

The accruals anomaly was first outlined in Sloan (1996) who argued that investors are unable to distinguish between the more persistent cash component of earnings 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 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, Xie (2001) shows that it is the discretionary component of accruals that are mispriced while Richardson et al. (2005) document that the mispricing is greater for accruals that are less reliable (non-current accruals) than for accruals that are more reliable (change in working capital and financing accruals).

There is vast and unsettled literature examining whether the returns to accruals strategies represent an anomaly or whether they represent returns to omitted risk factors. Khan (2008) argues that the returns to the accruals strategy disappear in a well specified intertemporal CAPM model. Hirshleifer, Hou and Teoh (2011) however argue that the accruals anomaly results from mispricing, as it is the accrual characteristic that is associated with returns as opposed to an accruals-based factor. Desai, Rajgopal and Venkatachalam (2004) do not address whether the accruals anomaly is caused by risk or mispricing, but focus on whether it is an independent effect. They conclude that the accruals anomaly is a manifestation of the book-to-market or value- glamour effect from Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994). However, a recent paper by Allen, Larson and Sloan (2009) suggests that the predictable returns and earnings that follow extreme accruals are explained by extreme accrual reversals.

Prior research has also examined how, a trading rule with returns as high as the accruals 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 accruals distribution. They find that such 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 accruals 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 accruals 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 accruals anomaly.

2.1.2 Cash Flow Forecasts

The issuance of cash flow forecasts by analysts is a relatively 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 with 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 contents of analysts' reports that contain cash flow forecasts and conclude that the forecasts are not mere 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 than earnings forecasts. However, they do not test whether cash flow forecasts improve the quality of earnings forecasts, something that Call, Chen and Tong (2009) document. Further, Call, Chen and Tong (2011) analyze the contents of analysts' cash flow forecasts and show that these forecasts are not naïve extensions of earnings forecasts, but instead entail sophisticated analyses of accruals.

The research on cash flow forecasts also provides evidence on the underlying mechanism for the accruals 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 (2008) finds that the accruals are more likely to be fully impounded in prices when firms disclose accrual information in preliminary earnings announcements. This suggests that when investor demand for accrual information is met through additional disclosure, the mispricing associated with accruals is mitigated. 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 (Call, Chen and Tong 2009). Further, recent research by Allen, Larson and Sloan (2009) indicates that the driving force behind the accrual anomaly appears to be the predictable reversal in accruals for firms with extreme accruals. If financial analysts' are sophisticated enough to understand the predictable reversal in accruals and incorporate this in their cash flow forecasts and earnings forecasts, then one should observe mitigation in the accruals anomaly with the growing incidence of cash flow forecasts.

Recent work by Collins and McInnis (2011) shows that accruals are less likely to be manipulated in firms when analysts also issue cash flow forecasts. Further, Xie (2001) documents that the accruals anomaly is primarily driven by the mispricing of abnormal accruals. Combining these two results suggests that the increasing incidence of cash flow forecasts might mitigate the mispricing of accruals by reducing the magnitude of abnormal accruals.

Countering this however is evidence in Givoly, Hayn and Lehavy (2009) that cash flow forecasts do not provide reliable information to capital markets. Further, Bradshaw, Richardson and Sloan (2001) document that analysts misprice accruals, though their evidence stems from a period before cash flow forecasts were prevalent. Finally, Eames, Glover and Kim (2010) show that the I/B/E/S definition of cash flows does not map exactly or consistently with the Compustat definition of cash flow from operations, which might limit the usefulness of these forecasts. However, using I/B/E/S forecast and actuals data, they find evidence that analysts' implicit forecasts of accruals do predict realizations of accruals, albeit noisily.

Given the recent evidence regarding the improved earnings forecasts and reduced accruals manipulation in the presence of cash flow forecasts, I expect that cash flow forecasts will mitigate the mispricing of accruals. Prior research has shown a negative relationship between the accrual component of earnings and future returns. If this relationship is less negative for firms with cash flow forecasts, then this would reject the null and indicate that cash flow forecasts mitigate accruals mispricing. My first hypothesis, stated in the alternate form, is:

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

2.2.2 The Accruals Anomaly and the Initiation/Termination of Cash Flow Forecasts

If cash flow forecasts mitigate accruals mispricing, the effect should be apparent at the time when they first become available, as the capital markets have access to a signal that they did not have access to earlier on. Conversely, if cash flow forecasts cease to be available, this should exacerbate the mispricing of accruals. My second hypothesis, stated in the alternate form is

$H2_a$: The relationship between the accrual component of earnings and future returns is less negative for firms in the year of initiation of cash flow forecasts.

$H2_b$: The relationship between the accrual component of earnings and future returns is more negative for firms in the year of termination of 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 accruals anomaly will eventually depend on the accuracy of the cash flow forecasts. If, as Givoly, Hayn and Lehavy (2009) indicate, cash flow forecasts are inaccurate, their usefulness may be limited. However, when cash flow forecasts are accurate, then they are potentially more useful in mitigating the mispricing of accruals. I hypothesize a weakening of the accruals anomaly when cash flow forecasts are more accurate. I state the hypothesis in the alternate form as follows.

$H3_a$: The relationship between the accrual component of earnings and future returns is less negative for firms with more ex-post accurate cash flow forecasts.

In addition, the prior accuracy of cash flow forecasts can influence the likelihood that capital markets pay attention to them. Prior research has documented that investors are more likely to respond to new information from analysts who have been more accurate in the past (Stickel 1992, Park and Stice 2000, Gleason and Lee 2003). Relatedly, Brown (2001) documents that practitioners pay the greatest attention to past accuracy while evaluating analysts, as prior accuracy is the most important determinant of future accuracy. If cash flow forecasts for a given firm have been more accurate in the past, I hypothesize that they are more likely to mitigate the mispricing of accruals. I state the hypothesis in the alternate form as follows.

$H3_b$: The relationship between the accrual component of earnings and future returns is less negative for firms with more ex-ante accurate cash flow forecasts.

3. Preliminary Evidence on the Decline in the Accruals Anomaly and Cash Flow Forecasts

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 2009, to ensure that stock returns for the next fiscal year can be calculated.[1] The full sample analyzed consists of 70,867 firm-years corresponding to 10,177 distinct firms.

To determine whether a firm had a 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.

I follow the definition from Richardson et al. (2005) for the measurement of accruals (figures in parentheses represent the mnemonics for the data items from the Compustat FUNDA annual file). Total accruals (TACC) is defined as $TACC = \Delta WC + \Delta NCO + \Delta FIN$ where:

[1] As return data is available only till Dec 2010, the future returns for 2009 are part-year returns.

(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 (ACT) - Cash and Short Term Investments (CHE), and COL = Current Liabilities (LCT) - Debt in Current Liabilities (DLC).

(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 (AT) - Current Assets (ACT) - Investments and Advances (IVAO), and NCOL = Total Liabilities (LT) - Current Liabilities (LCT) - Long-Term Debt (DLTT).

(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 (IVST) + Long Term Investments (IVAO), and FINL = Long Term Debt (DLTT) + Debt in Current Liabilities (DLC) + Preferred Stock (PSTK).

Each component of earnings is scaled by average total assets (AT). Return on assets (ROA) is operating income after depreciation (OIADP) scaled by average total assets (AT). Consistent with Richardson et al. (2005), each component of earnings is winsorized at +1 and -1.

I use two measures of accruals. First, I use the total accruals (TACC) as used in Sloan (1996). Second, as in Richardson et al. (2005), I break down TACC into change in net operating assets (ΔNOA) and change on financial assets (ΔFIN), where ΔNOA equals change in net working capital (ΔWC) plus 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 on CRSP and adjusted for delistings as in Shumway (1997) [2].

[2] 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.

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 6.4%. The mean of total accruals (TACC 0.058) equals the mean change in net operating assets (ΔNOA 0.070) plus the mean change in financial assets (ΔFIN -0.011). The mean size-adjusted one-year-ahead return is -0.5%. CFF has a mean of 0.157, indicating that 15.7% of all firm-year have a cash flow forecast. The sample firms had mean total assets of $1650 million and mean market capitalization of $2009 million.

Panel B presents the correlations. Consistent with Sloan (1996), total accruals (TACC) are 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, CFF is positively correlated with profitability (ROA), firm size (ASST and MCAP) and stock return performance ($RETS_{t+1}$). In tests that follow, I control for sample selection bias either using a Heckman (1979) 2-stage approach or with a propensity-score matched sample approach.

3.3 CASH FLOW FORECASTS AND THE ACCRUALS ANOMALY: PRELIMINARY EVIDENCE

Panel A of Table 2 presents evidence on the increasing incidence of cash flow forecasts. In 1993, only 23 firms out of 4,227 had cash flow forecasts, while 1,958 firms had EPS forecasts. Cash flow forecasts increase gradually till 2001 and jump up dramatically in 2002. In 2001, only 238 firms had cash flow forecasts, representing only 6% of all firms and 11% of firms with analyst following (EPS forecasts). In 2002, 945 firms had cash flow forecasts, representing 25% of all firms and 44% of followed firms. Since 2002, the proportion of firms with cash flow forecast has continued to increase gradually. In 2009, 1,443 firms had cash flow forecasts, representing almost 42% of all firms and almost 55% of firms with analyst following.

Panel A of Table 2 also presents the returns to the accruals strategy. Firms are annually sorted into quintiles based on either total accruals (TACC) or change in net operating assets (ΔNOA). Hedge returns are computed as the difference between average size-adjusted returns for the lowest accrual quintile (long) and the highest accrual quintile (short). The results show that 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 weakened considerably in recent years. Figure 1 graphs the increasing incidence of cash flow forecasts and the decline in the accruals anomaly. As cash flow forecasts have become more prominent since 2002, the accruals anomaly has weakened.

Panel A of Table 2 also presents preliminary evidence on the impact of cash flow forecasts on hedge returns to accruals based strategies. The small number of observations with cash flow forecasts precludes one from implementing an accruals-based trading strategy on the subset of firms with cash flow forecasts, especially for the early period in the sample.[3] Instead, I estimate the impact of cash flow forecasts on the returns to the accruals anomaly by excluding firms with cash flow forecasts. If cash flow forecasts mitigate accruals based mispricing, then excluding such firms should potentially increase the returns to accruals-based trading strategies.

The average hedge returns for a strategy based on TACC ($HRET_{TACC}$) is 9.6%. When one excludes cash flow forecast firms, the mean $HRET_{TACC}$ increases to 10.5%, with the difference statistically significant at the 10% level (t-stat 1.88). Similarly, the average hedge returns for a strategy based on ΔNOA ($HRET_{\Delta NOA}$) increases from 13.9% for all firms to 15.0% for firms

[3] Till 2001, either the lowest accrual quintile or the highest quintile or both had less than 30 observations among firms with cash flow forecasts.

without cash flow forecasts, with the difference significant at the 5% level (t-stat 2.16). Partitioning the results into an earlier period (1993-2001) when cash flow forecasts were less prevalent and a later period (2002-2009) when cash flow forecasts were more common suggests that the differences in hedge returns are less pronounced earlier and more pronounced later. For instance in the later period, $HRET_{\Delta NOA}$ increases from 6.2% for all firms to 8.1% for firms without cash flow forecasts (t-stat for difference 1.83).[4] $HRET_{TACC}$ shows a similar trend, but the difference is not significant. However, it must be noted that the returns to the accruals anomaly also decline for firms without cash flow forecasts. This suggests that the presence of cash flow forecasts can only be a partial explanation for the decline in the accruals anomaly.

Why do cash flow forecasts help mitigate the mispricing of accruals? Call et al. (2009) show that firms with cash flow forecasts in addition to earnings forecasts have lower average absolute forecast error. I confirm that this holds in my sample as well as shown in Panel B of Table 2. In every year of the sample, the mean absolute forecast error (AFE) is lower for the subsample with cash flow forecasts than the subsample without cash flow forecasts. Interestingly, the differences in absolute forecast error between the two subsamples are increasingly significant in the latter years of the sample when the number of cash flow forecasts increased and the returns to the accruals anomaly declined.

4. Results

4.1 THE WEAKENING OF THE ACCRUALS ANOMALY OVER TIME

I first analyze whether the accruals anomaly is getting weaker over time. I run the following regressions to analyze the pricing of the components of earnings

[4] Since 2002, the subset of firms with cash flow forecasts has enough observations to test hedge strategies meaningfully (more than 30 firms per year in extreme quintiles). The mean $HRET_{TACC}$ is 4.7% and mean $HRET_{\Delta NOA}$ is only 1.8% for the subset of firms without cash flow forecasts, significantly lower than the mean returns for the subset with cash flow forecasts

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

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 operating income after depreciation scaled by average total assets, $TACC_t$ is total accruals, ΔNOA is change in net operating assets and ΔFIN is change in financial assets (see section 3.1 for details).

In the above regressions, the coefficient on ROA represents the pricing of all components of earnings (cash flow and accruals). The coefficient on TACC in equation 1 (on ΔNOA and ΔFIN in equation 2) represents the differential pricing of the accrual component(s) of earnings. If the accruals anomaly is indeed present in the time period being analyzed, 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 above specifications as pooled regressions, with time and industry fixed effects (2 digit SIC code) and t-statistics that control for clustering by firm.[5] A similar approach is used for all accruals pricing regressions in this paper. The results are presented in Table 3.

The first set of columns present regressions for the entire time period and confirm the accruals anomaly. Both accruals measures (TACC and ΔNOA) are strongly negatively correlated with future returns. Also, consistent with Richardson et al. (2005), the coefficient on ΔNOA (-0.2598) is significantly more negative than that on TACC (-0.1719).

I next examine the trend in the pricing of accruals. I first define an indicator variable called LATER, which equals 1 for the years 2002-2009 and 0 for the years 1993-2001. I interact

[5] All the regressions in Tables 3 through 7 are rerun as annual Fama and MacBeth (1973) regressions with corrections for auto-correlation in the coefficients across time, using the correction in Bernard (1995). Results are broadly similar and significant, but the levels of significance are lower and occasionally insignificant. This can be attributed to two factors. Firstly, the sample has only 17 years to average coefficients across. Secondly, the number of observations with cash flow forecasts is very low until 2002.

LATER with the components of earnings growth and test whether the pricing of accruals changed across time. As the regression includes time fixed-effects, it is not required to include LATER as an intercept term. The modified regressions that are run are hence

$$RETS_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \beta_{11} * ROA_t * LATER + \beta_{21} * TACC_t * LATER + \varepsilon \quad (3)$$

and

$$RETS_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \delta_{11} * ROA_t * LATER + \delta_{21} * \Delta NOA_t * LATER + \delta_{31} * \Delta FIN_t * LATER + \varepsilon \quad (4)$$

The results are presented in the last two columns of Table 3. The coefficient β_{21} on the interaction of TACC with LATER is significantly positive (0.1202), consistent with a decline in the mispricing of accruals. Similarly, the coefficient δ_{21} on the interaction of ΔNOA with LATER is also significantly positive (0.1913). The regressions confirm the preliminary evidence in Table 2 and Figure 1 that the accruals anomaly has declined over time.[6]

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 specifications 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

$$RETS_{t+1} = \alpha_0 + \alpha_1 * CFF + \beta_1 * ROA_t + \beta_{11} * ROA_t * CFF + \beta_2 * TACC_t + \beta_{21} * TACC_t * CFF + \varepsilon \quad (5)$$

and

$$RETS_{t+1} = \gamma_0 + \gamma_1 * CFF + \delta_1 * ROA_t + \delta_{11} * ROA_t * CFF + \delta_2 * \Delta NOA_t + \delta_{21} * \Delta NOA_t * CFF +$$

[6] As an alternate specification, I define a time trend variable TIME which increases from 1 in 1993 to 17 in 2009 and use TIME instead of LATER in the regressions. The interaction of TIME with both TACC as well as ΔNOA is significantly weaker than that for LATER reported in Table 3. This suggests that the pricing of accruals did not change gradually across time but rather differed between the early and later periods. Hence, for all regressions in the rest of paper, LATER is used as to test for differences between the early and later periods.

$$\delta_3 * \Delta FIN_t + \delta_{31} * \Delta FIN_t * CFF + \varepsilon \quad (6)$$

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_{21} on TACC*CFF in model (3) and the coefficient δ_{21} on ΔNOA*CFF in model (4) to be significantly positive.

The first set of columns of Table 4 presents the results from the regressions in equations (5) and (6) for the entire sample. There is support for the hypothesis that the presence of cash flow forecasts reduces the mispricing of accruals. For the specification with total accruals, the coefficient β_2 on TACC is -0.1729, while the incremental coefficient β_{22} on TACC*CFF is 0.0713 (t-stat 1.87), indicating that the negative relationship between accruals and future returns is weaker in the presence of cash flow forecasts. Similarly, the coefficient δ_2 on ΔNOA is -0.2668, while the incremental coefficient δ_{22} on ΔNOA*CFF is 0.0913 (t-stat 1.93). The results hence reject the null of hypothesis H1 and indicate that the incidence of cash flow forecasts is associated with less mispricing of accruals.

The above results are from the 1993-2009 time period, which includes the initial years where cash flow forecasts were less prevalent. To test whether the mitigating effect of cash flow forecasts on the mispricing of accruals is constant throughout the sample period, I include interactions with LATER. As before, as the regression includes time fixed-effects, it is not required to include LATER as an intercept term. The regression specifications are hence

$$RETS_{t+1} = \alpha_0 + \alpha_1 * CFF + \beta_1 * ROA_t + \beta_{11} * ROA_t * CFF + \beta_{111} * ROA_t * CFF * LATER + \beta_2 * TACC_t$$
$$+ \beta_{21} * TACC_t * CFF + \beta_{211} * TACC_t * CFF * LATER + \varepsilon \quad (7)$$

and

$$RETS_{t+1} = \gamma_0 + \delta_1 * CFF + \delta_1 * ROA_t + \delta_{11} * ROA_t * CFF + \delta_{111} * ROA_t * CFF * LATER + \delta_2 * \Delta NOA_t + \delta_{21} * \Delta NOA_t$$

$$*CFF + \delta_{211}*\Delta NOA_t*CFF*LATER + \delta_3*\Delta FIN_t + \delta_{31}*\Delta FIN_t*CFF + \delta_{311}*\Delta FIN_t*CFF*LATER + \varepsilon \quad (8)$$

The results are presented in the last two columns of table 4. Interestingly, cash flow forecasts have an insignificant effect in the early period as the coefficient on TACC*CFF is insignificant (-0.1419, t-stat -1.30). However, cash flow forecasts appear to mitigate mispricing of accruals in the later periods, as the coefficient on TACC*CFF*LATER is significantly positive (0.2799, t-stat 3.66). The net impact of cash flow forecasts in the later periods can be calculated as the sum of the above two coefficients, which is 0.1380, which is significantly greater than zero at the 5% level. Results are similar when the ΔNOA specification is used.

The fact that cash flow forecasts did not mitigate the mispricing of accruals in the early period is consistent with the finding in Bradshaw, Richardson and Sloan (2001) that analysts also misprice accruals. However, the mitigating effect in the later period is consistent with the more recent findings in Call, Chen and Tong (2009).

4.3 CONTROLS FOR SAMPLE SELECTION BIAS/CORRELATED OMITTED VARIABLES

One issue that can affect the interpretation of the results from these regressions is that the documented impact of cash flow forecasts may reflect selection bias. In other words, the weaker accruals anomaly in the presence of cash flow forecasts may stem from the fact that these firms are less subject to accrual mispricing than other firms, independent of the cash flow forecast. I control for sample selection bias as described below.

Sample Selection Regression

The prior research on cash flow forecasts indicates that firms with cash flow forecasts are larger, more capital intensive, more likely to be in financial distress, have higher absolute accruals and have more volatile earnings. If these factors are also associated with the pricing of accruals, then the mitigating effect of cash flow forecasts shown earlier may simply result from sample selection. To control for sample selection bias, I run a first stage PROBIT regression with CFF as the dependent variable. I use the following independent variables used in prior research examining the incidence of cash flow forecasts (Defond and Hung 2003, Call 2008): VOL - a proxy for volatility of earnings, CYCLE – the cash cycle for the firm, Z– the Altman's Z measure of the probability of bankruptcy, CAPINT – capital intensity, ABSACC – the absolute value of total accruals and LMCAP – log of market capitalization.[7] The probit regression specification is hence

$$PR\ (CFF=1) = \alpha_0 + \beta_1 * VOL + \beta_2 * CYCLE + \beta_3 * Z + \beta_4 * CAPINT + \beta_5 * ABSACC + \beta_6 * LMCAP \qquad (9)$$

The results of the PROBIT regression are presented in Panel A of Table 5. Because of data requirements, the sample size drops to 61,910 observations. All the coefficients are significant at the 1% level and of the hypothesized sign, with the exception of ABSACC which has a significant negative coefficient.[8]

The first stage regression is used to control for sample selection bias in two ways. First, consistent with Heckman (1979), I include the inverse-mills ratio from the first stage regression in the accrual pricing tests. Second, I rerun the tests by matching the cash flow forecast sample

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[7]VOL is estimated as the ratio of the coefficient of variation of earnings (IB) scaled by total assets (AT) to the coefficient of variation of cash flows (OANCF) also scaled by total assets, measured over the four prior years ensuring that at least 2 years data are available. CYCLE is measured as days receivable (365 divided by receivable turnover) plus days inventory (365 divided by inventory turnover) minus days payable (365 divided by payables turnover). Days receivable is sales (SALE) divided by average accounts receivable (RECT). Days inventory is cost of goods sold (COGS) divided by average inventory (INVT). Days payable is purchases (COGS + change in INVT) divided by average accounts payable (AP) . Z-SCORE is measured as 1.2*working capital/total assets + 1.4*retained earnings/total assets + 3.3* EBIT/total assets + 0.6*market value of equity/book value of liabilities + 1*sales/total assets. The data items used are - Working Capital : Current Assets (ACT) – Current Liabilities (LCT), Total assets (AT), Retained Earnings (RE), EBIT : Operating Income after depreciation (OIADP) plus non-operating income (NOPI), Market Capitalization: Shares Outstanding (CSHO) times Stock Price (PRCC_F), Book Value of Liabilities (LT) and Sales (SALE). CAPINT is capital intensity measured as the ratio of gross PPE (PPEGT) to total assets (AT). ABSACC is the absolute value of total accruals (TACC, defined earlier) scaled by total assets (AT). LMCAP is log of market capitalization.

[8] One potential reason for the difference in sign with respect to ABSACC is the fact that prior research has focused on the determinants of cash flow forecasts among firms with analyst forecasts while this regression is being run in the universe of firms which also includes firms without analyst following. Untabulated results confirm this, as the mean value of ABSACC is indeed lower for firms with analyst following than firms without analyst following; however within this group, firms with cash flow forecasts have higher mean ABSACC.

with observations without cash flow forecasts based on their propensity to issue cash flow forecasts. The results are presented in Panels B and C of Table 5.

Heckman (1979) 2nd Stage Regression

Panel B of Table 5 repeat the analysis in Table 4 with the addition of the inverse mills ratio as an additional independent variable. The first two columns present the results from the basic regressions for the entire time period (equations 5 and 6). The results are essentially unchanged. The coefficient on TACC*CFF continues to be significantly positive (0.0681, t-stat 1.85), while for the NOA specification, the coefficient on ΔNOA*CFF remains significant (0.0899, t-stat 2.23). The next two columns repeat the analysis with the interactions with LATER (equations 7 and 8). The results are essentially unchanged, with the coefficient on TACC*CFF*LATER remaining significant (0.3238, t-stat 3.96), and for the ΔNOA specification, the coefficient on ΔNOA*CFF*LATER remaining significant (0.3966, t-stat 4.85).

Propensity Score Matched Regression

From the first stage PROBIT regression, the probability of CFF=1 is calculated for each observation. Each of the cash flow forecasts are matched in the same year with non-forecast observations from the same industry (based on 2 digit SIC code) with the closest estimated probability of CFF=1. The accrual pricing regressions are then rerun in the subsample consisting of the cash flow forecasts and the matched non-forecast observations. This approach based on propensity score matching successfully randomizes across the determinants of cash flow forecasts. This approach is similar to that discussed in Francis and Lennox (2008) and implemented in Doyle, Ge and McVay (2007).

The results are presented in Panel C of Table 5. The number of observations declines to 20,206 corresponding to 10,103 cash flow forecasts for which the first-stage regression could be run to estimate a propensity score and a match found, and the matching non-forecast observations. Here again, the results are essentially unchanged. The first two columns present the basic regressions. The results are essentially unchanged as the coefficient on TACC*CFF continues to be significantly positive (0.0610, t-stat 1.68). For the NOA specification, the coefficient on ΔNOA*CFF also remains significant (0.0790, t-stat 1.85). The next two columns repeat the analysis with the interactions with LATER. The coefficient on TACC*CFF*LATER remains highly significant (0.3623, t-stat 4.33), and for the ΔNOA specification, the coefficient on ΔNOA CFF*LATER remains highly significant (0.4407, t-stat 5.22).

Thus, based on the results of the Heckman (1979) 2-stage approach as well as the propensity score matching approach, it is unlikely that the correlations shown between cash flow forecasts and accruals pricing are an artefact of sample selection bias.

4.4 THE ACCRUALS ANOMALY AND INITIATION/TERMINATION OF CASH FLOW FORECASTS

As a more direct test of the effect of cash flow forecasts on the pricing of accruals, I next test the impact of the initiation or termination of cash flow forecasts on the pricing of accruals. I define the indicator variable START that equals 1 for the first instance of a cash flow forecast for a given firm and 0 otherwise. Similarly, I define the indicator variable END that equals for firm-years without cash flow forecasts where the prior year had a cash flow forecast. To ensure that END is not just picking up the dropping of all coverage, I ensure that the firm continues to have analyst coverage (i.e. EPS forecasts). I include START and END as interaction variables in the regressions for the pricing of accruals.[9]

The regression specifications are hence

[9] Using these definitions, there were 3587 observations with START=1 and 1214 observations with END=1 in the sample.

$$RETS_{t+1}= \alpha_0 + \alpha_1*START + \alpha_2*END + \beta_1*ROA_t + \beta_{11}*ROA_t*START + \beta_{12}*ROA_t*END$$
$$+ \beta_2* TACC_t + \beta_{21}* TACC_t*START + \beta_{22}* TACC_t*END + \varepsilon \quad (10)$$

and

$$RETS_{t+1}=\gamma_0 +\gamma_1*START +\gamma_2*END + \delta_1*ROA_t + \delta_{11}*ROA_t*START + \delta_{12}*ROA_t*END + \delta_2*\Delta NOA_t + \delta_{21}*$$
$$\Delta NOA_t*START + \delta_{22}*\Delta NOA_t*END + \delta_{31}*\Delta FIN_t*START + \delta_{22}*\Delta FIN_t*END + \varepsilon \quad (11)$$

I expect the incremental relationship between future returns and accruals to be less negative when cash flow forecasts are initiated, i.e. I expect β_{21} on TACC*START in equation (10) and δ_{21} on ΔNOA*START in equation (11) to be significantly positive. Conversely, I expect the incremental relationship between future returns and accruals to be more negative when cash flow forecasts are terminated, i.e. I expect β_{22} on TACC*END in equation (10) and δ_{22} on ΔNOA*END in equation (11) to be significantly negative.

Table 6 presents the results from the regressions in equations (10) and (11). The first two set columns present the results for the entire sample. Consistent with hypotheses $H2_a$ and $H2_b$, I find that accrual mispricing is mitigated when cash flow forecasts are initiated and exacerbated when cash flow forecasts are terminated. The incremental coefficient β_{21} on TACC*START is 0.0833 (t-stat 1.86), while the incremental coefficient β_{22} on TACC*END is -0.1736 (t-stat -1.69). Similarly, for the ΔNOA specification, the incremental coefficient δ_{21} on ΔNOA*START is 0.1354 (t-stat 2.61), while the incremental coefficient δ_{22} on ΔNOA*END is -0.1969 (t-stat -1.85). The last two columns repeat the above analysis by controlling for sample selection bias using the Heckman (1979) 2-stage approach as before. The results are very similar.

4.5 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 forecasts are more accurate (Hypotheses $H3_a$ and $H3_b$). I measure forecast accuracy as the reciprocal of the unsigned forecast error in the cash flow forecast. I define ACCU as

$$ACCU_{t+1} = 1/(|CPS\_ACT_{t+1} – CPS\_EST_{t+1}|/PRICE_{t+1}) \qquad (12)$$

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_ACT_{t+1} is the actual realized cash flow per share and PRICE is the price per share at the time of the forecast. I use $ACCU_{t+1}$ to test hypothesis $H3_a$ pertaining to ex-post forecast accuracy, while I use $ACCU_t$ (prior period forecast accuracy) to test hypothesis $H3_b$ pertaining to ex-ante forecast accuracy. I modify the regressions in equations (5) and (6) by interacting TACC and ΔNOA with ACCU. The modified regressions are hence

$$RETS_{t+1}= \alpha_0 +\alpha_1*ACCU +\beta_1*ROA_t +\beta_{11}*ROA_t*ACCU +\beta_2*TACC_t +\beta_{21}*TACC_t*ACCU + \varepsilon \qquad (13)$$

and

$$RETS_{t+1}= \gamma_0 + \gamma_1*ACCU + \delta_1* ROA_t + \delta_{11}* ROA_t*ACCU +\delta_2* \Delta NOA_t + \delta_{21}* \Delta NOA_t*ACCU$$
$$+\delta_3* \Delta FIN_t + \delta_{31}* \Delta FIN_t*ACCU + \varepsilon \qquad (14)$$

I expect the incremental relationship between future returns and accruals to be less negative for more accurate cash flow forecasts, i.e. I expect β_{21} on TACC*ACCU in equation (13) and δ_{21} on ΔNOA*CFF in model (14) to be significantly positive.

The first set of columns in Table 7 presents the results from the regressions in equations (13) and (14) using ex-post realized forecast accuracy. The number of observations declines to 9,333 as forecast accuracy can only be computed for firms with both cash flow forecasts and realized cash flows. The results support $H3_a$ and indicate that more accurate cash flow forecasts are associated with a reduction in the negative relationship between accruals and future returns.

The incremental coefficient β_{21} on TACC*ACCU is 0.1138 (t-stat 4.39), while the incremental coefficient δ_{21} on ΔNOA*ACCU is 0.1339 (t-stat 4.80).

The next set of columns repeats the analysis using realized forecast accuracy from the prior period to calculate ACCU. The number of observations declines further to 8,792 because of the requirement that there be cash flow forecasts in the prior period as well. The results continue to be significant for all specifications, supporting $H3_b$. The incremental coefficient β_{21} on TACC*ACCU is 0.0892 (t-stat 2.94), while the incremental coefficient δ_{22} on ΔNOA*ACCU is 0.0895 (t-stat 2.82). One can interpret these results as suggesting that the stock market pays greater attention to cash flow forecasts that are likely to be accurate because they have been accurate in the past. Overall, the results from Table 7 strongly support Hypothesis 3 that the mispricing of accruals is reduced when analysts' cash flow forecast are more accurate.

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 anomalous relationship weakens further when cash flow forecast are initiated and strengthens when cash flow forecasts are terminated. Finally, accrual mispricing is mitigated when forecasts are 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 accruals anomaly may have weakened.

5. Alternative Explanations and Caveats

The period associated with increasing cash flow forecasts also witnessed a number of changes that may have affected the nature of accruals and the likelihood that they be mispriced. Bhojraj, Sengupta and Zhang (2009), henceforth BSZ, 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), henceforth GHS, propose a different explanation for the “demise of the accruals anomaly”. They suggest that the presence of a number of leading accounting academics in the quantitative hedge fund industry 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 alternate explanations. It is possible that all these changes 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 explanation is incremental to these alternative explanations. The aim is not to run a horse race between these explanations, but rather to test the robustness and incremental explanatory power of the cash flow forecast based explanation.

5.1 THE CHANGING NATURE OF ACCRUALS OVER TIME

BSZ suggest that one reason why the accruals 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 sharply declined in recent years after increasing in the late 1990s.[10] Figures 3-A and 3-B, which graph the mean of the 10th and 90th percentiles of earnings and accruals, indicate that the extreme accruals have indeed become less extreme over time.

[10] Undocumented analysis shows that the time-series correlation between annual hedge return to the accrual anomaly based on TACC (ΔNOA) and cross-sectional standard deviation in TACC (ΔNOA) is 0.41 (0.40) over the 40 year period from 1979-2009.

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.

$$ROA_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \varepsilon \tag{15}$$

and

$$ROA_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \varepsilon \tag{16}$$

where ROA_{t+1} is one-year-ahead return on assets (operating income after depreciation (OIADP) deflated by average total assets (AT)) and all other variables are defined as before.

The results are presented in Panel A of Table 8. 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. The incremental coefficient β_2 on TACC is -0.0435 (t-stat -12.99), while the incremental coefficient δ_2 on ΔNOA is -0.0603 (t-stat -14.72).

I next include interactions with LATER to test whether the observed patterns in persistence change across time. The regression specifications are hence

$$ROA_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * TACC_t + \beta_{11} * ROA_t * LATER + \beta_{21} * TACC_t * LATER + \varepsilon \tag{17}$$

and

$$ROA_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta NOA_t + \delta_3 * \Delta FIN_t + \delta_{11} * ROA_t * LATER + \delta_{21} * \Delta NOA_t * LATER + \delta_{31} * \Delta FIN_t * LATER + \varepsilon \tag{18}$$

The results are presented in the last two columns of Panel A of Table 8. As the results indicate, the persistence of accruals appears to have increased in later periods. The incremental coefficient β_{21} on TACC*LATER is 0.0299 (t-stat 4.06), while the incremental coefficient δ_{21} on ΔNOA*LATER is 0.0367 (t-stat 3.82). These results suggest that accruals have become more persistent with time, consistent with the BSZ explanation.

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 (2011) suggests that greater availability of cash flow forecasts contributed to the improved quality of accruals by limiting accrual manipulation.

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.

$$TACC_t = \alpha_0 + \beta_1*TACC_{t-1} + \beta_2*\Delta REV_t + \beta_3*PPE_t + \beta_4*ROA_t + \varepsilon \qquad (19)$$

where $TACC_t$ and $TACC_{t-1}$ are current and lagged total accruals scaled by average assets, ΔREV is change in revenues (#12) less change in receivables (#2) scaled by average assets, PPE is total gross PPE (#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

$$TACC_t = \alpha_0 + \alpha_1*CFF + \beta_1*TACC_{t-1} + \beta_{11}*TACC_{t-1}*CFF + \beta_2*\Delta REV_t + \beta_3*PPE_t + \beta_4*ROA_t + \varepsilon \qquad (20)$$

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 $\beta_{11}*TACC_{t-1}$ to be positive. The results are presented in Panel B of Table 8.

The first set of columns present the results for the entire sample. The first regression runs the model in equation (19). The coefficient β_1 on $TACC_{t-1}$ is -0.0767 (tstat -12.74), consistent with reversals in accruals. When the regression is run with interactions for cash flow forecasts, the coefficient β_{11} on $TACC_{t-1}$*CFF is 0.0770 (tstat 5.00). This indicates that the reversal in accruals essentially disappears for observations with cash flow forecasts. The next set of columns repeats the analysis with controls for sample selection bias using the Heckman (1979) 2-stage approach. The results are essentially similar as the interaction term TACC*CFF continues to be significantly positive (β_{11} = 0.0582, tstat 3.81).

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 (2011) and provides an alternate explanation for why accruals have become more persistent[11]

5.2 CHANGES IN THE ACCOUNTING STANDARD FOR RESTRUCTURING

Dechow and Ge (2006) show that a substantial portion of the accruals anomaly can be attributed to markets not understanding the transitory nature of special items. Restructuring charges are the most common and significant 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 markets are unable to anticipate the mechanical future revival, these firms will likely have positive excess returns in the future.

[11] I conduct additional tests examining the association between earnings quality measures and cash flow forecasts. I find that firms have lower absolute discretionary accruals (from cross-sectional performance-adjusted modified Jones model) once they have cash flow forecasts. Further, 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.

BSZ state that “The inability to efficiently price restructuring firms…. largely drives the accruals anomaly for firms with low accruals.” They show that FAS 146 reduced both the incidence of excessive restructuring charges and the mispricing of restructuring charges. To ensure that my 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. The pattern in the returns to the accruals anomaly is essentially unchanged. The results from Table 2 indicate that the time series average of the returns to the accrual strategy ($HRET_{TACC}$) is 12.9% in the early period (1993-2001) and declines to 5.9% in the recent period (2002-2009). The mean $HRET_{TACC}$ after eliminating the bottom decile of special items is 13.0% for the early period and 5.2% for the later period. Second, I eliminate observations with non-zero restructuring information on COMPUSTAT (8,589 firm-years in 2001-2009). The mean $HRET_{TACC}$ after eliminating observations with restructuring charges is 12.8% for the early period and 4.9% for the later period. Results for $HRET_{\Delta NOA}$ and all regressions are also essentially unchanged when observations in the bottom decile of special items or observations with restructurings are deleted. Hence, the core result that cash flow forecasts mitigate the mispricing of accruals is incremental to any improvement in accruals quality related to improved accounting for restructuring items.

5.3 GREATER INSTITUTIONAL INTEREST IN ACCRUALS BASED STRATEGIES

GHS conjecture that the driving factor for the decline in the accruals 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 investment in accrual based strategies and arbitraged away any excess returns. They provide two related strands of evidence to support their claim. First, they document a significant increase in trading turnover for firms with extreme accruals. Second, they show that this increase in turnover is positively associated with the aggregate size of assets under management for hedge funds, after controlling for other determinants of trading volume.

Using trading information from CRSP, I first attempt to replicate their findings. I calculate the monthly trading turnover for a given stock as the ratio of shares trades to shares outstanding and compute the annual average of this metrics for each firm, using the same period used for compounding returns in prior analyses. Panel A of Table 9 presents the trends in average monthly trading turnover for the entire sample as well as for quintiles based on accruals. Consistent with GHS, average turnover almost doubles from 0.803 in 1993 to 1.593 in 2009. However, the increasing trend in trading turnover is actually the strongest for the middle three quintiles of accruals and not for the extreme quintiles.

I next investigate whether the increase in trading turnover is associated with an increase in institutions trading on the anomaly or with greater availability of cash flow forecasts. I begin by replicating the regression in GHS who regress trading turnover on proxies for hedge fund activity, transaction costs and idiosyncratic risk for the sub-sample with extreme accruals. I add a proxy for cash flow forecasts and run the following time-series regression on portfolios with extreme accruals (quintiles 1 and 5).

$$\text{LTURN} = \alpha_0 + \beta_1\text{*LAUM} + \beta_2\text{*IDIO} + \beta_3\text{*LPRC} + \beta_4\text{*CFF} + \varepsilon \quad (21)$$

where LTURN is the value-weighted mean of log of monthly turnover (Shares Traded/ Shares Outstanding), LAUM is the log of assets under management by hedge funds[12], IDIO is the value-weighted average of firm-level idiosyncratic risk[13] and LPRC is the value-weighted

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

[13] 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.

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 the regression separately for low and high accrual firms.

Panel B of Table 9 presents the results of the regression. The first two columns present the regression excluding CFF and corroborate the finding in GHS that the increase in share turnover is strongly associated with the level of assets managed by hedge funds (LAUM). However, when I add CFF to this regression, it is strongly significant for both extreme quintiles. LAUM ceases to be significant for the highest accrual quintile and reduces in significance for the low accrual quintile. The insignificance of LAUM for the high accrual quintile potentially weakens the explanation offered by GHS, as the effect of institutional investment ought to be the strongest in the high accrual portfolio, given the difficulties small investors face shorting stocks.

5.4 CAVEATS TO A CASH FLOW FORECAST BASED EXPLANATION

The results in sections 5.1 to 5.3 suggest that the cash flow forecast based explanation for the decline in the accruals anomaly is incremental to alternate explanations. However, it is still important to note the following important caveats.

First, the period where cash flow forecasts have become prevalent and the accruals anomaly has disappeared is short. A reappearance of returns to an accruals strategy despite the continued availability of cash flow forecasts would weaken the explanation offered. As the results in Table 2 indicate, the accruals anomaly generated significant returns for 2008 (i.e. returns in 2009). However, this may also be related to the financial crisis.

Second, the disappearance of the accruals anomaly is 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 different explanations offered for the weakening of the accruals anomaly are probably interrelated. For instance, 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.

Third, cash flow forecasts can only partially explain the decline in the accruals anomaly. As the trends in Table 2 indicate, the returns to an accruals-based trading strategy also decline for the subset of firms without cash flow forecasts.

Finally, Levi (2008) shows that firms that provide voluntary disclosure of accrual information with their preliminary earnings announcements are less likely to have mispriced accruals. It is plausible that firms with cash flow forecasts might also be providing such voluntary disclosures, either in response to investor demand for cash flow information or in response to demand from the analysts themselves. Hence, the mitigation of accruals mispricing attributed in this paper to cash flow forecasts might in fact stem from the voluntary accrual disclosures from the firm. The critical issue is whether the voluntary disclosure of accruals information complements or substitutes for cash flow forecasts.[14]

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 mispricing of accruals (Hirshleifer, Hou and Teoh 2011). Recent research has also examined

[14] First call has a database of company issued guidelines. I searched for guidelines related to either cash flows or fund flows. I was able to identify 206 firm-years in my sample where a company issued a guideline about either cash flows or fund flows. The correlation between such guidelines and cash flow forecasts is an insignificant 0.02. Further, deleting these 206 observations does not materially affect the results in any way.

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 since 2002. What could explain the disappearance of a once robust effect? In this paper, I suggest that one potential explanation for this decline is the increase in cash flow forecasts from analysts. I hypothesize that the diminished returns to accruals based strategies are related to reduced mispricing of accruals, as markets get forecasts of 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. In a direct test of the impact of cash flow forecasts on the pricing of accruals, I find that the mispricing of accruals is mitigated when analysts start issuing cash flow forecasts and exacerbated when they stop issuing cash flow forecasts. Further, the mispricing of accruals is weaker when forecasts that are either ex-post more accurate or ex-ante more likely to be accurate. This empirically supports the notion that the decline in the returns to the accruals anomaly is associated with the greater availability of cash flow forecasts.

There are alternative explanations for the decline in the accruals anomaly. Bhojraj, Sengupta and Zhang (2009) suggest that the weakening of the anomaly is related to improvements in accruals quality because of the passage of SOX in 2002, which diminished accruals-based earnings management and FAS 146 in 2003, which reduced firms' ability to manipulate restructuring costs. I find that while accruals persistence has improved since 2002, this increased persistence is associated with the incidence of cash flow forecasts. Results are also robust when restructuring firms are excluded.

Green, Hand and Soliman (2009) on the other hand attribute the decline in the accruals anomaly to greater investment in accruals-based strategies by hedge funds advised by senior accounting academics. They provide evidence of increased turnover in firms with extreme accruals and show that this increase is associated with the level of assets managed by hedge funds. I find that the increase in trading turnover is not unique to firms with extreme accruals. Further, the association between increased turnover and assets managed by hedge funds weakens after controlling for the incidence of cash flow forecasts. Thus, the result that the decline of the accruals anomaly is strongly associated with the greater availability of cash flow forecasts is robust and incremental to other explanations for the decline in the accruals anomaly.

The results of this paper corroborate recent international evidence on the accruals anomaly. Gordon, Petruska and Yu (2010) show that cash flow forecasts help attenuate the fixation of investors on accruals, especially in common law countries. More generally, the results of this paper 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. Thus, while analysts were themselves like to misprice accruals earlier (Bradshaw, Richardson and Sloan 2001), they later played a role in mitigating the mispricing of accruals.

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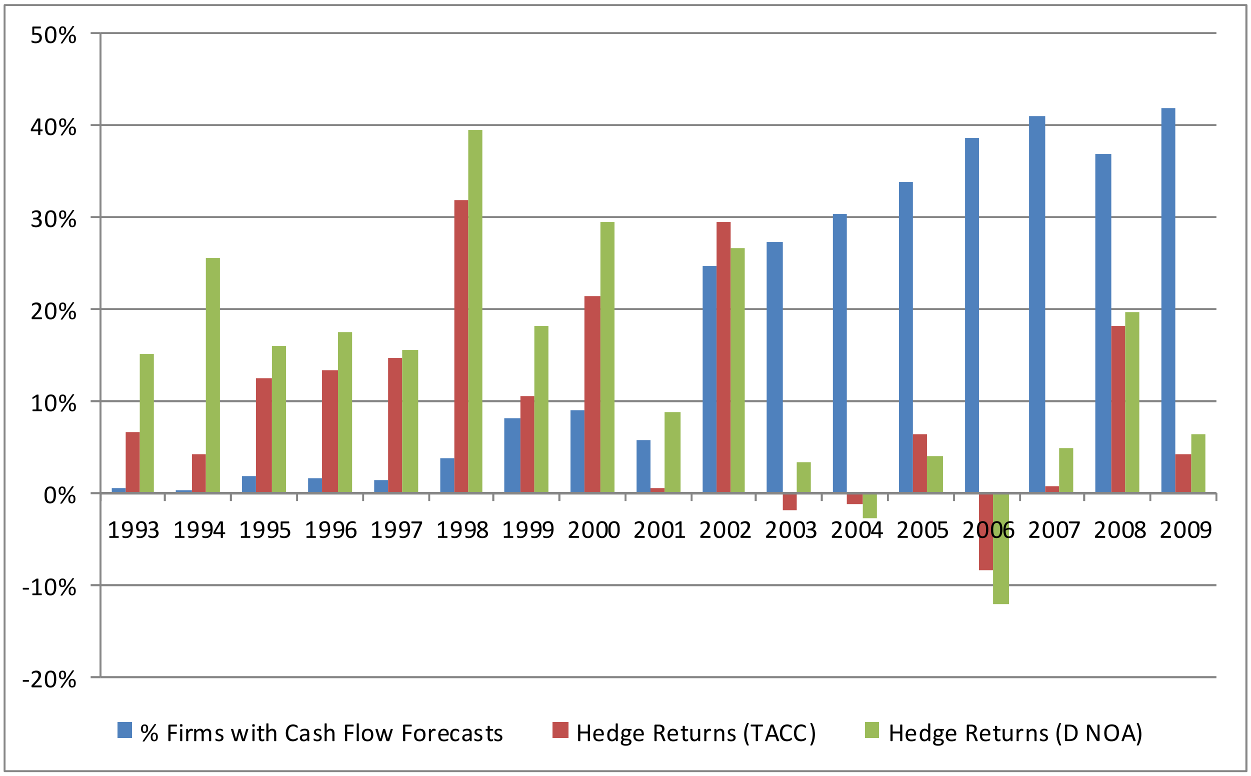

Figure 1: The Accruals anomaly and Incidence of Cash Flow Forecasts across Time

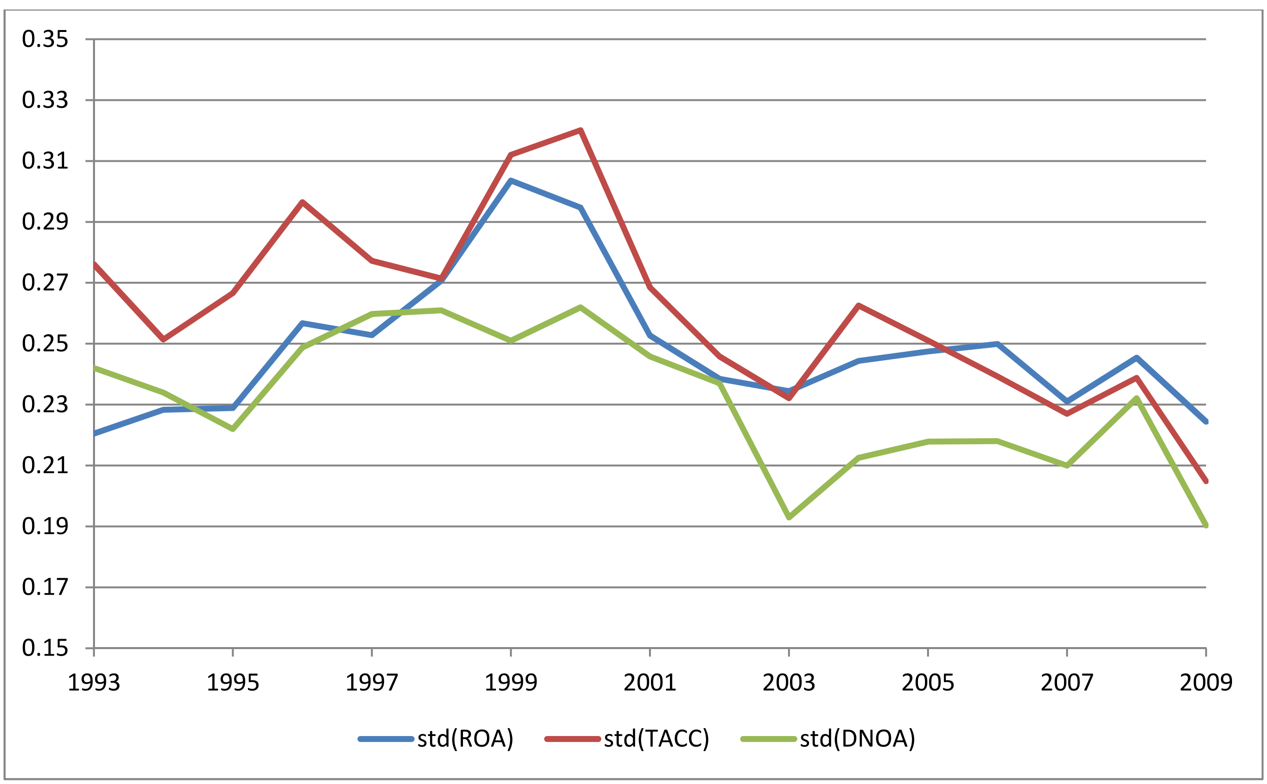

Figure 2: Cross-sectional Variability of Earnings and Accruals across Time

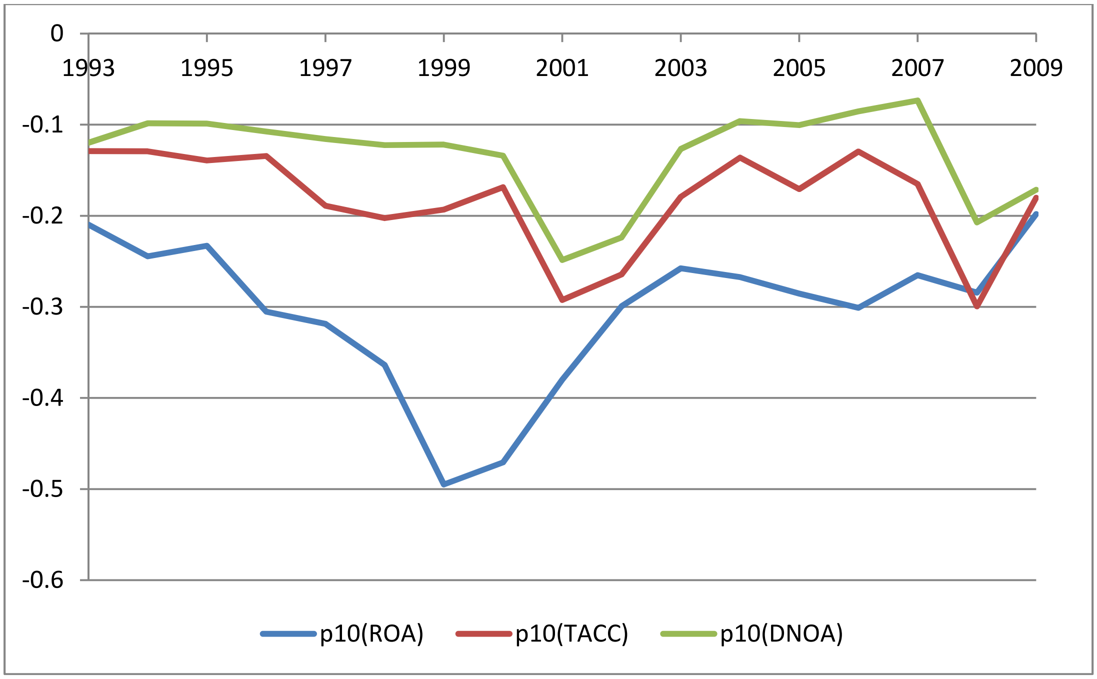

Figure 3-A: 10th Percentile of Earnings and Accruals across Time

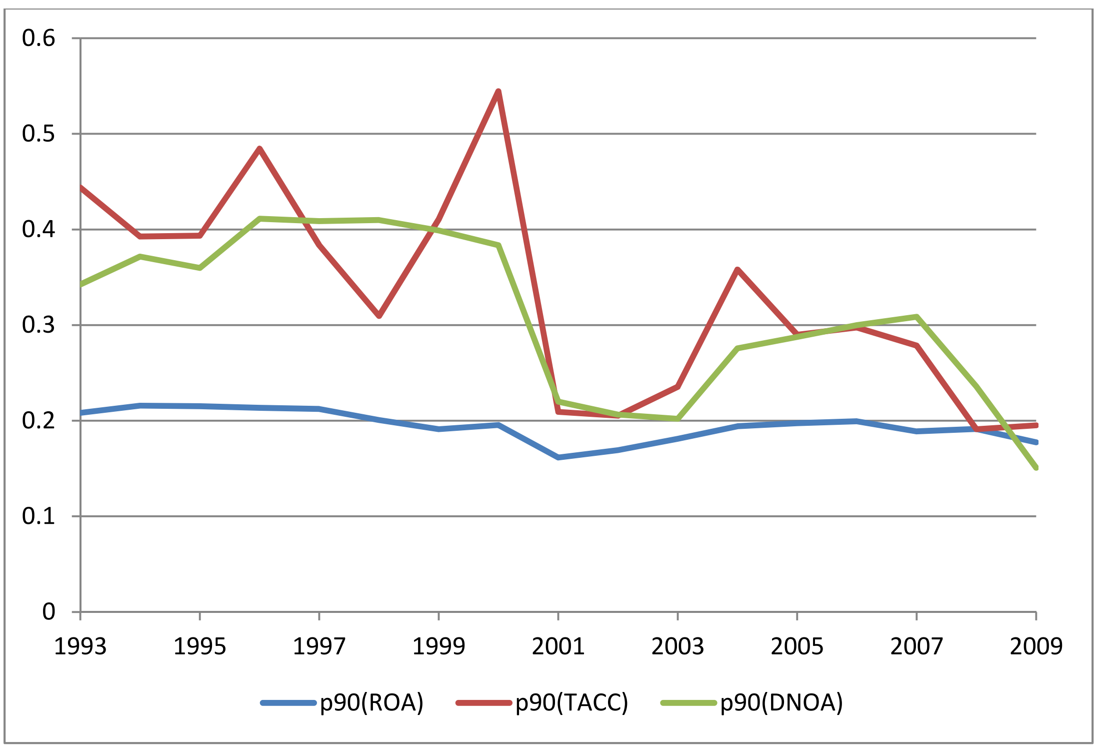

Figure 3-B: 90th Percentile of Earnings and Accruals across Time

TABLE 1: Sample Descriptive Statistics and Correlations

Panel A: Sample Descriptive Statistics

Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl
ROA_t	-0.002	0.253	-0.040	0.064	0.126
$TACC_t$	0.058	0.270	-0.039	0.035	0.131
ΔNOA_t	0.070	0.239	-0.034	0.038	0.147
ΔFIN_t	-0.011	0.246	-0.082	0.000	0.055
$RETS_{t+1}$	-0.005	0.647	-0.391	-0.092	0.213
ROA_{t+1}	-0.002	0.243	-0.041	0.062	0.123
CFF	0.157	0.364	0.000	0.000	0.000
$ASST_t$	1650	7785	39	146	669
$MCAP_t$	2009	11330	43	172	749

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		0.216	0.170	0.075	0.069	0.843	0.144	0.092	0.109
$TACC_t$	0.316		0.570	0.582	-0.044	0.125	0.031	-0.013	0.005
ΔNOA_t	0.244	0.602		-0.320	-0.060	0.089	0.045	-0.004	0.002
ΔFIN_t	0.098	0.388	-0.360		0.009	0.049	-0.011	-0.012	0.002
$RETS_{t+1}$	0.128	-0.032	-0.054	0.023		0.181	0.017	0.006	0.001
ROA_{t+1}	0.814	0.189	0.129	0.084	0.292		0.135	0.093	0.109
CFF	0.156	0.043	0.060	-0.019	0.058	0.143		0.180	0.155
$ASST_t$	0.389	0.036	0.072	-0.028	0.137	0.372	0.373		0.762
$MCAP_t$	0.421	0.168	0.156	0.020	0.091	0.384	0.378	0.862	

Sample consists of 70,867 non-financial firms in the time period 1993-2009 with financial information on COMPUSTAT and stock returns on CRSP. ROA_t is return on assets defined as operating income after depreciation (OIADP) scaled by average total assets (AT). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See section 3.1 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 (AT) and MCAP is market capitalization (Shares outstanding (CSHO)* Stock price (PRCC_F).

TABLE 2: Preliminary Evidence on Accruals Anomaly and Cash Flow Forecasts across time

Panel A: Impact of Cash Flow Forecasts on the Accruals anomaly across Time

YEAR	N	N_{CPS}	N_{EPS}	N_{CPS}/N	N_{CPS}/N_{EPS}	$HRET_{TACC}$ All Firms	$HRET_{TACC}$ No CFF Firms	Difference	$HRET_{\Delta NOA}$ All Firms	$HRET_{\Delta NOA}$ No CFF Firms	Difference
1993	4227	23	1958	0.5%	1.2%	6.7%	6.9%	0.2%	15.2%	15.5%	0.3%
1994	4417	12	2139	0.3%	0.6%	4.1%	4.2%	0.1%	25.6%	25.7%	0.1%
1995	4673	80	2382	1.7%	3.4%	12.5%	12.6%	0.1%	15.9%	16.0%	0.1%
1996	5338	84	2682	1.6%	3.1%	13.4%	13.7%	0.3%	17.5%	18.0%	0.5%
1997	5306	72	2787	1.4%	2.6%	14.7%	15.0%	0.3%	15.5%	15.1%	-0.4%
1998	4893	183	2653	3.7%	6.9%	31.9%	34.4%	2.5%	39.6%	40.7%	1.1%
1999	4965	407	2690	8.2%	15.1%	10.6%	12.7%	2.1%	18.2%	18.3%	0.1%
2000	4525	409	2436	9.0%	16.8%	21.5%	21.3%	-0.2%	29.5%	29.8%	0.3%
2001	4072	238	2197	5.8%	10.8%	0.5%	1.0%	0.5%	8.8%	10.6%	1.8%
2002	3833	945	2150	24.7%	44.0%	29.5%	30.1%	0.6%	26.7%	29.0%	2.3%
2003	3800	1035	2310	27.2%	44.8%	-2.0%	-1.1%	0.9%	3.3%	6.9%	3.6%
2004	3821	1156	2403	30.3%	48.1%	-1.2%	-0.7%	0.5%	-2.7%	-4.5%	-1.8%
2005	3725	1261	2495	33.9%	50.5%	6.3%	10.0%	3.7%	4.0%	6.3%	2.3%
2006	3206	1239	2449	38.6%	50.6%	-8.5%	-7.1%	1.4%	-12.2%	-10.7%	1.5%
2007	2933	1203	2325	41.0%	51.7%	0.7%	-3.5%	-4.2%	4.9%	3.5%	-1.4%
2008	3684	1359	2591	36.9%	52.5%	18.2%	23.1%	4.9%	19.6%	26.8%	7.2%
2009	3449	1443	2645	41.8%	54.6%	4.2%	5.4%	1.2%	6.3%	7.4%	1.1%
Average Entire Period						9.6%	10.5%	0.9%	13.9%	15.0%	1.1%
								(1.88)			(2.16)
Average (1993-2001)						12.9%	13.5%	0.7%	20.6%	21.1%	0.4%
								(2.03)			(1.94)
Average (2002-2009)						5.9%	7.0%	1.1%	6.2%	8.1%	1.9%
								(1.18)			(1.83)

Panel B: Impact of Cash Flow Forecasts on Forecast Accuracy

Year	N_{CFF}	Mean AFE_{CFF}	$N_{NO\ CFF}$	Mean AFE_{NOCFF}	Difference	t-stat
1993	23	1.24%	1935	2.77%	-1.52%	-4.25
1994	12	2.51%	2127	3.32%	-0.80%	-1.04
1995	80	2.63%	2302	3.10%	-0.47%	-1.02
1996	83	1.84%	2599	3.09%	-1.25%	-3.19
1997	72	2.74%	2715	3.02%	-0.28%	-0.62
1998	183	3.56%	2470	3.92%	-0.36%	-0.86
1999	407	3.67%	2283	3.77%	-0.10%	-0.32
2000	408	3.23%	2028	4.69%	-1.46%	-5.30
2001	237	2.45%	1960	2.91%	-0.46%	-1.48
2002	945	2.32%	1205	4.12%	-1.80%	-8.41
2003	1035	1.68%	1275	2.53%	-0.84%	-5.53
2004	1156	1.69%	1247	3.00%	-1.31%	-8.45
2005	1256	1.45%	1239	2.97%	-1.53%	-10.07
2006	1238	1.65%	1211	3.41%	-1.76%	-10.44
2007	1202	2.67%	1123	4.93%	-2.26%	-9.52
2008	1359	3.92%	1232	6.12%	-2.20%	-8.95
2009	1443	2.43%	1202	3.69%	-1.26%	-2.81
Entire Period	9434	2.36%	26700	3.52%	-1.15%	-22.14

Sample consists of 70,867 non-financial firms in the time period 1993-2009 with financial information on COMPUSTAT and stock returns on CRSP. N is the number of firms. N_{CPS} and N_{EPS} are the number of firms with cash flow forecasts and earnings forecasts respectively on I/B/E/S. TACC is total accruals and ΔNOA is change in net operating assets, both scaled by average assets. See section 3.1 for detailed definitions. Hedge Returns, calculated each fiscal year as the difference between mean size-adjusted one-year-ahead buy-and-hold returns for the lowest quintile and the highest quintile of TACC (ΔNOA), are labelled as $HRET_{TACC}$ ($HRET_{\Delta NOA}$). Hedge returns are calculated for the entire sample as well as for the subset that excludes firms with cash flow forecasts. In Panel B, N_{CFF} and N_{NOCFF} are the number of observations with and without cash flow forecasts within the sample with analyst following. AFE is the absolute forecast error defined as the absolute difference between the EPS estimate and realized EPS scaled by stock price at time of the estimate. T-stat for differences are calculated using a pooled estimate of standard error.

TABLE 3 Weakening of the Accruals anomaly across Time

	Model 1	Model 2	Model 5	Model 6
ROA	0.2214 (18.79)	0.2264 (19.25)	0.2497 (16.70)	0.2543 (17.07)
TACC	-0.1719 (-15.92)		-0.2053 (-15.68)	
ΔNOA		-0.2598 (-20.19)		-0.3130 (-20.21)
ΔFIN		-0.0741 (-6.00)		-0.0845 (-5.63)
ROA*LATER			-0.0958 (-4.18)	-0.0984 (-4.30)
TACC*LATER			0.1202 (5.41)	
ΔNOA*LATER				0.1913 (7.03)
ΔFIN*LATER				0.0367 (1.47)
N	70,867	70,867	70,867	70,867
Adj. R^2	1.77%	2.06%	1.85%	2.16%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 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 (OIADP) scaled by average total assets (AT). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. LATER is an indicator variable that equals 0 for years 1993 to 2001 and 1 for 2002 to 2009. See section 3.1 for detailed definitions. Regressions are pooled across time, with industry (2 digit SIC code) and year fixed effects. Figures in parentheses represent t-statistics that control for clustering by firm.

TABLE 4: The Accruals anomaly and Incidence of Cash Flow Forecasts

	Model 1	Model 2	Model 3	Model 4
ROA	0.2276	0.2324	0.2277	0.2325
	(18.41)	(18.84)	(18.42)	(18.84)
TACC	-0.1729		-0.1731	
	(-15.17)		(-15.18)	
ΔNOA		-0.2668		-0.2671
		(-19.42)		(-19.44)
ΔFIN		-0.0708		-0.0708
		(-5.44)		(-5.44)
CFF	0.0205	0.0168	0.0196	0.0167
	(2.65)	(2.17)	(2.52)	(2.16)
ROA*CFF	-0.1578	-0.1570	-0.1545	-0.1561
	(-3.44)	(-3.39)	(-1.46)	(-1.45)
TACC*CFF	0.0713		-0.1419	
	(1.87)		(-1.30)	
ΔNOA*CFF		0.0913		-0.1450
		(1.93)		(-1.36)
ΔFIN*CFF		-0.0439		-0.1750
		(-1.12)		(-1.92)
LATER				
ROA*CFF*LATER			-0.0014	-0.0069
			(-0.01)	(-0.06)
TACC*CFF*LATER			0.2799	
			(3.66)	
ΔNOA*CFF*LATER				0.3178
				(4.17)
ΔFIN*CFF*LATER				0.1737
				(1.76)
N	70,867	70,867	70,867	70,867
Adj. R^2	1.81%	2.10%	1.83%	2.13%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 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 (OIADP) scaled by average total assets (AT). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. CFF is an indicator variable that equals 1 for firm-years with cash flow forecasts and 0 otherwise. LATER is an indicator variable that equals 0 for years 1993 to 2001 and 1 for 2002 to 2009. See section 3.1 for detailed definitions. Regressions are pooled across time, with industry (2 digit SIC code) and year fixed effects. Figures in parentheses represent t-statistics that control for clustering by firm.

Table 5: Controlling for the effects of Sample Selection Bias

Panel A: Sample Selection PROBIT Regression for CFF
Figures in parentheses are z-statistics.

Intercept	VOL	CYCLE	Z	CAPINT	ABSACC	LMCAP	N	Pseudo-R^2
-3.429	0.0048	-0.0015	-0.0203	0.0471	-0.2377	0.4295	61,910	22.68%
(109.87)	(6.71)	(-13.60)	(17.98)	(13.16)	(-5.69)	(100.65)		

Panel B: Controlling for sample selection using Heckman 2-stage Regressions

	Model 1	Model 2	Model 3	Model 4
ROA	0.2476	0.2522	0.2465	0.2523
	(16.52)	(16.97)	(16.52)	(16.97)
TACC	-0.2098		-0.2101	
	(-16.05)		(-16.07)	
ΔNOA		-0.2980		-0.2984
		(-19.38)		(-19.4)
ΔFIN		-0.1012		-0.1011
		(-6.60)		(-6.60)
CFF	0.0714	0.0609	0.0696	0.0609
	(5.98)	(4.67)	(5.36)	(4.68)
ROA*CFF	-0.1820	-0.1824	-0.1570	-0.1601
	(-3.21)	(-3.81)	(-1.45)	(-1.47)
TACC*CFF	0.0681		-0.1850	
	(1.85)		(-1.43)	
ΔNOA*CFF		0.0899		-0.1700
		(2.23)		(-1.26)
ΔFIN*CFF		0.0008		-0.0962
		(0.02)		(-1.01)
ROA*CFF*LATER			-0.0294	-0.0422
			(-0.28)	(-0.39)
TACC*CFF*LATER			0.3238	
			(3.96)	
ΔNOA*CFF*LATER				0.3966
				(4.85)
ΔFIN*CFF*LATER				0.1289
				(1.26)
Inverse Mills Ratio	-0.0221	-0.0186	-0.022	-0.0185
	(-5.08)	(-4.28)	(-5.04)	(-4.24)
N	61,910	61,910	61,910	61,910
Adj. R^2	1.87%	2.15%	1.91%	2.19%

Panel C: Controlling for sample selection using Propensity Score Matched Regressions

	Model 1	Model 2	Model 3	Model 4
ROA	0.1677	0.1755	0.1677	0.1757
	(5.45)	(5.73)	(5.45)	(5.73)
TACC	-0.1706		-0.1710	
	(-5.55)		(-5.56)	
ΔNOA		-0.2334		-0.2339
		(-6.12)		(-6.13)
ΔFIN		-0.1001		-0.0992
		(-2.77)		(-2.75)
CFF	0.0062	0.0060	0.0034	0.0046
	(0.66)	(0.64)	(0.37)	(0.50)
ROA*CFF	-0.1494	-0.1477	-0.1822	-0.1879
	(-2.75)	(-2.71)	(-1.57)	(-1.62)
TACC*CFF	0.0610		-0.1309	
	(1.68)		(-1.47)	
ΔNOA*CFF		0.0790		-0.1517
		(1.85)		(-1.49)
ΔFIN*CFF		0.0267		-0.0841
		(0.51)		(-0.82)
ROA*CFF*LATER			0.0483	0.0410
			(0.43)	(0.36)
TACC*CFF*LATER			0.3623	
			(4.33)	
ΔNOA*CFF*LATER				0.4407
				(5.22)
ΔFIN*CFF*LATER				0.1481
				(1.43)
N	20,206	20,206	20,206	20,206
Adj. R^2	2.11%	2.27%	2.27%	2.47%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 with financial information on COMPUSTAT and stock returns on CRSP. Panel A presents the results of a PROBIT regression with the dependent variable being CFF, an indicator variable that equals 1 for firm-years with cash flow forecasts and 0 otherwise. The independent variables are: VOL is a proxy for volatility of cash flows . CYCLE is the cash cycle Z-SCORE is Altman's Z. CAPINT is capital intensity, ABSACC is the absolute value of total accruals , LMCAP is log of market capitalization. See section 4.3 for detailed definitions. For Panels B and C, 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 (OIADP) scaled by average total assets (AT). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. CFF is an indicator variable that equals 1 for firm-years with cash flow forecasts and 0 otherwise. LATER is an indicator variable that equals 0 for years 1993 to 2001 and 1 for 2002 to 2009. The regressions in Panel B also include the inverse-mills ratio from the first regression. See section 3.1 for detailed definitions. Regressions are pooled across time, with industry (2 digit SIC code) and year fixed effects. For Panels B and C, figures in parentheses represent t-statistics that control for clustering by firm.

TABLE 6: Initiation and Termination of Cash Flow Forecasts

	Model 1	Model 2	Model 3	Model 4
ROA	0.2232	0.2280	0.2317	0.2381
	(18.52)	(18.96)	(15.88)	(16.37)
TACC	-0.1729		-0.2101	
	(-15.43)		(-16.41)	
ΔNOA		-0.2630		-0.2958
		(-19.68)		(-19.84)
ΔFIN		-0.0731		-0.1029
		(-5.70)		(-6.86)
START	0.0022	-0.0018	0.0083	0.0033
	(0.19)	(-0.16)	(0.69)	(0.27)
END	0.0421	0.0416	0.0464	0.0469
	(2.58)	(2.45)	(2.6)	(2.55)
ROA*START	-0.0501	-0.0456	-0.0368	-0.0307
	(-0.73)	(-0.65)	(-0.53)	(-0.44)
TACC*START	0.0833		0.1352	
	(1.86)		(2.85)	
ΔNOA*START		0.1354		0.1632
		(2.61)		(2.88)
ΔFIN*START		0.0191		0.0792
		(0.36)		(1.45)
ROA*END	-0.0495	-0.0604	-0.0766	-0.0864
	(-0.45)	(-0.55)	(-0.63)	(-0.71)
TACC*END	-0.1736		-0.1815	
	(-1.69)		(-1.75)	
ΔNOA*END		-0.1969		-0.2167
		(-1.85)		(-1.96)
ΔFIN*END		-0.0974		-0.0838
		(-0.88)		(-0.74)
Inverse Mills Ratio			-0.0076	-0.0059
			(-3.05)	(-2.38)
N	70,867	70,867	61,910	61,910
Adj. R^2	1.81%	2.11%	1.85%	2.14%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable $RETS_{t+1}$ 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 (OIADP) scaled by average total assets (AT). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. START equals 1 for the first incidence of cash flow forecasts for a given firm and 0 otherwise. END equals 1 when the lagged firm-year has a cash flow forecast but current firm-year does not (but continues to have analyst coverage) and 0 otherwise. See section 3.1 for details. Regressions are pooled across time, with industry (2 digit SIC code) and year fixed effects. Figures in parentheses represent t-statistics that control for clustering by firm.

TABLE 7: The Accruals anomaly and Accuracy of Cash Flow Forecasts

	Ex-Post Forecast Accuracy		Prior Forecast Accuracy	
	Model 1	Model 2	Model 3	Model 4
ROA	0.0248 (0.15)	0.0557 (0.33)	0.1717 (1.05)	0.1596 (0.98)
TACC	-0.6073 (-5.21)		-0.6097 (-4.71)	
ΔNOA		-0.7162 (-5.75)		-0.641 (-4.72)
ΔFIN		-0.4253 (-3.24)		-0.4969 (-3.42)
ACCU	-0.0311 (-5.58)	-0.0329 (-5.80)	-0.0086 (-1.35)	-0.0089 (-1.37)
ROA*ACCU	0.0092 (0.24)	0.0038 (0.10)	-0.0399 (-0.95)	-0.0372 (-0.89)
TACC*ACCU	0.1138 (4.39)		0.0892 (2.94)	
ΔNOA*ACCU		0.1339 (4.80)		0.0895 (2.82)
ΔFIN*ACCU		0.0797 (2.78)		0.0774 (2.25)
N	9333	9333	8792	8792
Adj. R^2	5.25%	5.39%	5.39%	5.47%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 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 (OIADP) scaled by average total assets (AT). ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. See section 3.1 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. The first two regressions use ex-post realized forecast accuracy ($ACCU_{t+1}$) while the last two regressions use lagged realized forecast accuracy ($ACCU_t$). Regressions are pooled across time, with industry (2 digit SIC code) and year fixed effects. Figures in parentheses represent t-statistics that control for clustering by firm.

TABLE 8: Increased Persistence in the Accrual Component of Earnings across Time

Panel A: Increased Persistence in the Accrual Component of Earnings across Time

	Model 1	Model 2	Model 3	Model 4
ROA	0.8059 (168.29)	0.8068 (168.95)	0.7893 (140.70)	0.7900 (141.07)
TACC	-0.0435 (-12.99)		-0.0512 (-13.29)	
ΔNOA		-0.0603 (-14.72)		-0.0700 (-15.91)
ΔFIN		-0.0259 (-7.27)		-0.0308 (-7.33)
ROA*LATER			0.0590 (6.47)	0.0594 (6.50)
TACC *LATER			0.0299 (4.06)	
ΔNOA*LATER				0.0367 (3.82)
ΔFIN*LATER				0.0198 (2.44)
N	62,677	62,677	62,677	62,677
Adj. R^2	71.48%	71.54%	69.48%	69.56%

Panel B: Impact of Cash Flow Forecasts on the Increased Persistence of Accruals

	Model 1	Model 2	Model 3	Model 4
ΔREV	0.1909 (35.8)	0.1903 (35.75)	0.1503 (31.72)	0.1504 (31.72)
PPE	-0.0434 (-13.83)	-0.0430 (-13.74)	-0.0259 (-9.43)	-0.0261 (-9.48)
ROA	0.2170 (28.49)	0.2210 (28.81)	0.2956 (36.11)	0.2951 (35.92)
$TACC_{t-1}$	-0.0767 (-12.74)	-0.0821 (-12.87)	-0.0440 (-7.51)	-0.0494 (-7.81)
CFF		-0.0246 (-9.66)		-0.0066 (-1.65)
$TACC_{t-1}$*CFF		0.0770 (5.00)		0.0582 (3.81)
Inverse Mills Ratio			-0.0046 (-5.94)	-0.0033 (-2.40)
N	57264	57264	52019	52019
Adj. R^2	14.40%	14.52%	16.94%	17.08%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 with financial information on COMPUSTAT and stock returns on CRSP. For Panel A, the dependent variable is $ROA_{t+1,}$ which is the one-year ahead Return on Assets. ROA_t is return on assets defined as operating income after depreciation (OIADP) scaled by average total assets (AT). $TACC_t$ is total accruals, ΔNOA_t is change in net operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. LATER is an indicator variable that equals 0 for years 1993 to 2001 and 1 for 2002 to 2009. See section 3.1 for detailed definitions.
For Panel B, the dependent variable is $TACC_{t,}$ which is total accruals scaled by average assets. $TACC_{t-1}$ is lagged total accruals. 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 (SALE) less the change in receivables (RECT) scaled by lagged assets (AT). PPE is gross PP&E (PPEGT) scaled by lagged assets. Regressions are pooled across time, with industry (2 digit SIC code) and year fixed effects. Figures in parentheses represent t-statistics that control for clustering by firm.

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

Panel A: Trends in Monthly Trading Turnover

Year	N	Entire Sample	Accrual Quintile 1	Accrual Quintiles 2-4	Accrual Quintile 5
1993	4227	0.803	0.728	0.700	1.190
1994	4417	1.003	1.060	0.853	1.395
1995	4673	1.035	1.028	0.877	1.516
1996	5338	1.092	1.075	0.983	1.437
1997	5306	1.070	1.158	0.941	1.374
1998	4893	1.266	1.518	1.058	1.642
1999	4965	1.198	1.197	1.026	1.724
2000	4525	1.050	0.903	0.957	1.484
2001	4072	1.001	0.829	0.933	1.382
2002	3833	1.336	1.475	1.181	1.672
2003	3800	1.356	1.397	1.254	1.624
2004	3821	1.447	1.364	1.367	1.767
2005	3725	1.548	1.491	1.497	1.759
2006	3206	1.765	1.621	1.754	1.939
2007	2933	1.790	1.662	1.817	1.836
2008	3684	1.622	1.582	1.586	1.769
2009	3449	1.593	1.436	1.592	1.750
Time Trend		0.053	0.044	0.063	0.033
(t-stat)		(8.23)	(4.41)	(9.38)	(5.61)

Panel B: 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	0.5256	0.8683	0.6818	0.6388
	(1.61)	(2.14)	(2.63)	(1.99)
LAUM	0.0703	0.0308	0.0359	-0.0021
	(8.44)	(2.36)	(2.77)	(-0.14)
LIDIO	3.4905	2.1458	7.4908	7.9729
	(1.17)	(0.58)	(2.82)	(2.34)
LPRC	-0.0155	-0.009	-0.0844	0.0089
	(-0.19)	(-0.08)	(-1.25)	(0.1)
CFF			1.0535	0.935
			(3.07)	(3.15)
N	17	17	17	17
Adj. R^2	85.4%	29.2%	91.1%	58.0%

Sample consists of 70,867 non-financial firms in the time period 1993-2009 with financial information on COMPUSTAT and stock returns on CRSP. Panel A presents the mean monthly trading turnover measured as the ratio of shares traded to shares outstanding averaged for a given firm-year over a 12 month period beginning 4 months after fiscal year end. Panel B presents the results from time series regressions run for the two extreme accrual quintiles (quintiles 1 and 5) with average share turnover as the dependent variable. 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, LPRC is the value-weighted average of the mean month-end log of stock price and CFF is the proportion of firms with analysts cash flow forecasts in the corresponding year. Figures in parentheses represent t-statistics.