Analysts' Cash Flow Forecasts and the Decline of the Accruals Anomaly *

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* Accepted by Steve Salterio. An earlier version of the paper was presented at the 2012 *Contemporary Accounting Research* Conference, generously supported by the **Canadian Institute of Chartered Accountants.** The author would like to thank the editor Steve Salterio, the discussant Katherine Schipper, two anonymous referees, Sid Balachandran, Urooj Khan, Gordon Richardson, Julian Yeo and seminar participants at the 2012 CAR Conference, Columbia Business School, University of Toronto, Ohio State University, Carnegie-Mellon University, IIM-Bangalore, INSEAD, RSM-Erasmus University and the Indian School of Business. The author acknowledges generous research support funding from the Certified General Accountants of Ontario (CGA Ontario) and the Rotman School of Management.

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Abstract: The accruals anomaly, demonstrated by Sloan (1996), generated significant excess returns consistently for over four decades until 2002, but has apparently weakened in the subsequent period. In this paper, I argue that one factor responsible for this decline is the increasing incidence of analysts' cash flow forecasts that provides 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 cash flow forecasts but continues after cash flow forecasts are terminated. Further, the mitigating effect of cash flow forecasts is greater for forecasts that are more accurate. The results are incremental to explanations based on the improved accrual quality, reduced manipulation of special items and restructuring charges and greater investment in accruals strategies by hedge funds and highlight the increasing importance of analysts' cash flow forecasts in the appropriate valuation of stocks.

Keywords: Accrual Anomaly, Cash flow forecasts, Market mispricing, Equity valuation

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 that 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 theory of efficient markets. Not surprisingly, the research examining the accruals anomaly is divided on whether the anomaly is real or illusory. One line of research argues that the observed returns to the accruals anomaly represent appropriate rewards for risk. Khan (2008) shows that the accrual anomaly weakens considerably in a well-specified inter-temporal CAPM model. Wu, Zhang and Zhang (2010) argue that the returns to the accruals anomaly are rational returns according to the Q-theory of investment. Another line of research argues that the accruals anomaly cannot be explained by risk factors and point to mispricing as the root cause of the accruals anomaly. Hirshleifer, Hou and Teoh (2012) show that the accrual characteristic rather than an accrual factor predicts returns, consistent with mispricing. Allen, Larson and Sloan (2013) demonstrate that the returns and earnings following extreme accruals are explained by extreme accrual reversals unanticipated by the stock markets.

At the heart of the mispricing argument is the notion that stock markets are unable to anticipate the lower persistence of accruals. If mispricing of accruals drives the accruals anomaly, 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 accrual mispricing. In this paper, I test this directly by asking whether cash flow forecasts help reduce the apparent mispricing of accruals.

Traditionally, analysts have focused much of 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 IBES. This proportion has increased dramatically since 2002, to the point that by 2010, almost half of all firms have cash flow forecasts and close to 60% of analysts who issue any kind of forecast issue cash flow forecasts. Interestingly, the time period when cash flow forecasts have become common also corresponds to the time period when the returns to accruals based strategies declined (Richardson, Wysocki and Tuna 2010; Green, Hand and Soliman 2011). This paper tests whether the decline in the accruals anomaly is associated with the increase in the availability of cash flow forecasts.

There are other potential explanations for the decline in the accruals anomaly. Green et al. (2011) suggest that the decline is driven by greater investments by large quantitative hedge funds as evidenced by the correlation between increased trading turnover in extreme accrual stocks and the level of assets managed by hedge funds. Bhojraj, Sengupta and Zhang (2009) argue that the passage of the Sarbanes-Oxley bill (SOX) and the SFAS No. 146 related to restructuring expenses improved the quality of accruals by reducing accruals-based manipulation of earnings and reducing improperly stated restructuring charges. In my tests related to the pricing of accruals, I control for both these factors. Further, as the sample of firms with cash flow forecasts is unlikely to be random, I also control for sample selection bias.

I first hypothesize that accrual mispricing should be less prevalent in firms which have a cash flow forecast. Supporting this, I find that the negative relationship between accruals and future returns is significantly weaker for firms with cash flow forecasts. I next hypothesize and find that accruals are less likely to be mispriced when cash flow forecasts are initiated for the first time but continue 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.

The results suggest that investors who apparently naively mispriced the accrual component of earnings are less likely to do so when financial analysts provide them with forecasts of future accruals through cash flow forecasts. This has important implications for the research examining whether the accruals anomaly is caused by risk or mispricing, as it supports mispricing as the underlying cause of the accruals anomaly. It also has important implications for the research examining the usefulness of cash flow forecasts, as it suggests that these forecasts are useful signals that assist capital markets in appropriately pricing accruals.

A concurrent paper by Radhakrishnan and Wu (2013) also examines the impact of cash flow forecasts on accrual mispricing and finds results consistent with this paper. There are considerable differences between the two papers – the focus here is on the decline in the accrual anomaly while their paper is focused on the cross-sectional impact of cash flow forecasts on accrual mispricing. Further, this paper explicitly controls for alternate explanations for the decline in accruals mispricing and also examines the impact of the accuracy of cash flow forecasts on accrual mispricing. Still, the fact that two independent papers find consistent evidence despite their differences can be viewed as a testament to the strength of the underlying result – that cash flow forecasts played an important role in mitigating accrual mispricing.

The rest of the paper is organized as follows. In section 2, I review the related research on the accruals anomaly as well as cash flow forecasts and use this to motivate my hypotheses. In section 3, I describe the data and provide preliminary evidence on the decline of the accruals anomaly. In section 4, I present the main results of the paper. Finally, I conclude in section 5.

2. Related research and hypothesis development

Related research on 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 that has a greater tendency to reverse. Investors are thus 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.

There is considerable disagreement as to whether the returns to accruals strategies represent an anomaly at all in the first place. Kraft, Leone and Wasley (2006) argue that the relationship between accruals and returns show an inverted U shape pattern once outliers are deleted, inconsistent with the accrual fixation hypothesis. Zach (2007) shows that while low returns for high accrual firms are consistent with accrual fixation, high returns to low accrual firms can instead be attributed to bankruptcy risk. Richardon, Tuna and Wysocki (2010) survey the literature on the accrual anomaly and conclude that "most studies that follow Sloan (1996) find that "the accrual anomaly is robust in various samples, and that it is mainly attributable to investors' inability to incorporate the implications of discretion in accruals for the persistence of earnings in their forecasts of future earnings." In their own empirical analysis, they document robust returns to accruals strategies, even while focusing on the 1000 largest firms.

Researchers have also studied whether the accruals anomaly is an artefact of improper adjustment for risk. Khan (2008) argues that the returns to the accruals strategy disappear in a well-specified inter-temporal CAPM model. Hirshleifer, Hou and Teoh (2012) however demonstrate 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. Corroborating the mispricing argument, Allen et al. (2013) show that the predictable returns and earnings that follow extreme accruals are explained by extreme accrual reversals. Also, Fama and French (2008) evaluate the accruals anomaly and note, “measured net of the effects of size and B/M, the equal- and value-weight abnormal hedge portfolio returns associated with accruals are strong for all size groups (and thus pervasive)”.

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. One of the goals of this paper is to examine if these very same analysts played a role in the weakening of the accruals anomaly by providing capital markets with cash flow forecasts.

The recent decline in the accruals anomaly has been the focus of recent research. Green et al. (2011) suggest that the presence of a number of leading accounting and finance academics in the quantitative hedge fund industry lead to a greater investment in accruals based strategies which eliminated excess returns over time. Richardson et al. (2010) find this explanation appealing because it is consistent with the notion of adaptive market efficiency from Grossman and Stiglitz (1980). Bhojraj et al. (2009) argue that the passage of the Sarbanes-Oxley bill (SOX) and the SFAS No. 146 related to restructuring expenses improved the quality of accruals by reducing accruals-based manipulation of earnings and reducing improperly stated restructuring charges. Thus, any test of the conjecture offered in this paper that the increased availability of cash flow forecasts played a role in the decline of the accruals anomaly has to control for these alternative explanations.

Related research on cash flow forecasts

The issuance of cash flow forecasts by analysts is a relatively new phenomenon, first appearing on the IBES database in 1991. Call, Chen and Tong (2009) document that the proportion of U.S. firms in the IBES database with at least one cash flow forecast 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) also analyze analysts' reports that contain cash flow forecasts and conclude that these forecasts are not mechanical adjustments of earnings forecasts for routine 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 than earnings forecasts. However, they do not test whether cash flow forecasts improve the quality of earnings forecasts, something that Call et al. (2009) document. Further, Call, Chen and Tong (2012) 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.

Finally, Levi (2008) finds that the accruals are more likely to be impounded in prices when firms disclose accruals in preliminary earnings announcements. Similarly, Baber, Chen and Kang (2006) find that investors are less likely to be misled by earnings management when additional balance sheet information is disclosed in earnings announcements. This suggests that when investor demand for accrual information is met by additional disclosure, accrual mispricing is mitigated. Analysts' cash flow forecasts may play a similar role.

Hypothesis development

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' earnings forecasts (Call et al. 2009). Further, recent research by Allen, Larson and Sloan (2013) indicates that the driving force behind the accruals anomaly appears to be the predictable reversal in accruals for firms with extreme accruals. If financial analysts understand the predictable reversal in accruals and incorporate this in their cash flow forecasts and earnings forecasts, then one should observe mitigation in accruals mispricing with the growing incidence of cash flow forecasts.

Recent work by McInnis and Collins (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 accrual mispricing by reducing the magnitude of abnormal accruals. Countering this however is evidence in Givoly et al. (2009) that cash flow forecasts do not provide reliable information to capital markets. Further, Bradshaw et al. (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 IBES 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 IBES 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 accrual mispricing. Prior research has shown a negative relationship between the accrual component of earnings and future returns. If cash flow forecasts mitigate accruals mispricing, this relationship should be less negative for firms with cash flow forecasts. My first hypothesis, stated in the alternate form, is:

HYPOTHESIS 1. *The relationship between the accrual component of earnings and future returns is less negative for firms with cash flow forecasts.*

The accruals anomaly and the initiation/termination of cash flow forecasts

Grossman and Stiglitz (1980) argue that markets are adaptively efficient, i.e. capital market participants learn about the relevance of information for security prices and impound the information into prices accordingly. Cash flow forecasts potentially represent new information that can help market participants better understand the components of earnings.

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, the mispricing of accruals should resume, as the markets no longer have access to the mitigating impact of cash flow forecasts. My second hypothesis, stated in the alternate form is

HYPOTHESIS 2_a. *The relationship between the accrual component of earnings and future returns is less negative for firms after the initiation of cash flow forecasts.*

HYPOTHESIS 2_b. *The relationship between the accrual component of earnings and future returns is no longer less negative for firms after the termination of cash flow forecasts.*

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 et al. (2009) indicate, cash flow forecasts are inaccurate, their usefulness may be limited. However, when cash flow forecasts are accurate, they are potentially more likely to mitigate accrual mispricing. I hypothesize a weakening of the accruals anomaly when cash flow forecasts are more accurate and state the hypothesis in the alternate form as follows.

HYPOTHESIS 3_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, prior research has documented that investors are more likely to respond to new information from analysts with high prior accuracy (Stickel 1992, Park and Stice 2000, Gleason and Lee 2003). Brown (2001) documents that practitioners pay the greatest attention to prior accuracy while evaluating analysts, as it is the most important determinant of future accuracy. Building on these results, I hypothesize that if the cash flow forecasts for a given firm have been more accurate in the past, they are more likely to mitigate accrual mispricing. I state the hypothesis in the alternate form as follows.

HYPOTHESIS 3_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. Data and preliminary evidence

Choice of accruals variables

Richardson, Sloan, Soliman and Tuna (2005) show that the mispricing of accruals varies with the reliability of the underlying accrual variables. Dechow, Richardson and Sloan (2008) recommend the use of a broad based measure of accruals to forecast future earnings and returns, because they show that the accruals anomaly subsumes other growth anomalies such as the external financing anomaly. I use the accruals definitions from Richardson et al. (2005), starting with an aggregate measure of total accruals (TACC). I analyze the pricing of accruals using two approaches. First, I decompose total accruals (TACC) into change in net operating assets (ΔNOA) and change in financial assets (ΔFIN). Second, I decompose ΔNOA further into change in net working capital (ΔWC) plus change in net non-current operating assets (ΔNCO).

Data sources and definitions of accruals variables

I use the IBES database to identify firm-years with cash flow forecasts, consistent with prior research on cash flow forecasts.[1] I collect financial information from COMPUSTAT and returns from CRSP. 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 sample starts in 1991, the year in which cash flow forecasts appeared for the first time, and ends in 2010, to ensure that future stock returns can be calculated. To determine if 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 analysis in this paper is at the annual level, similar to prior research on the accruals anomaly. The final sample consists of 86,090 firm-years corresponding to 10,367 distinct firms.

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[1] While FIRSTCALL also provides cash flow forecasts, many of these forecasts on FIRSTCALL appear to be mere adjustments made by the data provider for items such as depreciation, and not really analyst provided cash flow forecasts.

I follow the definitions from Richardson et al. (2005) for the measurement of accruals Total accruals (TACC) is defined as TACC = ΔNOA + ΔFIN, where ΔNOA is change in net operating assets and ΔFIN is change in net financial assets. ΔNOA is further decomposed into ΔWC, change in working capital and ΔNCO, change in net non-current operating assets.[2] All earnings components are scaled by average total assets (AT). Return on assets (ROA) is operating income after depreciation (OIADP) scaled by average total assets (AT).

Firm level returns are computed as buy-and-hold returns for the 12-month period starting four months after fiscal year end. Returns are adjusted for delisting as per Shumway (1997)[3]. Returns are adjusted for the size and book-to-market effects using the following procedure. The universe of firms with CRSP monthly returns and Compustat data required to calculate size and book-to-market is independently divided into quintiles based on size (market capitalization) and book-to-market. Monthly value-weighted returns for each of the 25 portfolios created by the

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[2] The components of accruals are calculated as follows (figures in parentheses represent data items from Compustat). 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). 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). FIN, the net financial assets is calculated as 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).

[3] 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.

intersection of the size and book-to-market quintiles are obtained from Ken French's data library.[4] RETSB is the difference between the annual buy-and-hold return for the firm and the buy-and-hold return for the portfolio with the same size and book-to-market quintile.

Descriptive statistics and correlations

Table 1 presents the sample descriptive statistics and correlations. Panel A of Table 1 presents the sample descriptive statistics. Mean ROA for the sample is close to zero, while median ROA is 6.5%. Mean change in net operating assets (ΔNOA) is 6.7%, which equals mean change in working capital (ΔWC 1.1%) plus mean change in non-current operating assets (ΔNCO 5.6%). Mean change in financial assets, ΔFIN, equals -0.5%. Mean size and book-to-market adjusted one-year-ahead return is -0.5%. 15% of all firm-years have a cash flow forecast. Mean total assets is $1759 million and mean market capitalization is $2041 million.

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Panel B presents the correlations. Consistent with prior papers examining the pricing of accruals, most of the accrual measures are negatively correlated with future returns ($RETSB_{t+1}$). ΔNOA and its two components ΔWC and ΔNCO are negatively correlated with future returns, while ΔFIN shows a weak positive correlation with future returns. This is consistent with Richardson et al. (2005), who find that financial accruals are the most reliable and least likely to be mispriced. Finally, CFF is positively correlated with profitability (ROA), firm size (ASST and MCAP) and stock return performance ($RETSB_{t+1}$).

Panel C provides the descriptive statistics partitioned by whether the firm-year had a cash flow forecast or not. Cash flow forecast (CFF) observations appear to be more profitable as mean

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

and median ROA is significantly greater. Further, CFF observations have a much lower incidence of losses. While ΔNOA_t appears to be similar for both groups, CFF observations have less working capital accruals and greater non-working capital accruals. CFF observations also have greater returns and are significantly larger both in terms of assets and market capitalization. Panel C of Table 1 also compares additional firm characteristics such as analyst following, forecast accuracy, sales growth and the P/E ratio. CFF observations have significantly lower mean sales growth, but the difference in medians is insignificant. CFF observations also have a slightly lower mean P/E ratio, but the difference in medians is in the opposite direction. Overall, the results in Panel C suggest that firms with cash flow forecasts are quite different from firms without cash flow forecasts. It will hence be important to control for sample selection while testing for the relationship between accrual mispricing and cash flow forecasts.

Cash flow forecasts and trends in the accruals anomaly

Panel A of Table 2 presents evidence on the increasing incidence of cash flow forecasts. In 1991, only 1 firm out of 3,812 had cash flow forecasts, while 1,595 firms had EPS forecasts. Cash flow forecasts increase gradually till 2000. The year 2001 sees a decline in cash flow forecasts which may be related to the delisting of companies at the end of the internet bubble (the number of firms and the number of followed firms also decline). The period since 2001 sees a dramatic increase in cash flow forecasts. In 2001, only 242 firms had cash flow forecasts, representing 6% of all firms and 11% of firms with analyst following (EPS forecasts). In 2002, 956 firms had cash flow forecasts, representing 24% of all firms and 44% of followed firms. Since 2002, the proportion of firms with cash flow forecast has continued to increase gradually. By 2010, 1516 firms had cash flow forecasts, representing 44% of all firms and 59% of firms with analyst following.

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Panel A of Table 2 also presents the returns to the accruals strategy. Firms are annually sorted into deciles based on ΔNOA, ΔWC or ΔNCO. Hedge returns are computed as the difference between average size and book-to-market adjusted returns for the lowest accrual quintile (long) and the highest accrual quintile (short). The hedge returns are consistently positive through 2003. Further, consistent with Richardson et al. (2005), the returns to a strategy based on ΔNOA are generally greater. The returns to the accruals trading strategy have weakened considerably in recent years. The average hedge returns to a strategy based on ΔNOA yielded an average return of 18.2% in the 1991-2000 period, which declines to 7.2% in the 2001-2010 period (difference -11.0%, t-stat -2.72). Figure 1 graphs the trends in hedge returns along with the availability of cash flow forecasts. As the graph indicates, the decline in the accruals anomaly appears to begin around 2003, one year after cash flow forecasts start to become more readily available.

Panel B 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 for the early period in the sample (1991-1994). I therefore compare hedge returns to the accrual strategies for the sample partitioned into firms with and without cash flow forecasts over the 1995-2010 period. A strategy based on ΔNOA yields significantly lower hedge returns within the sub-sample of firms with cash flow forecasts (5.3%) than the subsample of firms without cash flow forecasts (15.3%). Similar results are also obtained for strategies based on ΔWC and ΔNCO (results not tabulated for brevity). Thus, the accruals anomaly is significantly weaker in the subset of firms with cash flow forecasts, consistent with cash flow forecasts mitigating accrual mispricing. As discussed later, this trend might also be consistent with other correlated factors such as increased institutional investment and improved accounting quality.

Why might cash flow forecasts potentially help mitigate accrual mispricing? Call et al. (2009) show that firms with cash flow forecasts in addition to earnings forecasts have lower average absolute forecast error. The last set of columns in Panel B of Table 2 compares the earnings forecast accuracy of firms with and without cash flow forecasts. In every year, 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. This is an interesting departure from the results in Bradshaw, Richardson and Sloan (2001) that showed that analysts were also likely to misprice accruals. It is consistent with analysts improving their forecasting ability by incorporating the forecasting of accruals (i.e. cash flow forecasts) into their forecasting process.

4. Results

The weakening of the accruals anomaly over time

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

$$RETSB_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * \Delta NOA_t + \beta_3 * \Delta FIN_t + \varepsilon \quad (1)$$

and

$$RETSB_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta WC_t + \delta_3 * \Delta NCO_t + \delta_4 * \Delta FIN_t + \varepsilon \quad (2)$$

where $RETSB_{t+1}$ is the one-year-ahead size and book-to-market adjusted return, ROA_t is operating income after depreciation scaled by average total assets, ΔNOA is change in net operating assets, ΔNWC is change in working capital, ΔNCO is change in non-current operating assets and ΔFIN is change in financial assets. In the above regressions, the coefficient on ROA represents the pricing of all components of earnings (cash flow and accruals). The coefficients on ΔNOA and Δ FIN in equation 1, and ΔWC, ΔNCO and ΔFIN in equation 2 represent the differential pricing of the accrual components of earnings. If the accruals anomaly is indeed present in the time period being analyzed, I expect the coefficient β_2 and β_3 in equation 1 (δ_2, δ_3 and δ_4 in equation 2) to be significantly negative. The regression is run using robust regressions to minimize the impact of outliers. Further, the reported t-statistics control for two-way clustering by firm and time, consistent with Petersen (2009) and Gow, Ormazabal and Taylor (2010).[5] All regressions in this paper follow this approach.

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The results are presented in Table 3. The first column presents the regression using the specification in equation 1. Both accruals measures (ΔNOA and ΔFIN) are strongly negatively correlated with future returns. Also, consistent with Richardson et al. (2005), the coefficient on ΔNOA (-0.198) is significantly more negative than that on ΔFIN (-0.019). The next column presents the regression using the specification in equation 2. The results confirm the negative association between accruals and future returns, with significant negative coefficients on both ΔWC (-0.233) and ΔNCO (-0.181).

[5] Leone, Minutti and Wasley (2012) recommend the robust regression approach over ad-hoc or arbitrary cutoffs typically used for truncation or winsorization. Consistent with their recommendation, I run PROC ROBUSTREG in SAS with the MM approach. I then use the weights provided by the robust regression and re-run the regressions using PROC SURVEYREG to compute two-way clustered t-statistics.

I next examine the trend in the pricing of accruals. I first define an indicator variable called LATER, which equals 1 for the 10-year period from 2001-2010 and 0 for the 10 year period from 1991-2000. I interact LATER with the components of earnings and test whether the pricing of accruals changed across time. The modified regressions that are run are

$$RETSB_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * \Delta NOA_t + \beta_3 * \Delta FIN_t + \alpha_1 * LATER + \beta_{21} * \Delta NOA_t * LATER + \beta_{31} * \Delta FIN_t * LATER + \varepsilon \quad (3)$$

and

$$RETSB_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta WC_t + \delta_3 * \Delta NCO_t + \delta_4 * \Delta FIN_t + \gamma_1 * LATER + \delta_{21} * \Delta WC_t * LATER + \delta_{31} * \Delta WC_t * LATER + \delta_{41} * \Delta FIN_t * LATER + \varepsilon \quad (4)$$

The results are presented in the last two columns of Table 3. The coefficient β_{21} on the interaction of ΔNOA with LATER is significantly positive (0.155), consistent with a decline in accrual mispricing. The coefficient β_{31} on the interaction of ΔFIN with LATER is however insignificant; however, it must be noted that the mispricing of ΔFIN was not very strong. The last column presents the regression using the disaggregated accruals breakdown. The coefficients δ_{21} and δ_{31} on the interactions of ΔWC and ΔNCO respectively with LATER are significantly positive (0.102 and 0.161 respectively). To summarize, the results suggest that the negative association between accruals, measured either as ΔNOA or decomposed further into ΔWC and ΔNCO, and future returns has lessened in the last decade, consistent with a decline in accrual mispricing. In the following sub-section, I test whether this decline in mispricing of accruals is associated with the increased incidence of cash flow forecasts.

Controlling for sample selection bias

Before analyzing the impact of cash flow forecasts on accrual mispricing, it is important to note that the sample of firms with cash flow forecasts is not random. This was evident in the differences in firm characteristics observed earlier in Panel C of Table 1. Any relationship shown between accrual mispricing and cash flow forecasts may simply be the result of sample selection bias – i.e. 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 forecasts. I control for sample selection bias, as described below.

I first run a first stage PROBIT regression with CFF as the dependent variable, where CFF is an indicator variable that equals 1 for a firm-year with a cash flow forecast and 0 otherwise. The prior research on cash flow forecasts (DeFond and Hung 2003, Call 2008) 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. Correspondingly, I use the following independent variables: 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.[6] The PROBIT regression specification is

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[6]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

$$\Pr(CFF=1) = \alpha_0 + \beta_1{*}VOL + \beta_2{*}\ CYCLE + \beta_3{*}\ Z + \beta_4{*}CAPINT + \beta_5{*}ABSACC + \beta_6{*}\ LMCAP \quad (5)$$

The results of the PROBIT regression are presented in Panel A of Table 4. Because of data requirements, the sample size drops to 81,163 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.[7]

---------------------------------- INSERT TABLE 4 HERE ---

The PROBIT 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 with observations without cash flow forecasts based on their propensity to issue cash flow forecasts, using the expected probabilities from the PROBIT regression. This approach based on propensity score matching attempts to randomize across the determinants of cash flow forecasts and is similar to Francis, Lennox and Zhang (2012) and Doyle, Ge and McVay (2007). Each of the cash flow forecasts are matched in the same year with non-forecast observations from the same industry

(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.

[7] Prior research had examined the subset of firms with analyst following. Here, I consider the general population of firms. Indeed, if the PROBIT is rerun among firms with analyst following, ABSACC loads positively.

(based on 2 digit SIC code) with the closest estimated probability of CFF=1. I also impose the additional requirement that all control firms have analyst following to ensure that control firms are more similar to sample firms.

Despite this, significant differences remain between the CFF firms and the matched non-CFF firms. Panel B of Table 4 presents a comparison of the characteristics and estimated propensity to issue CFF for both the CFF firms and the control firms. Clearly, the matching algorithm is only partially successful as CFF firms have at 42.9% propensity to have cash flow forecasts as opposed to 20.4% for non-CFF firms. To ensure that the treatment firms and control firms are appropriately matched, I impose the condition that the estimated probability of having cash flow forecasts is within 10%. This reduces the sample size, but ensures better matching as suggested by the comparison of characteristics and estimated propensity to issue cash flow forecasts in Panel C of Table 4. In this reduced sample, the estimated propensity to issue cash flow forecasts is 25.5% for CFF firms as opposed to 24.2% for non-CFF firms.

The accruals anomaly and incidence of cash flow forecasts

To test for the impact of cash flow forecasts on the pricing of accruals, I modify the earlier regression specifications by introducing an interaction of the accrual components with an indicator variable CFF that equals 1 for a firm-year with a cash flow forecast and 0 otherwise.

The modified regressions are

$$RETS_{t+1} = \alpha_0 + \beta_1 * ROA_t + \beta_2 * \Delta NOA_t + \beta_3 * \Delta FIN_t + \alpha_1 * CFF + \beta_{21} * \Delta NOA_t * CFF + \beta_{31} * \Delta FIN_t * CFF + \varepsilon \quad (6)$$

and

$$RETS_{t+1} = \gamma_0 + \delta_1 * ROA_t + \delta_2 * \Delta WC_t + \delta_3 * \Delta NCO_t + \delta_4 * \Delta FIN_t + \gamma_1 * CFF + \delta_{21} * \Delta WC_t * CFF + \delta_{31} * \Delta WC_t * CFF + \delta_{41} * \Delta FIN_t * CFF + \varepsilon \quad (7)$$

If cash flow forecasts reduce accrual mispricing, 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} and β_{31} in model (6) and δ_{21}, δ_{31} and δ_{41} in model (7) to be significantly positive.

The first set of columns of Table 5 presents the results from the regressions in equations (6) and (7) for the entire sample, without any control for sample selection bias. There is support for the hypothesis that the presence of cash flow forecasts reduces accrual mispricing. For the first specification (equation 6), the coefficient β_2 on ΔNOA is -0.204, while the incremental coefficient β_{21} on ΔNOA*CFF is 0.092 (t-stat 4.04), indicating that the negative relationship between accruals and future returns is weaker in the presence of cash flow forecasts. The incremental coefficient on ΔFIN*CFF is insignificant. For the specification decomposing ΔNOA further, the incremental coefficient δ_{31} on ΔNCO*CFF is 0.092 (t-stat 3.75). However, the incremental coefficients on the interactions of ΔWC and ΔFIN with CFF are insignificant.

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The next two columns repeat the analysis within the subset of firms that have analyst following. This is done to ensure that the documented effect can be attributed to cash flow forecasts in particular and not just to analyst following, as all firms with cash flow forecasts also have earnings forecasts. As the results indicate, among followed firms, there is evidence consistent with lowered accrual mispricing among firms with cash flow forecasts. The coefficient on ΔNOA*CFF continues to be significantly positive (0.164, t-stat 7.47), while for the second specification, the coefficient on both ΔWC*CFF (0.156, t-stat 2.58) and ΔNCO*CFF (0.154, t-stat 6.34) are significant.

The next two columns in Table 5 repeat the analysis with the addition of the inverse mills ratio from the sample selection regression as an additional independent variable. The results are essentially unchanged. The coefficient on ΔNOA*CFF continues to be significantly positive (0.127, t-stat 5.48), while for the second specification, the coefficient on ΔNCO*CFF remains significant (0.131, t-stat 5.29).

The last columns present the results of the regression in the propensity-matched regression. The number of observations declines to 6,278 corresponding to 3,139 cash flow forecasts with appropriate matching control firm-years. Here again, the results support hypothesis 1. In the first specification, the coefficient on ΔNOA*CFF continues to be significantly positive (0.159, t-stat 2.72). For the second specification, the coefficient on ΔNCO*CFF also remains significant (0.172, t-stat 2.64).[8]

The results indicate that the incidence of cash flow forecasts is associated with less mispricing of accruals. While this is not true for all components of accruals, the accrual components identified by prior research as having the lowest reliability (ΔNOA, ΔNCO) are significantly less likely to be mispriced when firms have cash flow forecasts. Hence the results reject the null of hypothesis 1.

[8] The coefficient on the CFF indicator variable is significantly positive in all specifications except for the Heckman specification. The positive coefficient potentially represents the higher returns earned by CFF firms, which was also seen in Panel C of Table 1. In the Heckman specification, the CFF variable is very strongly correlated with the inverse mills ratio – which explains why the coefficient on CFF flips in sign.

Controlling for alternative explanations

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. Green et al. (2011) suggest that the presence of a number of leading accounting and finance academics in the quantitative hedge fund industry lead to a greater investment in accruals based strategies which eliminated excess returns over time. They show that the mispricing of the accrual component of earnings reduces when the aggregate institutional investment by hedge funds increases. Bhojraj et al. (2009) argue that the passage of the Sarbanes-Oxley bill (SOX) and the SFAS No. 146 related to restructuring expenses improved the quality of accruals by reducing accruals-based manipulation of earnings and reducing improperly stated restructuring charges. They argue that the accrual anomaly weakened because of improved accounting quality.

I attempt to control for these effects by incorporating proxies for institutional investment in accruals based strategies and for earnings quality. While it is not possible to identify the exact amount of investment focussed on accruals based strategies, I use the total assets managed by hedge funds as a proxy consistent with Green et al. (2011). I define LAUM as the log of assets under management by hedge funds (obtained from www.barclayshedge.com). LAUM is a time-series variable measured annually. I measure earnings quality using the approach from Dechow and Dichev (2002), as modified by McNichols (2002). For each industry (based on 2 digit SIC) and year, a regression is run with total current accruals (change in current assets other than cash minus change in current liabilities other than debt) as the dependent variable and current, lagged and future cash from operations as the main independent variables in addition to gross PPE and change in revenues, where all variables are scaled by average assets. Each firm's earnings quality is the variance of the five lagged residuals from this regression. I define DD as the negative of this variance to ensure that a larger number corresponds to higher earnings quality. Both LAUM and DD are interacted with the components of accruals.

I modify the earlier regression specification (6) by introducing an interaction of the accrual components with DD and LAUM. The modified regression is

$$\begin{aligned} RETSB_{t+1} = \alpha_0 &+ \beta_1{*}ROA_t + \beta_2{*}\Delta NOA_t + \beta_3{*}\Delta FIN_t \\ &+ \alpha_1{*}CFF + \beta_{21}{*}\Delta NOA_t{*}CFF + \beta_{31}{*}\Delta FIN_t{*}CFF \\ &+ \alpha_2{*}LAUM + \beta_{22}{*}\Delta NOA_t{*}LAUM + \beta_{32}{*}\Delta FIN_t{*}LAUM \\ &+ \alpha_3{*}DD + \beta_{23}{*}\Delta NOA_t{*}DD + \beta_{33}{*}\Delta FIN_t{*}DD + \varepsilon \end{aligned} \tag{8}$$

As before, I expect the incremental coefficient on β_{21} on ΔNOA_t*CFF to remain significantly positive. If increased institutional investment mitigates accrual mispricing, I expect the incremental coefficient on β_{22} on ΔNOA_t*LAUM to be significantly positive. If improved earnings quality mitigates accrual mispricing, I expect the incremental coefficient on β_{32} on ΔNOA_t*DD to be significantly positive. The results are presented in Table 6.

---------------------------------- INSERT TABLE 6 HERE ---

The first column presents the regression for the entire sample without any control for sample selection. Consistent with hypothesis 1, the incremental coefficient β_{21} on ΔNOA*CFF continues to be significant at 0.067 (t-stat 2.04). Further, the regression also provides support for the alternate explanation for the decline in the accruals anomaly. Consistent with mitigating impact of increased institutional investment, the incremental coefficient β_{22} on ΔNOA*LAUM is significantly positive at 0.015 (t-stat 3.55). Further, consistent with the impact of increasing earnings quality, the incremental coefficient β_{23} on ΔNOA*DD is significantly positive at 0.470 (t-stat 2.86).[9]

The next three columns repeat the regression using the same three specifications used earlier – within the subset of firms with analyst forecast, with the inverse mills ratio to control for sample selection and finally, within a propensity score matched sample. In all three specifications, I find that the incremental coefficients β_{21}, β_{22} and β_{23} on ΔNOA*CFF, ΔNOA*LAUM and ΔNOA*DD respectively are all significantly positive.

The results lend support for all three conjectures for the decline in the accruals anomaly – the increasing incidence of cash flow forecasts, the greater investment by institutional investors in accruals based strategies and the improved quality of accruals information potentially related to regulatory changes. More importantly for this paper, the results suggest that the cash flow forecast based explanation is not subsumed by alternate explanations. It is plausible that these three effects are interrelated. For instance, analysts may have 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. Similarly, it is also plausible that institutional investors were more likely to invest in accruals based strategies once analysts started providing cash flow forecasts. Conversely, analysts might potentially have started issuing cash flow forecasts in response to demands from institutional investors.

Initiation and termination of cash flow forecasts

[9] I also ran specification with CFF, DD and LAUM interacted with more disaggregated accrual specification (ΔWC, ΔNCO and ΔFIN). The results mirror earlier results with the interactions of all three variables with ΔNCO showing significant positive coefficients, and the interactions of ΔWC and ΔFIN being insignificant. The results are not tabulated for brevity.

I next test the impact of the initiation or termination of cash flow forecasts on the pricing of accruals (Hypothesis 2_a and Hypothesis 2_b). I do this by modifying my research design to identify the instances when firms initiate and terminate cash flow forecasts. I define the following three indicator variables. START equals 1 in the first year that a cash flow forecast appears for a given firm and 0 otherwise. CONT equals 1 for cash flow forecasts other than the first instance for a given firm and 0 otherwise. END equals 1 for the year immediately after the last cash flow forecast for a given firm.[10]

To ensure that START picks up the impact of cash flow forecasts and not just the initiation of coverage along with cash flow forecasts, I require that the firm in question have coverage without cash flow forecasts in the year prior to initiation. Similarly, to ensure that END picks up the impact of termination of cash flow forecasts and not just the cessation of coverage, I also require that the firm in question continue to have coverage without cash flow forecasts in the subsequent year. Using these definitions, there were 2608 initiations and 1360 terminations in the sample. I modify the earlier regression specification (6) by interacting the accrual components with START, CONT and END instead of CFF. The modified regression is

$RETSB_{t+1} = \alpha_0 + \beta_1*ROA_t + \beta_2*\Delta NOA_t + \beta_3*\Delta FIN_t$

[10] While a better understanding of why analysts would initiate or terminate forecasting cash flows for a given firm is important, this paper considers this question from the market's perspective. How do markets react to accrual information, now that they have access to (or have lost access to) a signal that they did not have (had) before? The initiation of cash flow forecasts has been studied by DeFond and Hung (2003) among others. Termination of cash flow forecasts has not really been studied; a preliminary check of the terminated observations in my sample suggests that the main reason for this appears to be the fact the solitary analyst on IBES who issued cash flow forecasts for a given firm either stops following that firm or drops out of IBES

$$+ \alpha_1{*}START \;+\; \beta_{21}{*}\Delta NOA_t{*}START \;+\; \beta_{31}{*}\Delta FIN_t{*}START$$

$$+ \alpha_2{*}CONT \;+\; \beta_{22}{*}\Delta NOA_t{*}CONT \;+\; \beta_{32}{*}\Delta FIN_t{*}CONT$$

$$+ \alpha_3{*}END \;+\; \beta_{23}{*}\Delta NOA_t{*}END \;+\; \beta_{33}{*}\Delta FIN_t{*}END \;+\; \varepsilon \qquad (9)$$

If, as hypothesized, the mispricing of accruals reduces with the initiation of cash flow forecasts, I expect the coefficient β_{21} on ΔNOA_t*START to be significantly positive. Further, given the results in Table 5 and 6, I expect that the coefficient β_{22} on ΔNOA_t*CONT to be significantly positive. Finally, I expect that the coefficient β_{23} on ΔNOA_t*END to be insignificant, as accrual mispricing resumes in the absence of cash flow forecasts. The results are presented in Table 7.

---------------------------------- INSERT TABLE 7 HERE --

The first column presents the regression for the entire sample without any control for sample selection. Consistent with hypothesis 2_a, the incremental coefficient β_{21} on ΔNOA*START is significant at 0.078 (t-stat 1.74), suggesting that the initiation of cash flow forecasts is associated with lower accrual mispricing. Interestingly, the incremental coefficient β_{21} on ΔNOA*CONT is slightly higher at 0.104 (t-stat 4.85). This is consistent with greater mitigation of mispricing as time goes by, though the difference in coefficients is not significant (0.026, t-stat 0.52). Consistent with hypothesis 2_b, the incremental coefficient β_{23} on ΔNOA*END is insignificant at 0.033 (t-stat 0.54). However, the difference between β_{22} and β_{23} is not statistically significant (-0.071, t-stat -1.10) – i.e. the evidence of a change in mispricing after cash flow forecasts stop is weak. The next three columns repeat the regression using the same three specifications used earlier – within the subset of firms with analyst forecast, with the inverse mills ratio to control for sample selection and finally, within a propensity score matched sample. In all three specifications, I find that the incremental coefficients β_{21} on ΔNOA*START and β_{22} on ΔNOA*CONT are significantly positive, while the coefficient β_{23} on ΔNOA*END is insignificant.[11]

To summarize, the results suggest that the mitigation of accruals mispricing starts with the initiation of cash flow forecasts, persists as cash flow forecasts continue to be made and ceases when cash flow forecasts are no longer available.

The accruals anomaly and accuracy of cash flow forecasts

If cash flow forecasts mitigate accrual mispricing, then the effect should be larger when the forecasts are more accurate (Hypotheses 3_a and 3_b). I measure forecast accuracy as the negative of the unsigned forecast error in the cash flow forecast. I define ACC as

$$ACC_{t+1} = - |CPS\_ACT_{t+1} - CPS\_EST_{t+1}|/PRICE_{t+1} \quad (10)$$

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 ACC_{t+1} to test hypothesis 3_a (ex-post forecast accuracy), while I use ACC_t (prior period forecast accuracy) to test hypothesis

[11] To test that the START variable truly represents an important event, I randomly pick one of the years prior to the actual initiation as a pseudo-initiation year and replicate the regression in Table 7. Recall that the coefficient on ΔNOA*START is 0.074 (t-stat 1.74) for the baseline regression. When I replace START with the pseudo-start variable (PSTART), the coefficient on ΔNOA*PSTART is only 0.052 (t-stat 1.32). Further, when I include both START and PSTART, the coefficient on ΔNOA*START remains at 0.074 (t-stat 1.74) while the coefficient on ΔNOA*START is 0.051 (t-stat 1.32). This lends credence to CFF initiation being a significant event.

3_b (ex-ante forecast accuracy). I modify the accrual pricing regressions by interacting the accrual components with ACC. The modified regressions are

$$RETSB_{t+1} = \alpha_0 + \beta_1 * ACC + \beta_1 * ROA_t + \beta_2 * \Delta NOA_t + \beta_{21} * \Delta NOA_t * ACC + \beta_3 * \Delta FIN_t + \beta_{31} * \Delta FIN_t * ACC + \varepsilon \tag{11}$$

and

$$RETSB_{t+1} = \gamma_0 + \gamma_1 * ACC + \delta_1 * ROA_t + \delta_2 * \Delta WC_t + \delta_{21} * \Delta WC_t * ACC + + \delta_3 * \Delta NCO_t + \delta_{31} * \Delta NCO_t * ACC + \delta_4 * \Delta FIN_t + \delta_{41} * \Delta FIN_t * ACC + \varepsilon \tag{12}$$

I expect the incremental relationship between future returns and accruals to be less negative for more accurate cash flow forecasts. The results are presented in Table 8. As these tests are run within the subset of firms with cash flow forecasts, there is no need for any controls for sample selection bias.

---------------------------------- INSERT TABLE 8 HERE --

The first set of columns in Table 8 presents the results from the regressions in equations (11) and (12) using ex-post realized forecast accuracy. The number of observations declines to 11,079 as forecast accuracy can only be computed for firms with both cash flow forecasts and realized cash flows. The results support hypothesis 3_a and indicate that more accurate cash flow forecasts are associated with a reduction in the negative relationship between accruals and future returns. In the first regression, the incremental coefficient β_{21} on ΔNOA*ACC is 1.119 (t-stat 2.77), while the incremental coefficient β_{31} on ΔFIN*ACC is 1.379 (t-stat 2.79). In the second regression, the incremental coefficient is significant for both ΔWC and ΔNCO. The incremental coefficient δ_{21} on ΔWC*ACC is significant at1.060 (t-stat 2.03), while the incremental coefficient δ_{31} on ΔNCO*ACC is also significant at 1.421 (t-stat 3.22).

The next set of columns repeats the analysis using prior forecast accuracy. The number of observations declines further to 10,716 because of the requirement that there be cash flow forecasts in the prior period as well. In the first regression, the incremental coefficient β_{21} on ΔNOA*ACC is 0.921 (t-stat 1.80), while the incremental coefficient β_{31} on ΔFIN*ACC is insignificant. In the second specification, the incremental coefficient δ_{31} on ΔNCO*ACC is significant 1.123 (t-stat 2.05), while the incremental coefficients on ΔWC*ACC and ΔFIN*ACC are insignificant. Still, the evidence largely suggests that accrual components are less likely to be mispriced when cash flow forecasts have been accurate in the past, supporting hypothesis 3_b. Overall, the results from Table 8 strongly support Hypothesis 3 that accrual mispricing is reduced when analysts' cash flow forecast are more accurate.

Sensitivity analysis

In addition to the tabulated results, I conducted the following untabulated sensitivity analyses to ensure the robustness of the tests. First, instead of the robust regression approach used in the paper, I reran all analyses with the conventional approach of winsorizing the data at 1% and 99% using annual distributions. The results are very similar. For instance, the coefficient on ΔNOA*CFF for the baseline regression for HYPOTHESIS 1 continues to be significant at 0.073 (t-stat 2.02), while the coefficient on ΔNOA*ACC for the baseline regression for hypothesis 3_a continues to be significant at 2.82 (t-stat 6.02). Second, one potential concern regarding the results might be lack of sample continuity, given the large number of small firms and technology firms that exited the sample in the late 1990s and early period just prior to the increase in cash flow forecasts. To account for this, I reran the tests in the subset of firms that continued to exist in the 1999-2009 period and find similar results. For instance, the coefficient on ΔNOA*CFF is 0.1383 (t-stat 3.72) in the baseline regression for hypothesis 1. Finally, I replaced the CFF indicator variable with a variable NUMCFF, defined as log(1+number of cash flow forecasts). I find that the interaction of NUMCFF with the accrual variables (ΔNOA and ΔNCO) is strongly positively associated with returns. For instance, the coefficient on ΔNOA*NUMCFF is 0.0463 (t-stat 2.24) in the baseline regression for hypothesis 1. This is also consistent with the results in Table 7 where continuing cash flow forecasts appear to have a slightly greater mitigating effect on the pricing of accruals over initial cash flow forecasts.

Dechow and Ge (2006) show that accruals anomaly can partially be attributed to markets not understanding the transitory nature of special items such as restructuring charges. Bhojraj et al. (2009) argue that the passage of SFAS No. 146, related to costs associated with exit or disposal activities, reduced the manipulation of restructuring charges which in turn contributed to the decline in the accruals anomaly. To ensure that my results are not driven by changes in the nature of restructuring charges and special items, I eliminate all observations in the bottom decile of special items and rerun the regressions. I also eliminate observations with non-zero restructuring information on COMPUSTAT (10,210 firm-years in 1991-2010). All regression results are also largely unchanged.

Finally, Hribar and Collins (2002) highlight the pitfalls of measuring accruals (primarily the ΔWC variable) using the balance sheet method and suggest using the information from the cash flow statement directly. This can affect the inferences drawn in this paper, if the error varies between CFF and non-CFF observations. I test for the difference in error (absolute value in the difference in ΔWC, scaled by lagged assets) between CFF and non-CFF firms using the methodology in Hribar and Collins (2002). To ensure that I am picking up the effect of cash flow forecasts, I compare the error and absolute errors in accrual measurement for CFF and non-CFF observations in the propensity matched sample (6278 observations). For these observations, the error variables are almost identical – the mean error (difference between cash flow measure and balance sheet measure) is 0.0230 for CFF observations and 0.0221 for non-CFF observations. Similarly, the unsigned error is 0.0682 for CFF observations and 0.0690 for non-CFF observations. Thus, any bias or measurement error in accrual measurement is unlikely to alter any inferences regarding cash flow forecasts and accruals mispricing.

Caveats

The results in this paper suggest that the increased information available to capital markets from cash flow forecasts helped mitigate accrual mispricing. However, it is important to note the following caveats. First, the period where cash flow forecasts have become prevalent and the accruals anomaly has weakened is short. A reappearance of returns to an accruals strategy despite the continued availability of cash flow forecasts would weaken the explanation offered. Second, as Chen, DeFond and Park (2002) illustrate, firms might be providing voluntary disclosure of accruals with their preliminary earnings announcements. Levi (2008) shows that such firms are less likely to have mispriced accruals. It is plausible that firms with cash flow forecasts might be providing such disclosures, either in response to investor demand or in response to demand from the analysts themselves. The mitigation of accruals mispricing attributed to cash flow forecasts might stem from these voluntary accrual disclosures. The critical issue is whether such voluntary disclosures complement or substitute for cash flow forecasts.[12]

Another caveat that must be highlighted is the relatively weak results with respect to working capital accruals (ΔWC). One would expect that some of the analysts' expertise in forecasting accruals would be reflected in more accurate estimation of working capital accruals and yet the interaction of the cash flow forecast variables with ΔWC is often insignificant. These

[12] First call has a database of company issued guidance. I searched for guidance related to either cash flows or fund flows. I was able to identify 222 firm-years in my sample where a company issued guidance about either cash flows or fund flows. The correlation between such guidance and cash flow forecasts is an insignificant 0.02. Further, deleting these 222 observations does not affect the results.

weak results may be potentially related to the relatively small size and greater variability of working capital accruals, especially when compared to non-working capital accruals. As Panel A of Table 1 indicates, the mean ΔWC_t at 1.1% is five times the mean of ΔNCO_t at 5.6%, but the standard deviation is more than half. Further, multicollinearity may also play a role. When I drop ΔNCO_t and run the regression with just ΔWC_t, I find that the interactions are significant.

5. 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. However, accruals based strategies have yielded significantly weaker returns in the past decade. What could explain the disappearance of a once robust effect?

The results in this paper suggest that the diminished returns to accruals based strategies are related to increasing incidence and accuracy of cash flow forecasts provided by analysts. I find that the negative relationship between future returns and accruals is mitigated in the presence of cash flow forecasts. This relationship persists after controlling for two other documented reasons for the decline in the accruals anomaly: the increased investment by hedge funds in accruals based strategies and the improving quality of accruals as a result of regulatory changes. I also find that accrual mispricing is mitigated when analysts start and exacerbated when analysts stop issuing cash flow forecasts. Further, accrual mispricing is weaker when forecasts that are either ex-post more accurate or ex-ante more likely to be accurate.

This paper has important implications for the issue of whether the accruals anomaly is driven by mispricing or risk. The results herein support the mispricing argument. As analysts provide capital markets with useful insight about the nature of accruals through their cash flow forecasts, the markets in turn are less likely to misprice accruals. This is consistent with markets being adaptively efficient, as propounded by Grossman and Stiglitz (1980). This corroborates international evidence in Gordon, Petruska and Yu (2010), who show that cash flow forecasts help attenuate investor fixation on accruals in common law countries where accrual mispricing is ex-ante higher.

The finding that analysts played a role in the weakening of the accruals anomaly is analogous to results seen for the post-earnings announcement drift. Zhang (2008) shows that firms covered by analysts who were quick to respond to earnings announcements did not experience any drift. The results in Zhang (2008) and this paper suggest that mispricing is not mitigated by the mere presence of analysts. Analysts also need to be diligent by being more responsive to earnings announcements or by analyzing accruals in a more sophisticated fashion.

The findings in this paper both corroborate and are corroborated by similar results shown in a contemporaneous paper by Radhakrishnan and Wu (2013). Despite differences in their approach and empirical tests, both papers demonstrate the mitigating impact that cash flow forecasts have on accrual mispricing. This can be viewed as a testament to the underlying strength of the relationship between cash flow forecasts and the appropriate pricing of accruals information.

Finally, this paper also contributes to research on the usefulness of analysts' cash flow forecasts. The finding that cash flow forecasts helped mitigate accrual mispricing suggests that they do provide valuable information to capital markets, consistent with Call et al. (2009, 2012) and counter to Givoly et al. (2009).

References

Allen, E., C. Larson and R. Sloan. 2013. Accrual reversals, earnings and stock returns. *Journal of Accounting and Economics* (forthcoming).

Baber, B., S. Chen and S. Kang. 2006. Stock price reaction to evidence of earnings management: Implications for supplementary financial disclosure. *Review of Accounting Studies* 1: 5-19.

Bhojraj, S., P. Sengupta and S. Zhang. 2009. Restructuring charges, regulatory changes and the accruals anomaly. Working Paper, Cornell University/George Mason University.

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

Brown, L. 2001. How important is past analyst forecast accuracy? *Financial Analysts Journal* 57: 44-49.

Call, A. 2008. Analysts' cash flow forecasts and the relative informativeness and pricing of the cash component of earnings. Working paper , University of Georgia.

Call, A., S. Chen and Y. Tong. 2009. Are analysts' earnings forecasts more accurate when accompanied by cash flow forecasts? *Review of Accounting Studies* 14: 358-391.

Call, A., S. Chen and Y. Tong. 2012. Are analysts' cash flow forecasts naïve extensions of their own earnings forecasts? *Contemporary Accounting Research* (forthcoming).

Chen, S., M. DeFond and C. Park. 2002. Voluntary Disclosure of Balance Sheet Information in Quarterly Earnings Announcements. *Journal of Accounting and Economics* 33: 229-251.

Dechow, P.M., and I. Dichev, 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35-59.

Dechow, P. and W. Ge. 2006. The persistence of earnings and cash flows and the role of special items: Implications for the accruals anomaly. *Review of Accounting Studies* 11: 253-296.

Dechow, P., S. Richardson and R. Sloan. 2009. The persistence and pricing of the cash component of earnings. *Journal of Accounting Research* 46: 537-566.

DeFond, M. and M. Hung. 2003. An empirical analysis of analysts' cash flow forecasts. *Journal of Accounting and Economics* 35: 73–100.

Doyle, J., W. Ge and S. McVay. 2007. Accruals quality and internal control over financial reporting. *The Accounting Review* 82: 1141-1170.

Eames, M., S. Glover and D. Kim. 2010. I/B/E/S reported forecasted and actual operating cash flows. Working paper , Santa Clara University.

Fama, E., and K. French. 2008. Dissecting Anomalies. *Journal of Finance* 63: 1653-1678.

Francis, J, C. Lennox and Z. Wang. 2012. Selection models in accounting research. *The Accounting Review* 87: 589-616.

Givoly, D., C. Hayn and R. Lehavy. 2009. The quality of analysts' cash flow forecasts. *The Accounting Review* 86: 1877-1911.

Gleason, C. and C. Lee. 2003. Analyst forecast accuracy: Do ability, resources and portfolio complexity matter? *Journal of Accounting and Economics* 27: 285-303.

Green, J., J. Hand and M. Soliman. 2011. Going, going, gone? The death of the US accruals anomaly. *Management Science* 57: 797-816.

Gordon, E., K. Petruska and M. Yu. 2010. Do analysts' cash flow forecasts mitigate the accrual anomaly? International evidence. Working Paper , Temple University.

Gow, I. Ormazabal, G. and D. Taylor. 2010. Correcting for Cross-Sectional and Time-Series Dependence in Accounting Research. *The Accounting Review* 85: 483-512.

Grossman, S. and J. Stiglitz. 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70: 393–408.

Heckman, J. 1979. Sample selection bias as a specification error. *Econometrica* 47: 153–61.

Hirshleifer, D., K. Hou and S. Teoh. 2012. The accrual anomaly: risk or mispricing? *Management Science* 58: 320-335.

Hribar, P. and D. Collins. 2002. Errors in Estimating Accruals: Implications for Empirical Research. *Journal of Accounting Research* 40: 105-134.

Jones, J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29: 193-228.

Khan, M. 2008. Are accruals mispriced Evidence from tests of an intertemporal capital asset pricing model, *Journal of Accounting and Economics* 45: 55-77

Kothari, S., Leone, A., and C. Wasley. 2004. Performance Matched Discretionary Accrual Measures. *Journal of Accounting and Economics* 39: 163-197.

Kraft, A., Leone, A. and C. Wasley. 2006. An Analysis of the Theories and Explanations Offered for the Mispricing of Accruals and Accrual Components. *Journal of Accounting Research* 44: 297-339.

Leone, A., Minutti-Meza, M. and C. Wasley. 2012. Outliers and inference in accounting research. Working paper , University of Miami.

Levi, S. 2008. Voluntary disclosure of accruals in earnings press releases and the pricing of accruals. *Review of Accounting Studies* 13: 1-21.

McInnis, J. and D. Collins. 2011. The effect of cash flow forecasts on accrual quality and benchmark beating. *Journal of Accounting and Economics* 51: 29-239.

McNichols, M. 2002. Discussion of the quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 61-69.

Park, C. and E. Stice. 2000. Analyst forecasting ability and the stock price reaction to forecast revisions. *Review of Accounting Studies* 5:

Petersen, M. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies* 22: 435-480.

Radhakrishnan, S. and S. Wu. Analysts' Cash Flow Forecasts and Accrual Mispricing. *Contemporary Accounting Research* (forthcoming).

Richardson, S, R. Sloan, M. Soliman and I. Tuna, 2005. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics* 39: 437-485.

Richardson, S, I. Tuna, and P. Wysocki. 2010. Accounting anomalies and fundamental analysis: A review of recent research advances. *Journal of Accounting and Economics* 50: 410–454.

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

Shumway, T. 1997. The delisting bias in CRSP data. *Journal of Finance* 52: 327-340.

Stickel, S. 1992. Reputation and performance among security analysts. *Journal of Finance* 47: 1811-1836.

Wu, J., L. Zhang, and F. Zhang. 2010. The Q-theory approach towards understanding the accrual anomaly. *Journal of Accounting Research* 48: 177-222.

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

Zach. T. 2007. Evaluating the 'accrual-fixation' hypothesis as an explanation for the accrual anomaly. Working paper , Washington University in St. Louis.

Zhang, Y. 2008. Analysts responsiveness and the post-earnings-announcement drift. *Journal of Accounting and Economics* 46: 201-215.

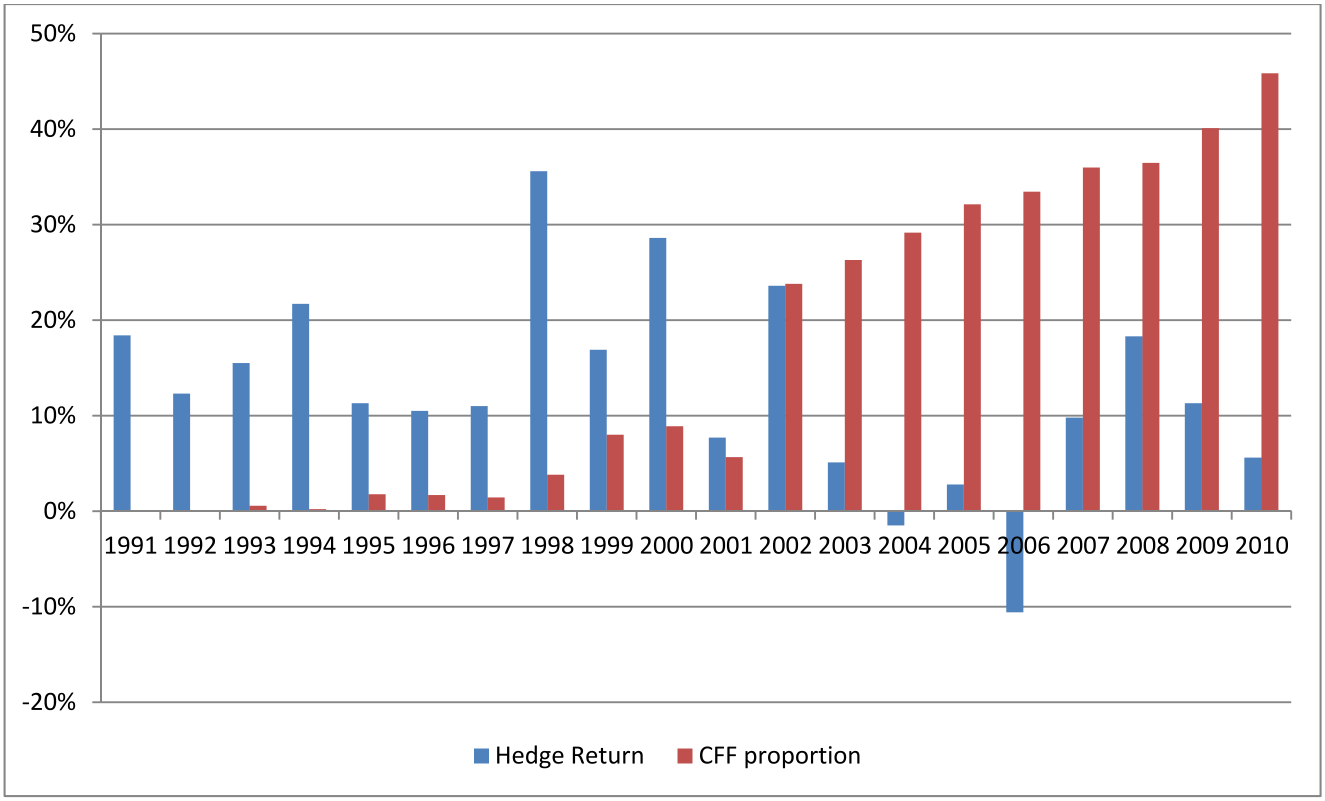

Figure 1 Trends in hedge returns to accruals strategy (ΔNOA) and availability of cash flow forecasts

TABLE 1

Sample Descriptive Statistics and Correlations

Panel A: Sample descriptive statistics

Variable	Mean	Std. Dev.	25th Pctl.	Median	75th Pctl.
ROA_t	0.6%	24.0%	-2.9%	6.5%	12.6%
ΔNOA_t	6.7%	23.6%	-3.4%	3.5%	14.0%
ΔWC_t	1.1%	11.3%	-2.7%	0.6%	4.7%
ΔNCO_t	5.6%	20.0%	-2.0%	1.9%	9.2%
ΔFIN_t	-0.5%	23.8%	-7.4%	0.0%	5.6%
$RETSB_{t+1}$	-0.5%	62.9%	-37.6%	-9.1%	20.7%
CFF	15.0%	35.7%	0.0%	0.0%	0.0%
$ASST_t$	1,759	8,004	41	154	720
$MCAP_t$	2,041	11,130	38	165	761

Panel B: Correlation matrix

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

	ROA_t	ΔNOA_t	ΔWC_t	ΔNCO_t	ΔFIN_t	$RETSB_{t+1}$	CFF	$ASST_t$	$MCAP_t$
ROA_t		0.16^{***}	0.20^{***}	0.07^{***}	0.06^{***}	0.00	0.14^{***}	0.08^{***}	0.10^{***}
ΔNOA_t	0.25^{***}		0.53^{***}	0.88^{***}	-0.32^{***}	-0.07^{***}	0.00	-0.01^{**}	0.00
ΔWC_t	0.24^{***}	0.58^{***}		0.07^{***}	-0.08^{***}	-0.03^{***}	-0.02^{***}	-0.02^{***}	-0.01^{***}
ΔNCO_t	0.20^{***}	0.82^{***}	0.14^{***}		-0.33^{***}	-0.06^{***}	0.01^{***}	0.00	0.01^{**}
ΔFIN_t	0.09^{***}	-0.37^{***}	-0.16^{***}	-0.35^{***}		0.01^{**}	0.00	-0.01^{***}	0.00
$RETSB_{t+1}$	0.10^{***}	-0.07^{***}	-0.04^{***}	-0.06^{***}	0.04^{***}		0.01^{**}	0.00	0.00
CFF	0.14^{***}	0.00	-0.04^{***}	0.02^{***}	0.00	0.08^{***}		0.24^{***}	0.20^{***}
$ASST_t$	0.34^{***}	0.02^{***}	-0.04^{***}	0.07^{***}	-0.03^{***}	0.10^{***}	0.43^{***}		0.75^{***}
$MCAP_t$	0.37^{***}	0.10^{***}	0.01^{***}	0.14^{***}	0.04^{***}	0.09^{***}	0.44^{***}	0.85^{***}	

Panel C: Comparison between firms with and without cash flow forecasts

N=12,881 for CFF=1; N=73,209 for CFF=0

Variable	Mean (CFF=1)	Mean (CFF=0)	Difference (t-stat)	Median (CFF=1)	Median (CFF=0)	Difference (z-stat)
ROA_t	8.4%	-0.7%	9.1% (59.85)	8.9%	5.9%	2.9% (40.78)
ΔNOA_t	6.6%	6.7%	-0.1% (-0.42)	3.2%	3.6%	-0.4% (-0.37)
ΔWC_t	0.5%	1.2%	-0.7% (-10.45)	0.2%	0.7%	-0.5% (-10.35)
ΔNCO_t	6.1%	5.5%	0.6% (3.63)	2.3%	1.8%	0.5% (6.62)
ΔFIN_t	-0.8%	-0.5%	-0.3% (-1.78)	0.0%	0.0%	0.0% (-0.14)
$RETSB_{t+1}$	2.8%	1.2%	1.6% (3.06)	-1.6%	-10.9%	9.3% (22.96)
$ASST_t$	6370	947	5422 (36.56)	1587	107	1481 (127.09)
$MCAP_t$	7430	1093	6338 (31.36)	1611	112	1499 (129.02)
FOLLOWED	100%	48%	52% (278.69)	100%	0%	100% (109.32)
NUMFORC	11.4	2.6	8.7 (131.67)	10	0	10 (150.21)
AFE	2.24%	3.41%	-1.17% (-25.36)	0.83%	1.30%	-0.47% (-24.49)
LOSS	20.0%	38.1%	-18.1% (-45.17)	0.0%	0.0%	0.0% (-39.14)
SGR	19.9%	28.0%	-8.1% (-13.83)	10.3%	9.8%	0.5% (1.63)
PE	34.4	39.4	-5.0 (-6.83)	19.8	18.7	1.1 (7.18)
DD	0.038	0.057	-0.020 (-53.08)	0.029	0.043	-0.015 (-47.77)

Sample consists of 86,090 non-financial firms in the time period 1991-2010 with financial information on COMPUSTAT and stock returns on CRSP. Panel A provides mean descriptive statistics for the analysis variables. Panel B presents correlations between the analysis variables. Panel C presents mean descriptive statistics for the sample partitioned on whether the firm-year had a cash flow forecast (CFF=1) or not (CFF=0). 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, ΔWC_t is change in working capital, ΔNCO_t is change in non-current operating assets. $RETSB_{t+1}$ is size and book-to-market adjusted one-year ahead buy and hold return. See section 3 for detailed definitions. $ASST_t$ is total assets (AT) and MCAP is market capitalization (Shares outstanding (CSHO)* Stock price (PRCC_F). CFF is a dummy variable that equals 1 for all firm-years with a cash flow forecast and zero otherwise. FOLLOWED is a dummy variable that equals 1 for all firm-years with analyst following and zero otherwise. NUMFORC is the number of analysts following a firm. 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. LOSS is a dummy variable that equals 1 for firms where income before extraordinary items (IB) is negative and zero otherwise. SGR is sales growth (SALE divided by lagged SALE -1). PE is the price to earnings ratio (PRCC_F divided by (IB/CSHO)) for observations with positive earnings. The significance level for the correlations is represented by *** (1% level) , ** (5% level) and * (10% level).

TABLE 2

Preliminary evidence on the accruals anomaly and cash flow forecasts

Panel A: Trends in cash flow forecasts on the accruals anomaly across time

YEAR	N	N_{CPS}	N_{EPS}	$HRET_{\Delta NOA}$	$HRET_{\Delta WC}$	$HRET_{\Delta NCO}$
1991	3,812	1	1,595	18.4%	16.3%	13.6%
1992	4,049	1	1,816	12.3%	4.8%	15.5%
1993	4,450	25	2,083	15.5%	8.7%	15.1%
1994	4,640	10	2,261	21.7%	11.3%	18.0%
1995	4,907	87	2,512	11.3%	7.2%	9.9%
1996	5,525	93	2,788	10.5%	15.3%	1.9%
1997	5,480	79	2,874	11.0%	10.2%	9.3%
1998	5,096	194	2,719	35.6%	32.6%	23.6%
1999	5,172	414	2,706	16.9%	-4.1%	20.5%
2000	4,721	420	2,437	28.6%	6.4%	27.3%
2001	4,282	242	2,205	7.7%	3.7%	6.9%
2002	4,016	956	2,158	23.6%	15.1%	22.8%
2003	3,958	1,041	2,291	5.1%	3.2%	0.2%
2004	3,970	1,158	2,368	-1.5%	-2.3%	-0.5%
2005	3,907	1,255	2,446	2.8%	0.0%	2.2%
2006	3,896	1,303	2,556	-10.6%	-5.8%	-9.4%
2007	3,752	1,350	2,572	9.8%	-2.6%	10.1%
2008	3,617	1,319	2,503	18.3%	6.0%	17.4%
2009	3,533	1,417	2,589	11.3%	13.8%	8.2%
2010	3,307	1,516	2,577	5.6%	2.0%	5.5%
Avg. 1991-2000				18.2%	10.9%	15.4%
Avg. 2001-2010				7.2%	3.3%	6.3%
Change across time				-11.0%	-7.6%	-9.1%
				(-2.72)	(-2.03)	(-2.44)

Panel B: Returns to accrual strategies and accuracy of cash flow forecasts

Year	N_{CFF}	$N_{NO\ CFF}$	$HRET_{\Delta NOA}$ CFF	$HRET_{\Delta NOA}$ No CFF	Difference	Mean AFE_{CFF}	Mean AFE_{NOCFF}	Difference
1995	87	4,820	27.3%	12.7%	14.6%	2.72%	3.12%	-0.40%
1996	93	5,432	-40.5%	13.4%	-53.9%	2.06%	3.07%	-1.01%***
1997	79	5,401	32.3%	13.8%	18.5%	2.62%	3.01%	-0.39%
1998	194	4,902	-2.9%	45.1%	-48.0%	3.76%	3.90%	-0.14%
1999	414	4,758	15.1%	19.2%	-4.2%	3.76%	3.77%	-0.01%
2000	420	4,301	25.9%	31.4%	-5.5%	3.23%	4.61%	-1.38%***
2001	242	4,040	-9.9%	10.9%	-20.7%	2.38%	2.80%	-0.42%
2002	956	3,060	6.0%	33.3%	-27.3%	2.15%	3.93%	-1.78%***
2003	1,041	2,917	-8.1%	7.7%	-15.8%	1.64%	2.46%	-0.83%***
2004	1,158	2,812	1.0%	-2.0%	2.9%	1.58%	2.80%	-1.21%***
2005	1,255	2,652	1.0%	4.6%	-3.6%	1.30%	2.66%	-1.36%***
2006	1,303	2,593	-13.0%	-10.3%	-2.7%	1.49%	3.29%	-1.80%***
2007	1,350	2,402	11.4%	9.1%	2.3%	2.61%	4.85%	-2.24%***
2008	1,319	2,298	23.6%	34.3%	-10.7%	3.86%	5.96%	-2.10%***
2009	1,417	2,116	11.1%	12.9%	-1.7%	2.06%	3.37%	-1.31%***
2010	1,516	1,791	4.7%	8.8%	-4.1%	1.55%	2.87%	-1.32%***
Average			5.3%	15.3%	-10.0%	2.42%	3.53%	-1.11%
			(1.15)	(4.27)	(-2.03)	(-1.83)	(14.98)	(-6.40)

Sample consists of 86,090 non-financial firms in the time period 1991-2010 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 IBES. ΔNOA_t is change in net operating assets, ΔWC_t is change in working capital, ΔNCO_t is change in non-current operating assets. See section 3 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 ΔNOA, ΔWC and ΔNCO, are labelled as $HRET_{\Delta NOA,}$ $HRET_{\Delta WC}$ and $HRET_{\Delta NCO}$ respectively. In Panel B, $HRET_{\Delta NOA}$ is estimated separately for sub-samples with and without cash flow forecasts in the 1995-2000 period. Panel B also presents analyst accuracy for the sample partitioned into whether analysts also issue cash flow forecasts or not. 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. Figures in parentheses are t-statistics for differences, calculated using a pooled estimate of standard error. The significance level for the differences in mean AFE by each year is represented by *** (1% level) and ** (5% level).

TABLE 3

Weakening of the accruals anomaly across time

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.091 (-51.40)	-0.091 (-51.70)	-0.117 (-46.49)	-0.117 (-46.77)
ROA	0.295 (39.21)	0.298 (39.14)	0.292 (39.27)	0.294 (39.05)
ΔNOA	-0.198 (-25.53)		-0.241 (-24.14)	
ΔWC		-0.233 (-15.31)		-0.243 (-13.00)
ΔNCO		-0.181 (-20.25)		-0.232 (-19.69)
ΔFIN	-0.019 (-2.53)	-0.016 (-2.16)	-0.021 (-2.28)	-0.021 (-2.18)
LATER			0.057 (17.14)	0.057 (17.17)
ΔNOA*LATER			0.155 (9.97)	
ΔWC*LATER				0.102 (3.27)
ΔNCO*LATER				0.161 (9.06)
ΔFIN*LATER			0.017 (1.13)	0.019 (1.23)
N	86,090	86,090	86,090	86,090
Adj. R^2	3.05%	3.07%	3.79%	3.81%

Sample consists of 86,090 non-financial firms in the time period 1991-2010 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETSB_{t+1,}$ which is the size and book-to-market adjusted one-year ahead buy and hold return. 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, ΔWC_t is change in working capital, ΔNCO_t is change in non-current operating assets, ΔFIN_t is change in financial assets, all scaled by average assets. LATER is an indicator variable that equals 0 for years 1991 to 2000 and 1 for 2001 to 2010. See section 3 for detailed definitions. Regressions are robust regressions using the MM method. Figures in parentheses represent t-statistics that are two-way clustered by firm and time.

TABLE 4

Controlling for sample selection bias

Panel A: Sample selection PROBIT regression for CFF.

Intercept	VOL	CYCLE	Z	CAPINT	ABSACC	LMCAP	N	Pseudo-R^2
-3.610	0.0022	0.0003	-0.0061	0.0482	-0.146	0.414	81,163	20.3%
(-129.03)	(3.91)	(6.78)	(-9.11)	(16.97)	(-2.55)	(112.23)		

Panel B: Mean characteristics of CFF firms and matched non-CFF firms (unrestricted)

Sample	N	VOL	CYCLE	Z	CAPINT	ABSACC	LMCAP	Prob(CFF)
CFF Firm	9,306	4.226	135.8	5.844	0.857	0.077	7.492	0.429
Control Firm	9,306	3.728	145.7	4.902	0.934	0.094	5.701	0.204
Difference		0.498	-9.8	0.942	-0.077	-0.018	1.791	0.225
		(3.47)	(-4.96)	(8.13)	(-3.02)	(-12.09)	(83.25)	(79.47)

Panel C: Mean characteristics of CFF firms and matched non-CFF firms (within 10% propensity)

Sample	N	VOL	CYCLE	Z	CAPINT	ABSACC	LMCAP	Prob(CFF)
CFF Firm	3,139	3.612	139.9	6.424	0.752	0.085	6.298	0.255
Control Firm	3,139	4.194	142.9	5.216	0.975	0.091	6.083	0.242
Difference		-0.582	-3.0	1.208	-0.223	-0.006	0.215	0.013
		(-2.04)	(-0.76)	(4.70)	(-4.60)	(-1.92)	(6.17)	(1.90)

Sample consists of 86,090 non-financial firms in the time period 1991-2010 with financial information on COMPUSTAT and stock returns on CRSP. Panel A presents the results of a PROBIT regression for CFF, which equals 1 for firm-years with cash flow forecasts and 0 otherwise Figures in parentheses are z-statistics. 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 for details. Panel B compares the characteristics of CFF firms with matched non-CFF firms from the same industry (2 digit SIC) in the same year with the closest estimate of probability of CFF. For Panel C, the additional condition is imposed that the estimated probability of CFF for the CFF firm and control firm be within 10% of each other. T-statistics for differences based on a pooled estimate of standard error (Satherthwaite estimation) are in parentheses.

TABLE 5

The accruals anomaly and incidence of cash flow forecasts

	Baseline Regression		Baseline Regression (followed firms)		Heckman 2nd Stage Regression		Propensity Score Matched Regression	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Intercept	-0.104 (-54.13)	-0.104 (-54.31)	-0.057 (-24.75)	-0.058 (-24.85)	-0.009 (-1.70)	-0.009 (-1.83)	-0.073 (-9.98)	-0.073 (-10.03)
ROA	0.278 (36.82)	0.278 (36.49)	0.193 (18.60)	0.197 (18.74)	0.258 (30.80)	0.258 (30.53)	0.249 (7.86)	0.249 (7.86)
ΔNOA	-0.204 (-24.97)		-0.282 (-24.64)		-0.224 (-25.91)		-0.184 (-4.73)	
ΔWC		-0.219 (-14.13)		-0.334 (-13.81)		-0.231 (-13.74)		-0.170 (-1.63)
ΔNCO		-0.193 (-20.34)		-0.264 (-19.26)		-0.218 (-21.79)		-0.180 (-4.10)
ΔFIN	-0.014 (-1.77)	-0.012 (-1.48)	-0.033 (-3.25)	-0.032 (-3.09)	-0.030 (-3.48)	-0.029 (-3.42)	-0.050 (-1.32)	-0.049 (-1.29)
CFF	0.078 (19.20)	0.078 (19.19)	0.039 (10.13)	0.039 (10.08)	-0.047 (-6.26)	-0.047 (-6.17)	0.020 (1.91)	0.020 (1.93)
ΔNOA*CFF	0.092 (4.04)		0.164 (7.47)		0.127 (5.48)		0.159 (2.72)	
ΔWC*CFF		0.031 (0.48)		0.156 (2.58)		0.064 (1.07)		0.070 (0.47)
ΔNCO*CFF		0.092 (3.75)		0.154 (6.34)		0.131 (5.29)		0.172 (2.64)
ΔFIN*CFF	-0.022 (-0.91)	-0.022 (-0.90)	-0.020 (-0.88)	-0.021 (-0.90)	0.007 (0.26)	0.008 (0.32)	0.078 (1.44)	0.080 (1.48)
Inverse Mills Ratio					0.049 (19.42)	0.049 (19.25)		
N	86,090	86,090	48,056	48,056	81,163	81,163	6,278	6,278
Adj. R^2	3.59%	3.59%	2.10%	2.11%	3.96%	3.98%	1.70%	1.70%

Sample consists of 86,090 non-financial firms in the time period 1991-2010 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETSB_{t+1,}$ size and book-to-market adjusted one-year ahead buy and hold return. CFF is a dummy variable that equals 1 for all firm-years with a cash flow forecast and zero otherwise. See the header to Table 3 for detailed definitions of $RETSB_{t+1}$, and all independent variables. Regressions are robust regressions using the MM method. Figures in parentheses are t-statistics two-way clustered by firm and time.

TABLE 6

Controlling for alternate explanations

	Baseline Regression	Baseline Regression (followed firms)	Heckman 2nd Stage Regression	Propensity Score Matched Regression
Intercept	-0.095 (-20.63)	-0.049 (-9.10)	-0.014 (-2.08)	-0.037 (-2.03)
ROA	0.249 (24.5)	0.149 (11.50)	0.236 (22.4)	0.222 (6.29)
ΔNOA	-0.165 (-6.05)	-0.373 (-9.74)	-0.195 (-7.03)	-0.438 (-1.82)
ΔFIN	0.011 (0.35)	0.009 (0.23)	-0.011 (-0.35)	-0.162 (-0.52)
CFF	0.057 (12.78)	0.030 (6.97)	-0.042 (-5.32)	0.016 (1.42)
ΔNOA*CFF	0.067 (2.04)	0.072 (2.33)	0.097 (2.37)	0.137 (2.54)
ΔFIN*CFF	-0.028 (-0.85)	-0.043 (-1.41)	-0.017 (-0.50)	0.025 (0.34)
LAUM	0.004 (5.51)	0.002 (2.12)	0.002 (3.13)	0.027 (4.87)
ΔNOA*LAUM	0.015 (3.55)	0.038 (6.05)	0.016 (3.67)	0.068 (1.90)
ΔFIN*LAUM	0.006 (1.12)	-0.001 (-0.22)	0.007 (1.32)	0.032 (0.71)
DD	0.474 (11.28)	0.263 (5.16)	0.325 (7.56)	0.315 (2.14)
ΔNOA*DD	0.470 (2.86)	0.412 (1.85)	0.472 (2.89)	1.184 (1.92)
ΔFIN*DD	0.266 (1.40)	-0.007 (-0.03)	0.21 (1.08)	0.638 (0.99)
Inverse Mills Ratio			0.042 (15.18)	
N	67,374	38,822	66,056	5,525
Adj. R^2	3.77%	2.62%	3.38%	2.13%

Sample consists of 86,090 non-financial firms in the time period 1991-2010 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETSB_{t+1,}$ size and book-to-market adjusted one-year ahead buy and hold return. CFF is an indicator variable which equals 1 for firm-years with cash flow forecasts and 0 otherwise. LAUM is log of assets under management by hedge funds. DD is the negative of the variance of the residuals from the

Dechow and Dichev (2002) model as modified by McNichols (2002). See section 3 for details on the accrual variables and $RESTSB_{t+1}$ and section 4 for details on LAUM and DD. Regressions are robust regressions using the MM method. Figures in parentheses represent t-statistics that are two-way clustered by firm and time.

TABLE 7

Initiation and termination of cash flow forecasts

	Baseline Regression	Baseline Regression (followed firms)	Heckman 2^{nd} Stage Regression	Propensity Score Matched Regression
Intercept	-0.116	-0.088	-0.017	-0.079
	(-69.09)	(-37.96)	(-3.85)	(-12.16)
ROA	0.294	0.246	0.271	0.254
	(44.91)	(25.13)	(37.75)	(9.51)
ΔNOA	-0.211	-0.286	-0.233	-0.180
	(-30.33)	(-26.01)	(-31.63)	(-4.94)
ΔFIN	-0.019	-0.034	-0.037	-0.043
	(-2.87)	(-3.46)	(-5.07)	(-1.21)
START	0.058	0.029	-0.065	0.001
	(8.37)	(4.26)	(-7.49)	(0.11)
ΔNOA*START(β_{21})	0.078	0.154	0.103	0.122
	(1.74)	(3.54)	(2.34)	(2.02)
ΔFIN*START	0.010	0.032	0.024	0.054
	(0.19)	(0.66)	(0.47)	(0.62)
CONT	0.086	0.059	-0.045	0.034
	(22.49)	(14.63)	(-6.58)	(3.28)
ΔNOA*CONT (β_{22})	0.104	0.187	0.142	0.165
	(4.85)	(8.31)	(6.42)	(2.88)
ΔFIN*CONT	-0.032	-0.015	0.001	0.074
	(-1.40)	(-0.63)	(0.04)	(1.50)
END	0.070	0.044	0.044	0.065
	(7.42)	(4.80)	(4.63)	(3.60)
ΔNOA*END (β_{23})	0.033	0.043	0.049	-0.017
	(0.54)	(0.97)	(0.81)	(-0.17)
ΔFIN*END	0.013	0.048	0.040	0.068
	(0.18)	(0.72)	(0.58)	(0.64)
Inverse Mills Ratio			0.051	
			(23.06)	
N	86,090	48,056	81,163	6,278
Adj. R^2	4.73%	3.85%	5.16%	2.44%
β_{22} - β_{21}	0.026	0.033	0.039	0.043
	(0.52)	(0.67)	(0.79)	(0.52)
β_{22} - β_{21}	-0.071	-0.144	-0.093	-0.182
	(-1.10)	(-2.90)	(-1.44)	(-1.58)

Sample consists of 86,090 non-financial firms in the time period 1991-2010 with financial information on COMPUSTAT and stock returns on CRSP. The dependent variable is $RETSB_{t+1,}$ size and book-to-market adjusted one-year ahead buy and hold return. START is an indicator variable which equals 1 for firm-years where cash flow forecasts are initiated for a given firm and 0 otherwise. CONT is an indicator variable which equals 1 for firm-years with cash flow forecasts other than the initial year and 0 otherwise. END is an indicator variable which equals 1 for firm-year when cash flow forecasts are terminated for a given firm and 0 otherwise. See section 3 for details on the accrual variables and $RESTSB_{t+1}$. Regressions are robust regressions using the MM method. Figures in parentheses represent t-statistics that are two-way clustered by firm and time.

TABLE 8

The accruals anomaly and accuracy of cash flow forecasts

	Ex-Post Forecast Accuracy		Prior Forecast Accuracy	
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.039 (-8.02)	-0.039 (-8.09)	-0.018 (-3.53)	-0.018 (-3.46)
ROA	0.175 (6.93)	0.178 (6.98)	0.135 (4.60)	0.133 (4.54)
ΔNOA	-0.066 (-2.78)		-0.065 (-2.37)	
ΔWC		-0.119 (-1.52)		-0.003 (-0.04)
ΔNCO		-0.059 (-2.38)		-0.073 (-2.53)
ΔFIN	-0.016 (-0.60)	-0.013 (-0.51)	-0.049 (-1.53)	-0.05 (-1.56)
ACC	-0.273 (-3.70)	-0.272 (-3.69)	-0.149 (-2.25)	-0.144 (-2.13)
ΔNOA*ACC	1.119 (2.77)		0.921 (1.80)	
ΔWC*ACC		1.060 (2.03)		0.911 (1.21)
ΔNCO*ACC		1.421 (2.53)		1.123 (2.05)
ΔFIN*ACC	1.379 (2.79)	1.397 (2.82)	0.203 (0.41)	0.200 (0.41)
N	11,079	11,079	10,716	10,716
Adj. R^2	0.80%	0.81%	0.53%	0.54%

Cash flow forecast accuracy is measured as ACC_{t+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 (ACC_{t+1}) while the last two regressions use lagged realized forecast accuracy (ACC_t). See section 3 for details on the accrual variables and $RESTSB_{t+1}$. Regressions are robust regressions using the MM method. Figures in parentheses represent t-statistics that are two-way clustered by firm and time.