# The role of accruals in predicting future cash flows and stock returns

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*Abstract:*

We revisit the role of the cash and accrual components of accounting earnings in predicting future cash flows using out-of-sample predictions, firm-specific regression estimates, and different levels of aggregation of the dependent variable, with market value of equity as a proxy for all future cash flows. We find that, on average, accruals improve upon current cash flow from operations in predicting future cash flows. However, accruals' contribution to the prediction of finite measures of cash flows is modest on average. We proceed to investigating determinants of accruals' predictive ability for future cash flows. We find that positive accruals are more likely to improve upon current cash flow in predicting future cash flows. Accruals' contribution is also increasing in cash flow volatility and decreasing in the magnitude of discretionary accruals. Finally, portfolios formed on stock return predictions using information from current accruals yield actual returns greater than portfolios based on cash flow only, which suggests that investors ignoring information from current accruals are worse off.

JEL Classifications: M41, G14, M43, M44

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## 1. Introduction

The amount of aggregate future cash flows is key to the valuation of a firm's securities. Alternative valuation models by both academics and financial analysts have focused on the prediction of free cash flows (Copeland et al. (1994)), or residual income (Preinreich (1938), Edwards and Bell (1961), Ohlson (1995)). The prediction of cash flows invariably is based on past accounting numbers. A question that has occupied much of the researchers' attention was whether past cash flows predicted future cash flows better than past earnings or past cash flows and accruals used separately.

Promoting the accrual basis of accounting, the FASB asserts that earnings and their components are a better predictor of future cash flows than current cash flow (SFAC No.1, §44). In spite of the FASB argument, scholars and practitioners argue that the subjectivity inherent to estimates embedded in accruals introduces noise that can have a negative impact on their informational value (Dechow and Dichev (2002)). Firm managers may engage in self-serving earnings manipulation by reporting numbers based on distorted estimates, which has been shown to decrease the value relevance of earnings (Marquardt and Wiedman (2004)). Hence, whether they are made in good faith or for manipulative purpose, accruals can be misleading and not representative of firm future performance. However, the empirical evidence to date with respect to the predictive ability of accruals for future performance remains inconclusive, due – among other things – to differences in samples and methodologies. In particular, there is a consensus in the literature that accruals exhibit a significant *association* with future cash flows incremental to current cash flow (see evidence in Barth, Cram and Nelson (2001)), but not in terms of out-of-sample *predictions*. For example, Lev et al. (2005) and Yoder

(2007) reach conflicting conclusions. Our study extends the literature on the role of publicly available data in predicting future cash flows and seeks to identify determinants of accruals' ability to form better cash flow predictions.

We first revisit the findings on cash flow predictability employing an improved methodology that simultaneously addresses the following three dimensions: 1. the level of aggregation of future cash flows as the predicted variable, 2. the estimation of firm-specific versus cross-sectional coefficients, 3. judgment of the superiority of the predictor being based on out-of-sample forecasts rather than in-sample properties such as $R^2$. Our evidence based on this set of methodological choices supports the view that accruals contribute to the prediction of future cash flows, but only to a limited extent.

Regarding the choice of evaluation of the superiority of our different sets of predictors, we deem out-of-sample predictions more appropriate than in-sample criteria. Indeed, in-sample predictions assume that parameters are stable through time and use data not available at the time of the predictions to estimate them. This can result in data overfitting (Clark (2004)). We focus our analysis on three key models wherein cash flows are predicted respectively by using 1. current cash flow, 2. current earnings and 3. current cash flow and total accruals. We choose this parsimonious set of models to avoid data mining, which can result in spurious inferences from out-of-sample forecasts (Granger (1990)).[1]

In addition, we compare out-of-sample forecasts of future market capitalizations using firm-specific regressions with and without accruals as a predictor. We consider market values of equity as the best available proxy for the present value of all future cash

[1] In this context, data mining refers to situations where researchers try different models and report the most accurate one, either within the same study or across several studies (Denton (1985), West (1996)).

flows, i.e. the highest level of aggregation of future cash flows. After obtaining these forecasts, we compute predicted returns derived from the forecasts and form portfolios on the basis of the sorted predicted returns. We are thus able to assess the economic significance of accruals' contribution to the prediction of market values by comparing stock returns earned on portfolios formed with and without the incorporation of accruals as predictors.

Our sample utilizes post-SFAS 95 quarterly data from Compustat. We define cash flow as cash flow from operations (CFO) and accruals as the difference between net income and CFO, consistent with Hribar and Collins (2002). In our main analysis, we require 56 time-series observations to develop firm-specific regression estimates. As a result, our holdout sample period is from the third quarter of 2002 to the fourth quarter of 2006. To account for seasonal variations in quarterly cash flows, we deseasonalize our data using the X11 method developed by the U.S. Bureau of Census.

We find evidence that accruals contribute to the prediction of finite measures of cash flows. Accruals reduce mean and median absolute prediction errors for finite measures of future cash flow from operations and free cash flows. When the predicted variable is current or one-quarter-ahead market value of equity, the model including accruals as a predictor along with CFO exhibits significantly smaller mean and median absolute prediction errors than the model using current CFO alone, by about 5% of total assets.

However, the contribution of accruals to the prediction of finite measures of cash flows is of small magnitude (the absolute prediction error from CFO and accruals is more than 90% of the absolute prediction error from CFO alone, on average.). To better understand under what circumstances accruals are more likely to help financial statement users predict future cash flows, we investigate cross-sectional determinants of accruals' contribution to future cash flow forecasts. We run a regression of the difference between the absolute forecast error from cash flow as the only predictor and the absolute prediction error based on cash flow and accruals at the firm-quarter level on various firm characteristics. We find that the contribution of accruals to the prediction of future cash flows (and market capitalization) is increasing in the volatility of cash flows, i.e. when the smoothing effect of accruals is most likely to be helpful in forecasting future cash flows. In contrast, accruals' incremental predictive power is decreasing in the absolute value of discretionary accruals, as measured using the Jones (1991) model. This result suggests that managers' ability to manipulate accruals can be detrimental to the forecasting properties of accruals. We also find that total accruals contribute significantly more to the improvement of cash flow predictions when they are positive. This result is consistent with the argument that positive accruals are more likely driven by a matching/smoothing prospective, which is useful in predicting future cash flows, while negative accruals are more likely related to fair-value accounting (Dechow and Ge, 2005).

Finally, when we form portfolios based on returns implied by the one-quarter-ahead market capitalization predictions, we find evidence suggesting that accruals contribute to the improvement of equity portfolio allocations. The improvement in terms of size-adjusted returns is in the order of 1% on average for a 90-day holding period when going long (short) on the highest (lowest) quintile of the quarterly predicted return distributions. The superiority of accruals and CFO as predictors of stock returns compared to CFO alone reinforces the conclusion that accruals contribute.

As a robustness check, we use two alternative models to address seasonality in our quarterly data. First, we add as independent variables indicators for fiscal quarters in order to account for the average component of seasonality in quarterly CFO. Second, we use data from four quarters prior to predict future cash flows. Our conclusions with respect to the contribution of accruals to future cash flow prediction remain unchanged. However, we observe that X11-adjusted data produce more accurate forecasts than the aforementioned alternatives, a result of potential relevance to financial statement users.

Our study contributes to the literature by demonstrating that while accruals' contribution to future cash flow predictions is of small magnitude, ignoring accruals leads to suboptimal portfolio allocations. Many studies show that cash flow and accruals exhibit higher *associations* with future cash flows and/or stock returns than current cash flow alone (e.g. Dechow, 1994; Barth, Cram and Nelson, 2001), but none provides such evidence in terms of out-of-sample *predictions*. Using pre-1987 annual data, Finger (1994) finds no evidence that earnings outperform current cash flow in predicting future cash flows. Lev et al. (2005) base their forecasts on cross-sectional estimations using annual data. They predict finite measures of cash flows up to three years ahead, and conclude that accruals do not improve upon current cash flow in predicting future cash flows. Yoder (2007) also uses cross-sectional estimates and annual data. He finds that a model derived from theoretical predictions using CFO, accrual components and expected sales growth as predictors yields lower absolute prediction errors for one-year-ahead CFO than current CFO alone. However, he provides no assessment of the economic significance of his results in terms of stock returns. Our paper, by identifying firm characteristics associated with accruals' ability to predict future cash flows, sheds light on why prior studies find limited support for the argument that accruals have predictive power for future cash flows.

In addition, our methodological considerations have practical implications, because they address issues of relevance to investors who use current accounting data for equity valuation purposes. With respect to finite cash flow predictions, finite horizon predictions are of particular relevance to equity valuation techniques that consist of forecasting earnings, cash flows or dividends over a finite period and computing a terminal value (Penman and Sougiannis (1998)).

Our study is subject to caveats that apply to most studies in this field. First, by using firm-specific regressions, we require time-series data that unavoidably reduce sample size, but also introduce potential survivorship bias.[2] Second, some accruals and deferrals are estimates subject to moral hazard between managers who report them and shareholders. Our attempt to separate accruals based on their discretionary or unverifiable components using the Jones (1991) model is subject to the usual criticism in terms of discretionary accruals estimation error.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 specifies the empirical tests. Section 4 describes the sample selection process and presents the main results. Section 5 summarizes and concludes.

## 2. Prior literature

Our paper relates to an extensive literature that investigates the valuation

[2] To address this issue, we lower our time-series requirement to 16 quarters of data available, and still find that accruals contribute to improving cash flow forecasts.

implications of components of accounting earnings, either indirectly through their association with future accounting measures, or directly through their association with market values of equity. Because this question has generated a vast number of studies, which generally differ by methodological choices, we provide a matrix (see Appendix A) that highlights key findings in prior research based on the three dimensions along which we define our contribution, and position our study accordingly. In this section, we provide a more detailed – albeit not exhaustive - review of the prior literature most directly comparable to our study.

A large number of studies investigate the association between components of GAAP earnings and future profitability measures. A widely cited study by Barth, Cram and Nelson (2001) finds – using a large sample – that current earnings disaggregated into their cash flow and several accrual components are more significantly associated with future cash flows than several lags of earnings and than cash flow only. There are, in contrast, relatively few papers which have assessed the predictive ability of accounting numbers with respect to future cash flows or market values of equity based on out-of-sample prediction errors. Most closely related to this paper, Lev et al. (2005) report that accruals do not significantly contribute to the prediction of future cash flows. Judging from stock returns earned on portfolio allocations derived from future cash flow predictions, they conclude that the accruals' contribution is not economically significant from an investor's point of view. Indeed, they find that one- to three-year returns earned on a hedge portfolio using cash flow and accruals to predict future free cash flow or earnings are not higher than those from a portfolio excluding accruals as a predictor. Another contemporaneous study by Yoder (2007) compares out-of-sample prediction accuracy of regression models for one year-head CFO. His results indicate that a model including short-term accrual components outperforms models using only current CFO as a predictor, but only if the independent variables are aggregated over three years. Our study differs from the two aforementioned as we use firm-specific estimates, which we expect to produce significantly lower prediction errors. We also test explicitly whether accruals contribute more to cash flow prediction as we aggregate the dependent variable, and include market value of equity as our proxy for the highest level of aggregation.

Another study by Barth et al. (2005) investigates the role of cash flows, accruals and their components in predicting current equity market values out of sample. Their study differs from ours as they use cross-sectional (pooled and by-industry) estimations with annual data and impose a linear information valuation model (LIM) structure. They also use a jack-knifing procedure where a given firm-year is predicted based on all prior firm-years but also all other firms in the same year. While technically out-of-sample, such test is not an ex-ante prediction (Pope (2005)).

Although the analysis in Kim and Kross (2005) is primarily based on associations rather than predictions, they document that the out-of-sample forecast accuracy of aggregate earnings has been increasing over their sample period. Kim and Kross (2005) use a cross-sectional analysis based on annual data from 1972 to 2001, and do not consider CFO and accruals as distinct predictors.

Finally, we know of three other prediction studies that employ firm-specific estimates. Using annual data, Finger (1994) investigates the relative predictive ability of current cash flow and earnings for future cash flows one to eight years ahead. She documents that current cash flow is a better predictor of future cash flows than earnings for short-term horizons, and finds no horizon over which earnings significantly improve upon cash flow. With quarterly data, Lorek and Willinger (1996) find that balance sheet numbers have explanatory power incremental to cash flows. They compare the predictive ability of a multivariate time-series model to that of ARIMA univariate models (i.e. using past cash flows only) and of cross-sectional multivariate models developed previously by Wilson (1986, 1987) using absolute out-of-sample prediction errors. Their multivariate firm-specific model includes past cash flows, operating income and working capital accounts (not change thereof). Dechow et al. (1998) report lower mean standard deviation of forecast errors for earnings versus cash flow where forecast errors are computed as the difference between current earnings (cash flow) and one- to three-year-ahead cash flow on a firm-specific basis. However, contrary to our study, none of the three papers mentioned above explicitly tests for the contribution of the accrual component of earnings. Overall, our study improves upon past and current literature by combining research design choices (out-of-sample predictions, future aggregate cash flows and market values of equity, firm-specific estimates) that we think are more appropriate in assessing the role of accruals in predicting future cash flows, and by documenting determinants of accruals' forecasting usefulness.

## 3. Research design

### *3.1. Prediction models*

We use regression models to predict various measures of future cash flows out of sample. In all models, we use the generic term $Predicted_{t+1}$ to designate the dependent variable, which can be either cash flow from operations (*CFO*), free cash flow (*FCF*)[3], both measured over one to eight quarters ahead, or market value of equity (*MKTCAP*), at the beginning or at the end of the fiscal quarter, as a proxy for the present value of all future cash flows.[4] All variables, whether they are being predicted or used as predictors, are scaled by total assets at the end of the previous fiscal quarter. Our main analysis is based upon firm-specific estimations using time-series data. Our benchmark "cash-flow only" model is the following:

$$CFO_t = \gamma_0 + \gamma_1 CFO_{t-1} + \varepsilon \quad (1)$$

Our accounting variables are subject to seasonality. This is particularly the case for firm-level quarterly cash flows time series, which exhibit purely seasonal characteristics, as documented by Lorek and Willinger (1996). Since we use adjacent quarters to make our predictions, we need to adjust for seasonality in our cash flow series. To do so, we employ the widely used X11 method as described in Appendix B.

To test whether accruals contribute to reducing prediction errors, we compare Model (1) to models wherein aggregate accruals are included as an independent variable, either aggregated with cash flows, or as a separate predictor:

$$CFO_t = \eta_0 + \eta_1 CFO_{t-1} + \eta_2 ACC_{t-1} + \varepsilon \quad (2)$$

$$CFO_t = \phi_0 + \phi_1 EARN_{t-1} + \varepsilon \quad (3)$$

*ACC* stands for total accruals, defined as the difference between net income before extraordinary items *EARN* (Compustat Quarterly data item 8) and cash flow from

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[3] We measure FCF using the definition of free cash flow to equity from Damodaran (2004), which is net income – (1-δ) x (Capital expenditure – Depreciation) – (1-δ) x Δ Working Capital, where δ is debt to total assets ratio. We repeat our analysis using better known definition of FCF (Cash flows from operations – Capital expenditures) and obtain similar results.

[4] Consistent with prior research, we measure market values of equity as of fiscal period end (see Barth, Cram and Nelson [2001], Barth et al. [2005]).

operations $CFO$ (Compustat Quarterly data item 108) net of extraordinary items/discontinued operations that affect cash flows (Compustat Quarterly data item 78).[5] In Model (3), the coefficients on the cash flow and accrual components of earnings are equal, whereas they are allowed to differ in Model (2). We include Model (3) to assess whether aggregate earnings improve upon current cash flow alone in predicting cash flows.

We further proceed to disaggregate total accruals into their components, based on the premise that different subsets of accruals carry different implications for future cash flows, such as stemming from the horizon over which cash collectibility is expected, or from differing degrees of subjectivity inherent in different subsets of accruals:

$$\begin{aligned} CFO_t &= \beta_0 + \beta_1 CFO_{t-1} + \beta_2 \Delta AR_{t-1} + \beta_3 \Delta INV_{t-1} + \beta_4 \Delta AP_{t-1} \\ &+ \beta_5 DEPAMOR_{t-1} + \beta_6 OTHER_{t-1} + \varepsilon \end{aligned} \tag{4}$$

Model (4) is similar to the cross-sectional regression that Barth, Cram and Nelson (2001) run to test the incremental explanatory power of disaggregated earnings. This model presents the highest level of accrual disaggregation that we consider. $\Delta AR$ , $\Delta INV$ and $\Delta AP$ are changes in working capital accounts, respectively accounts receivable, inventories and accounts payable. $DEPAMOR$ is depreciation and amortization. $OTHER$ is simply the difference between total accruals $ACC$ and ($\Delta AR +$ $\Delta INV - \Delta AP - DEPAMOR$). When available, we use data from the statement of cash flow for our individual accrual components, otherwise, we use changes in balance sheet accounts. That is, changes in accounts receivable, inventory and accounts payable, which are respectively Compustat Quarterly data items 103, 104 and 105, are used if available,

[5] Hribar and Collins (2000) note that Compustat reports year-to-date interim cash flow statement data, so we take differences between quarters t and t-1 to obtain quarterly numbers.

otherwise changes in data items 37, 38 and 46 from the previous fiscal quarter are used. Depreciation and amortization expense is Compustat Quarterly data item 77. Market capitalization is the product of Compustat Quarterly data items 14 and 61. Finally, our deflator is total assets (Compustat Quarterly data item 44) as of the beginning of the quarter. One major distinction among accrual components is the timing of their conversion into cash in- or outflows. The changes in working capital variables are expected to affect future cash flows in the near term (within a year). By contrast, *DEPAMOR* should exhibit a greater association with cash flows in the longer run. Indeed, depreciation and amortization expenses are intended to match costs of investments with their benefits over the expected life of the asset that is being depreciated/amortized, typically several years. Overall, while the use of individual accrual components may help improve prediction accuracy, the decrease in the number of degrees of freedom may offset such benefit for firm-specific estimations, for which the number of observations is limited.

Each firm-specific model is estimated using 56 consecutive quarterly.[6] We use rolling windows so that coefficients are "updated" every quarter. The requirement in terms of number of observations represents a trade-off between sample size and the reliability and stability of time-series estimates. Alternatively, we estimate coefficients cross-sectionally, separately for each fiscal quarter. Once we run a regression, we use the coefficient estimates to compute predicted values. For example, based on Model (1), $\widehat{\frac{CFO_{t+1}}{Assets_t}}$ is equal to $\widehat{\gamma_0} + \widehat{\gamma_1}\frac{CFO_t}{Assets_t}$, where $\widehat{\gamma_0}, \widehat{\gamma_1}$ are estimated from the regression. The

[6] X11 cannot be performed if there are missing observations in the middle of the series.

predicted value is then compared to the actual value. We compute our absolute prediction errors as follows:

$$ABSE_j = \frac{\left| CFO_{t+1} - \widehat{CFO_{t+1}} \right|}{Assets_t} \quad (5)$$

The subscript j indicates which model was used to compute the predicted value (1,2,3 or 4). Since the predicted and actual variables are scaled by total assets, so is $ABSE_j$. To compare the predictive ability of our different models, we compute the mean and median prediction errors across all firm-quarters in the holdout sample period.

*3.2. Multivariate analysis*

To investigate determinants of the contribution of accruals to the prediction of future cash flows, we use the following multivariate setting:

$$\begin{aligned} ABSE_1 - ABSE_2 = {} & \alpha_0 + \alpha_1 FOURTH\_QUARTER + \beta_1 ABS\_DISC\_ACC \\ & + \beta_2 SIGN\_ACC + \beta_3 SEASONALITY + \beta_4 CFO\_VOLATILITY \\ & + \beta_5 FIRM\_SIZE + \beta_6 BOOK\_TO\_MARKET + \sum_j \phi_j INDUS_j + \varepsilon \end{aligned} \quad (6)$$

The dependent variable is the difference between the absolute prediction error for future cash flows using CFO as the only predictor and the absolute prediction error using CFO and accruals as separate predictors. *FOURTH_QUARTER* is an indicator variable equal to one if the predicted variable is measured over the fourth fiscal quarter (this applies only when we predict one-quarter-ahead cash flow). The fourth fiscal quarter differs from others in terms of accrual properties because of the integral approach, which may have implication for quarterly cash flow predictions. The sign of the coefficient $\alpha_1$ is left as an empirical question. *ABS_DISC_ACC* is the absolute value of discretionary accruals, which we estimate using the firm-specific version of the modified Jones (1991) model as in Dechow et al. (1995). Details are provided in Appendix C. There are two main views in the literature regarding managers' motivations to use their discretion in reporting GAAP numbers. The first one (the "opportunistic" view) is that managers manipulate accounting reports to maintain the firm's stock price at artificially high levels and benefit from this overvaluation in terms of equity-based compensation. The second one (the "informational" view) is that managers use their discretion to signal their private information about future cash flows. Badertscher et al. (2007) argue and provide evidence that earnings managed with apparent informational purpose exhibit a higher association with future cash flows than earnings managed opportunistically do. Since we do not attempt to disentangle opportunistic from signaling motives behind discretionary accruals, we leave as an empirical question whether *ABS_DISC_ACC* exhibits a significantly positive or negative association with $ABSE_1 - ABSE_2$. With respect to *SIGN_ACCRUALS*, which is an indicator variable equal to one if total deseasonalized accruals are strictly positive, we test whether net positive accruals have greater predictive ability for future cash flows than negative accruals do. We predict a positive sign for $\beta_2$, based on the argument that positive accruals are more likely to reflect a smoothing/matching perspective, whereas negative accruals are more likely driven by impairments due to fair value accounting (Dechow and Ge, 2005). *SEASONALITY* is the degree to which quarterly cash flows are seasonal. We compute this variable by taking the difference between actual cash flow from operations and deseasonalized cash flow from operations. *CFO_VOLATILITY* is the standard deviation of firm-level cash flow from operations measured from t-n to t-1. We expect that accruals should be more helpful in predicting future cash flows, the more volatile current cash flows are. This should be reflected in a positive sign on $\beta_4$. Finally, we include firm size and book-to-market ratio as potential determinants of accruals' contribution to cash flow predictions. We expect a negative coefficient on both variables. With respect to firm size, larger firms are presumably more mature firms with more stable cash flows which can be predicted more easily using past cash flow observations. As for book-to-market ratio, we argue that accruals are likely to be informative about growth options beyond current cash flow, i.e. their contribution to future cash flow prediction should be higher in firms with a low book-to-market ratio.

*3.3. Portfolio analysis*

We test whether the contribution of accruals to future cash flow prediction accuracy translates into better stock performance for portfolio allocations based on CFO and accruals compared to CFO alone. To do so, we use the following methodology. First, using shares outstanding at time t, we compute predicted future price $\overline{P_{t+1}}$ based on predicted $MKTCAP_{t+1}$ (plus dividends) and calculate predicted quarterly stock returns as $\frac{\overline{P_{t+1}} - P_t}{P_t}$.[7] We then rank our observations within each fiscal quarter by predicted return and compute the difference between the mean returns across observations in the top decile/quintile of the predicted return distribution and in the bottom decile/quintile, where returns are cumulated from the day following each firm-quarter's 10-K or 10-Q filing date over a 90- to 365-day period. Finally, we compare this return across different

[7] The motivation for this procedure is to avoid using information not available at the time the prediction is being made, such as shares issued or repurchased during quarter t+1. Results are qualitatively unchanged when predicted $MKTCAP_{t+1}$ is divided by the number of shares outstanding at the end of quarter t+1. Note that we predict the sum of $MKTCAP_{t+1}$ and dividends, so our predictions are not based on actual dividends paid during t+1.

prediction models (i.e. based on which independent variables were used to predict $MKTCAP_{t+1}$ + dividends).

## 4. Sample selection and results

### *4.1. Sample*

We include in our sample all firms that meet our data requirements in the Compustat Quarterly database. The initial sample period covers years 1987 through 2006. We do not use data prior to 1987 because of difficulties in measuring cash flows from operations prior to SFAS 95 (Hribar and Collins, 2002).[8] Consistent with prior studies, we exclude firms in financial services (SIC 6000-6999) and regulated industries (SIC 4900-4999). To produce reliable firm-specific coefficient estimates in our regressions, we must use a reasonably large number of observations. We choose to require the availability of 56 consecutive quarterly observations prior to a given firm-quarter to predict the latter's cash flow (or aggregates of the predicted cash flow of that firm-quarter and those of following quarters). These requirements result in an upper bound of 16,594 predicted firm-quarters with data available to predict one-quarter-ahead CFO. Fiscal quarters 2002:3Q to 2006:4Q constitute our holdout period. For our cross-sectional regressions, we winsorize the independent variables at 1% and 99% of their quarterly distributions.

### *4.2. Descriptive statistics*

Table 1 reports summary statistics for the variables used in our analysis. Consistent with prior studies, mean and median earnings and CFO are positive, while mean and median accruals are negative. As explained in Barth, Cram and Nelson (2001),

[8] Hribar and Collins (2002) show that mergers, acquisitions and divestitures create significant errors in estimates of accruals measured with changes in balance sheet accounts.

this is most likely driven by depreciation and amortization, which is much larger than other accrual components on average.

Table 2 presents summary results for a subset of our firm-specific regression models. We report statistics for regression coefficients and $R^2$ with one-quarter-ahead *CFO* and market capitalization as dependent variables. In the regressions of $CFO_{t+1}$ on *CFO*, the mean and median coefficients on *CFO* are positive (0.66 and 0.68 respectively). In Model (2), the mean (0.897) and median (0.867) coefficients on *CFO* are about three times as large as the coefficients on *ACC* (mean 0.299 and median 0.231). The ratio is smaller when the dependent variable is $MKTCAP_{t+1}$. In terms of $R^2$, current deseasonalized *CFO* explains on average about 43% of the variation in deseasonalized $CFO_{t+1}$, but only 12% for $MKTCAP_{t+1}$. The explanatory power for $CFO_{t+1}$ ($MKTCAP_{t+1}$) increases to 45% (27%) on average when aggregate accruals are added as a predictor. Disaggregating accruals into their individual components also contributes to an increase in mean firm-specific $R^2$, 47% and 39% when the predicted variables are $CFO_{t+1}$ and $MKTCAP_{t+1}$ respectively. The superiority of CFO and accrual components in terms of $R^2$ is consistent with what Barth, Cram and Nelson (2001) document using cross-sectional regressions and annual data.

Fig. 1 plots mean firm-specific coefficients on *CFO* and *ACC* in Model (2). The graph clearly shows that the coefficient on current cash flow is monotonically decreasing as we increase the level of aggregation of the dependent variable (from 0.90 for no aggregation down to about 0.60 when eight quarters are aggregated), whereas the coefficient on accruals increases over the first three aggregated quarters and is stable across subsequent levels of aggregation at about 0.35. This result suggests that the relative importance of accruals compared to current *CFO* in predicting cash flows increases with the level of aggregation of the dependent variable.

*4.3. Prediction results*

*4.3.1. Mean and median absolute prediction errors across firm-specific estimates*

Tables 3 and 4 report the comparisons of absolute prediction errors (ABSE) for future *CFO* and *FCF* across firm-specific models with and without accruals as predictors, over horizons of one- to eight-quarter-ahead and with market capitalization as a proxy for all future cash flows.

Table 3 reports mean and median absolute prediction errors scaled by total assets as of the beginning of the quarter (*ABSE*) for Models (1), (2) and (3). At this stage, we do not report results from Model (4) because we wish to focus on the results for the larger sample where our data requirements are less constraining. The results for finite measures of cash flows are based on comparisons of predicted values with future deseasonalized cash flows. For all levels of aggregation of future cash flows, Model (2) produces lower mean and median absolute prediction errors than Model (1). The difference in means is statistically significant at conventional levels except when one-quarter-ahead cash flow is predicted. For example, the mean absolute prediction error for $CFO_{t+1,t+4}$ when CFO and accruals are the predictors is 1.36% of total assets whereas the mean absolute prediction error from CFO alone is 1.30%. The p-value for the difference in means is 0.02. In terms of medians, $ABSE_2$ is significantly smaller than $ABSE_1$ for all levels of aggregation of future CFO, at the 0.01 level two-tailed. In addition, we find that aggregate earnings do not outperform *CFO* and accruals as separate predictors in forecasting finite measures of cash flows. When FCF is the predicted variable, we also find that accruals help reduce absolute prediction errors at the mean and median levels. However, comparisons of mean $ABSE_1$ and $ABSE_2$ across all firm-quarters show that there is no statistically significant difference for free cash flow predictions. Hence, as with CFO, there is some evidence that accruals help improve free cash flow predictions, but only to a limited extent.

When $MKTCAP_t$ or $MKTCAP_{t+1}$ is the predicted value, the incremental contribution of accruals is statistically significant both in terms of mean and median. For example, mean $ABSE_2$ for the prediction of $MKTCAP_t$ is 54.01% compared to 59.63% for $ABSE_1$, with a t-stat of 5.31 (the corresponding p-value being below 0.01). In general, accruals improve upon CFO by reducing the mean and median absolute prediction errors for current or next quarter market value of equity by an order of magnitude of 5% of total assets.

The fourth (eighth) column reports mean (median) differences between $ABSE_1$ and $ABSE_2$ when prediction errors are matched by firm-quarter. In this case, we test whether the mean and median differences are different from zero. The results indicate that the mean contribution of accruals to finite CFO and FCF prediction is positive, and significantly so for all levels of aggregation. The highest mean contribution as a percentage of total assets is 0.068% when six quarters of CFO are predicted (not tabulated). Accruals also significantly contribute to prediction accuracy at the median level for finite CFO and FCF. The mean (about 5.6% of total assets) and median (2%) contribution of accruals at the firm-quarter level is also significantly positive at the 0.01 two-tailed level for current and one-quarter-ahead market values of equity.

*4.3.4. Contribution of accruals and level of aggregation of future cash flows*

We test whether accruals contribute more significantly to the prediction of higher levels of aggregation of future cash flows, as their conversion to cash in- or outflows does not necessarily occur within the next quarter. In Table 3, we have already compared mean and median absolute prediction errors of one- to eight-quarter-ahead (cumulative) CFO of firm-specific regressions based on CFO alone, to CFO and accruals as separate predictors. In Figure 3, we plot the differences in mean and median firm-specific $ABSE_2$ and $ABSE_1$ as a percentage of $ABSE_1$ , as a measure of the incremental contribution of accruals compared to current CFO alone, with the level of aggregation of the dependent variable on the horizontal axis. The graph indicates an upward trending contribution of accruals as aggregation increases. The incremental contribution is always higher in terms of median than mean, but from one to six cumulated CFOs of the quarters being predicted, the improvement of accruals is monotonically increasing at the mean level and reaches about 4% (6% for medians). The fact that the mean contribution of accruals tends to level off when the dependent variable is aggregated over more than six quarters suggests that the trade-off between increased noise and signal becomes more severe beyond six quarters. Also, untabulated results show that in terms of median, the incremental contribution of accruals for current market capitalization is 17.6%. Overall, our results tend to show that using one-period-ahead or finite short-horizon measures may understate accruals' usefulness in predicting future cash flows, especially on a quarterly basis.

*4.3.5. Disaggregating accruals into individual components and prediction accuracy*

When we require data to be available for individual accrual components as in Model (4), the sample is smaller. To evaluate whether accrual components contribute to the prediction of cash flows beyond current CFO but also beyond aggregate accruals, we compare absolute prediction errors across our models for all firm-quarters with data available for all variables in Model (4).

[Insert Table 4 about here]

Table 4 reports the results. The results indicate that mean absolute prediction error from current CFO and accrual components ( $ABSE_4$ ) is smaller than mean $ABSE_2$ (CFO and aggregate accruals) when the predicted variable is finite CFO aggregated over six to eight quarters and market values of equity. At the median level, $ABSE_4$ is smaller than $ABSE_2$ when the level of aggregation of predicted future CFO is four quarters or more. However, the differences are not statistically significant. The same holds for predictions of market values of equity. As for free cash flow predictions, $ABSE_4$ is greater than $ABSE_2$ at the mean and median levels. Hence, in our sample and with our research design choices, we find no statistically significant improvement in prediction accuracy for future cash flows when disaggregating accruals into individual components.[9,10,11]

*4.3.6. Multivariate results*

The results we provide thus far are averaged across firms with different economic

[9] We also attempt to distinguish between long-term accruals (depreciation and amortization) and others, but find no improvement compared to aggregate accruals.

[10] The evidence in Barth et al. (2005) also suggests that CFO and aggregate accruals tend to better predict market value of equity than CFO and accrual components in terms of median ABSE, while components do better at the mean level. They offer no explanation as to why this may be the case.

[11] This result may seem counterintuitive and disappointing. However, prior studies provide some intuition as to why disaggregate data may fail to produce more accurate forecasts than aggregate data. Grunfeld and Griliches (1960) argue that the choice between aggregate and disaggregate data for forecasting purposes consists of a trade-off between aggregation error and specification error (e.g. using components of earnings as separate predictors may ignore the correlations among those variables). While Grunfeld and Griliches (1960) consider aggregation/disaggregation at the macro versus micro levels, Fried (1978) shows that the distinction can be applied to components of earnings. That being said, their argument is based on the premise that one forecasts individual components separately and then sums the predicted components to obtain the aggregate forecast, which is slightly different from our approach. In addition, the use of quantum probabilities by Fellingham and Schroeder (2006) may provide further insight about this issue. Indeed, they show that synergies among individual components can result in aggregate measures of performance being more informative than the components taken individually.

and financial reporting attributes. We test whether the ability of accruals to contribute to future cash flow prediction varies with firms' accounting and economic properties as identified in Model (6).

[Insert Table 5 about here]

Table 5 reports regression results where the dependent variable is the difference between $ABSE_1$ and $ABSE_2$, i.e. the extent to which accruals improve upon current cash flow in predicting future cash flows. In the first column, the dependent variable is measured for one-quarter-ahead predictions of future CFO. The positive coefficient on *SIGN_ACC* suggests that net positive accruals are more likely to improve cash flow prediction than negative accruals. The coefficient is statistically significant (at the 0.01 level). This result is consistent with the argument that positive accruals are more likely to be driven by a matching perspective, and thus be useful in predicting future cash flows, especially in the short run. The coefficient on *CFO_VOLATILITY* is significantly positive. This suggests that the more volatile cash flows are, the more accruals will improve upon current cash flows in predicting future cash flows. This result is, again, consistent with the smoothing properties of accruals mitigating the volatile nature of cash flows time series. With respect to the discretionary component of accruals, the coefficient on *ABS_DISC_ACC* is significantly negative. This shows that the greater the magnitude of discretionary accruals, the lower the contribution of total accruals to the prediction of future cash flows. Hence, it appears that, on average, discretionary accruals, as estimated through the Jones (1991) model have a negative impact on the forecasting abilities of accruals. To the extent that our measure of discretionary accruals captures managerial discretion in financial reporting, the opportunistic view of their discretion appears to dominate the informational view. In contrast, the absolute value of non-discretionary accruals exhibits a significantly positive association with the contribution of accruals to one-quarter-ahead cash flow predictions. Finally, the negative coefficient on book-to-market ratio indicates that accruals contribute more in improving future cash flow predictions for growth firms.

In the second column of Table 5, the dependent variable is the contribution of accruals to predictions of CFO aggregated over the next four quarters. The coefficients on the independent variables generally exhibit the same signs as for one-quarter-ahead predictions, but the coefficient on the magnitude of non-discretionary accruals is no longer significant. In contrast, the coefficient on firm size is significantly positive. Hence, accruals are more likely to improve upon larger firms' cash flow predictions.

Finally, in the third column, we report regression coefficients where the dependent variable is the contribution of accruals to forecasts of market capitalization. As opposed to finite cash flow predictions, there is a significantly positive coefficient on the intercept, which corroborates the univariate findings in Tables 3 and 4. Also, there is a significantly positive coefficient on *SEASONALITY*. This suggests that the greater the seasonal component of current cash flow, the more useful are accruals in improving forecasts of market values of equity. Overall, the results indicate that the absolute value of discretionary accruals exhibits a negative association with total accruals' contribution to future cash flow predictions across different predicted values, whereas net positive accruals and cash flow volatility are positively associated with accruals' predictive power.

*4.4. Stock returns earned by portfolios based on predicted returns*

Since one of our predicted variables is one-quarter-ahead market value of equity, we can test whether accruals' contribution to prediction accuracy can translate into better portfolio allocations. From an equity investor's point of view, a stock return analysis is economically more meaningful.

Table 6 reports stock returns earned on hedge portfolios formed on $MKTCAP_{t+1}$ predictions using information from current accounting data. In Panel A, the average 90-day raw return to a zero-investment portfolio long in the highest and short in the lowest quintile compounded as of the first day of the fiscal quarter is 6.34% without accruals, and 8.58% with accruals: portfolio allocation based on CFO and accruals outperforms CFO alone by 2.24% per quarter on average. Neither aggregate earnings nor CFO and individual components of accruals (not tabulated) do better than CFO and aggregate accruals. Compounding returns as of the beginning of the fiscal quarter is not suitable for a trading strategy, because earnings and the breakdown between CFO and accruals are not publicly known at that time. If returns are compounded as of the most recent 10-K or 10-Q filing date[12], returns to all portfolios are lower than if compounded as of the fiscal quarter beginning, but the average return earned on the portfolio using predictions based on CFO and accruals is still greater than that based on CFO only: the average quarterly contribution of accruals is 1.16%.

When we extend the holding period to 180, 270 and 365 days, the hedge portfolio returns based on each set of predictors generally increase with the window length. The incremental returns earned by using accruals in addition to CFO to rank stocks persist and even slightly increase to over 1.60% when compounded over 270 days, but diminish

[12] Technically, we cannot form portfolios until the last Form 10-Q or 10-K of the quarter is filed. Alternatively, and as is conventional in the literature, we form portfolios as of the relevant filing deadline. We still find that accruals and CFO earn higher returns than CFO alone with that research design choice.

when compounded over 365 days. To evaluate the statistical significance of the incremental returns earned by forming portfolios using accruals in addition to CFO, we compute t-statistics using a Fama-McBeth procedure, based on the time-series of returns computed fiscal quarter by fiscal quarter, from 2002 to 2006. We find that the excess returns of the accrual-based portfolios are, on average, marginally significantly positive (at the 0.10 level for 90, 180 and 270 days). 365-day excess returns are not significantly different from zero.

The results using size-adjusted returns in Panel B are qualitatively similar. The excess returns generated by accruals over CFO exhibit greater statistical significance than with raw returns. For instance, the p-values for the 90-, 180- and 270-day mean excess returns are below 0.05.

Figure 3 plots the difference between hedge returns from portfolios based on CFO and accruals versus CFO only fiscal quarter by fiscal quarter. The graph shows that accruals help improve portfolio allocation in 14 out of 18 quarters in terms of raw and size-adjusted returns. Hence, it appears that the superiority of the model including accruals as an investment criterion in addition to current cash flow is relatively robust throughout time and not the mere manifestation of risk. Overall, the results show that the incremental contribution of aggregate accruals in predicting future market values of equity materializes in terms of improved portfolio allocation for investors using current accounting data for their investment decisions.

*4.5. Additional tests*

We supplement our main analysis by running additional tests that address issues related to: the use of X11-adjusted data; the relative prediction accuracy of firm-specific regressions compared to cross-sectional regressions; the time-series requirements of our firm-specific regressions; the use of current free cash flow instead of cash flow from operations to predict future free cash flows.

The X11 method to address seasonality is usually performed for macro-level data, and is, to our knowledge, unique in the accounting literature. Prior studies analyzing quarterly accounting data have generally treated seasonality by using variables four quarters apart. Accordingly, we repeat our main analysis by comparing absolute prediction errors from the following models:

$$CFO_t = \gamma_0 + \gamma_1 CFO_{t-4} + \varepsilon \tag{7}$$

$$CFO_t = \gamma_0 + \gamma_1 CFO_{t-1} + \gamma_2 CFO_{t-4} + \varepsilon \tag{8}$$

$$CFO_t = \sum_{j=1}^{4} \nu_j Q_j + \nu_5 CFO_{t-1} + \varepsilon \tag{9}$$

Where $Q_i$ (i=1,2,3,4) is an indicator variable equal to 1 if the predicted variable is from fiscal quarter i. We add $ACC_{t-4}$ and $ACC_{t-1}$ as a predictor to Model (7), (8) and (9) respectively to test accruals' contribution to cash flow predictions. Under those specifications, we still find that accruals contribute positively to cash flow forecast accuracy. However, we notice that the X11 method produces more accurate forecasts

To validate our claim that firm-specific regression estimates produce more accurate predictions than cross-sectional ones, we compare absolute prediction errors from Models (1) to (4) for a given predicted variable using different estimation procedures. We estimate regression coefficients at the following levels: 1. using all firms with data available in a given year, 2. by industry (two-digit SIC code) and 3. by operating cycle (estimated according to the Dechow, Kothari and Watts (1998) model), where firms are assigned to a quartile based on their estimated operating cycle. For each model, coefficients are estimated separately fiscal quarter by fiscal quarter. Untabulated results show that for a given set of predictor(s) and predicted variable, firm-specific regressions, on average, outperform any of the above cross-sectional models. The differences are statistically significant. Among the cross-sectional models, industry-level estimates are the most accurate ones.

To minimize any implications our time-series requirements might have for the generalizability of our results, we relax our requirements from 56 down to minimum of 16 consecutive observations (in which case we predict data from 2002:2Q to 2006:4Q). In that larger sample, we still find that accruals improve upon cash flow from operations in predicting future cash flows, although their incremental contribution diminishes beyond six quarters of aggregation of the dependent variable. As with the more restricted sample, accruals' contribution to finite cash flow predictions is very modest. In addition, we still find that firm-specific predictions are significantly more accurate than cross-sectional ones.

The results in Tables 3 and 4 suggest that absolute forecast errors are greater when free cash flows are the predicted variable compared to cash flow from operations. We test whether we can improve free cash flow forecasts by replacing current CFO with current free cash flow and accruals with the difference between net income and free cash flow. Untabulated results show that this set of predictors improves upon CFO and accruals in terms of forecast accuracy. It also appears that the difference between net income and free cash flow contributes to greater forecast accuracy for future free cash flow beyond current free cash flow.

## 5. Conclusion

This study investigates the role of earnings components in the prediction of future cash flows. While the FASB emphasizes the role of accrual accounting in helping investors to predict future cash flows, unintentional errors in accounting estimates and earnings manipulation can decrease the usefulness of accruals in predicting future cash flows. Our tests are primarily aimed at addressing this empirical issue, i.e. documenting whether accruals contribute to the prediction of future cash flows incrementally to current cash flow alone, and investigating cross-sectional determinants of accruals' contribution to cash flow predictions.

The key methodological features of our tests are the following: 1. Judgment of the superiority of our different models is based upon out-of-sample criteria, 2. coefficients are estimated at the firm-level, using time-series data and 3. predicted variables are not only finite measures of future cash flows but also market values of equity as a surrogate for the present value of all future cash flows. We use post-SFAS 95 data to measure cash flows directly from the statement of cash flow and we use quarterly data to obtain a sufficient number of observations for our firm-specific estimates. To address seasonality in quarterly accounting data, we use the X11 procedure developed by the U.S. Bureau of Census.

We find that the mean and median contributions of accruals in terms of absolute prediction errors are smaller compared to CFO only when predicting aggregated CFO and free cash flows over one to eight quarters. While the differences are generally statistically significant, their magnitude is small; accruals reduce the median absolute prediction error from CFO alone by no more than 8% of the error. When predicting contemporaneous or next quarter market value of equity as a proxy for all (expected) future cash flows, accruals clearly contribute. Indeed, mean and median absolute prediction errors are smaller by more than 5% of total assets when accruals are included as a predictor. These results show the importance of assessing the predictive ability of accruals for future cash flows by measuring the predicted variable over a sufficient long horizon.

We subsequently investigate what economic attributes of a firm and its financial reports can explain why accruals' contribution to cash flow predictions varies substantially across firm-quarters. We find that the magnitude of discretionary accruals, as measured using the Jones (1991) model, exhibits a significantly negative association with accruals' contribution. We interpret this result as evidence that managerial discretion in reporting estimates in financial statements is detrimental, on average, to the forecasting properties of total accruals. We also find that accruals are more likely to help improve cash flow predictions when they are positive, and when cash flows are volatile.

Finally, we document that portfolios based on out-of-sample predictions of one-quarter-ahead stock return could earn actual quarterly returns higher by about 1% when current accruals are included as a predictor, if formed one day after the filing date of a Form 10-Q or 10-K. This result shows that the improvement in future cash flow prediction accuracy attributable to accruals gives rise to more accurate predictions of stock returns to an economically significant extent.

We perform various robustness checks, such as lowering our time-series requirements, addressing seasonality using more conventional methods in the accounting literature (e.g. using data from quarter t-4 to predict quarter t) and estimating regression coefficients cross-sectionally (e.g. per industry). Our conclusions remain qualitatively unchanged by those alternative research design choices.

Collectively, our results can have implications for investors who use current accounting data for equity valuation purposes. While the ability of accruals to contribute to the prediction of finite measures of cash flows varies with model specifications and levels of aggregations of the dependent variable, it is robust and unequivocally significant when market value of equity is predicted.

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## Appendix A: prior literature matrix

This matrix summarizes the main findings in the empirical literature that assesses the role of earnings components in predicting future cash flows. The entries are based on research design differences among the studies included in the table:

- The first two columns include papers that predict (or investigate the association of earnings components with) finite measures of future cash flows.
- The last two columns include papers that predict (or investigate the association of earnings components with) market values of equity.
- Within each of the two above sets of columns, the first (second) column includes association (prediction) studies.
- The first row includes studies that use cross-sectional regression estimates
- The second row includes studies that use firm-specific regression estimates

| | Finite measure of future cash flows | | Market value of equity | |
|---|---|---|---|---|
| | In-sample goodness of fit | Out-of-sample prediction errors | In-sample goodness of fit | Out-of-sample prediction errors |
| Cross-sectional estimates | Barth, Cram and Nelson (2001): disaggregate earnings do better than cash flow alone and several lags of earnings | - Lev et al. (2005): accruals do not significantly contribute<br>- Kim and Kross (2005): forecast accuracy of earnings increases over time.<br>- Yoder (2007): short-term accruals contribute if independent variables are aggregated over three years. | Barth, Cram and Nelson (2001): disaggregate earnings do better than cash flow alone and several lags of earnings | Barth et al. (2005), using jackknifing procedure: smaller prediction errors with accruals; by-industry significantly outperform pooled regression estimates |
| Firm-specific estimates | Francis and Smith (2005): for most firms, accruals are as persistent as cash flow | - Finger (1994): annual earnings no better predictor of annual future cash flows (t+1 to t+8) than cash flow alone.<br>- Lorek and Willinger (1996): quarterly multivariate model using levels of working capital accounts does best in predicting future cash flows.<br>**- OUR STUDY** | | **OUR STUDY** |

## Appendix B: the X11 procedure

In this appendix, we provide a brief description of the X11 procedure, which we use in this paper to undo the seasonality in quarterly accounting data. This appendix is necessarily brief and superficial, since going into details would require a prohibitively long description.[13] We are unaware of previous studies in accounting that use X11. There is a considerable amount of research in economics on how to adjust for seasonality, including on X11. To implement X11, we rely on the built-in procedure from the SAS statistical software.

The X11 procedure was first developed by the US Bureau of Census in 1953. It is based on the "ratio to moving average" procedure described by Macaulay (1931). It consists of the following key steps:

1) Estimate the trend component ($T_t$) of the time-series by a moving average.
2) Remove the trend, leaving the seasonal ($S_t$) and irregular ($I_t$) components.
3) Estimate the seasonal component by moving averages to smooth out irregulars.

A good estimate of the trend requires prior seasonal adjustment, but seasonality is generally impossible to identify without knowing the trend (Shiskin, 1958). To circumvent this issue, X11 is based on an iterative process. Although the default model is a multiplicative one, we use an additive process to seasonally-adjust all but one of our variables (depreciation and amortization). The additive process is used when the magnitude of the seasonal and irregular components do not change with the level of the trend. The observed time-series data ($O_t$) is thus decomposed as follows: $O_t = T_t + S_t + I_t$

[13] Details can be found at the US Census Bureau website (http://www.census.gov/ts/TSMS/KarenH/X-11BookSummary.pdf). See also Ladiray and Quenneville (2001).

The outline of the iterative process is the following (adapted from Wallis 1982):

(a) Compute the differences between the original series and a centered 4-term moving average, as a first estimate of the seasonal and irregular components ($S_t$ and $I_t$). 2 values at each end of the series are lost.

(b) Apply a weighted 5-term moving average to each quarter separately, to obtain an estimate of the seasonal component ($S_t$). For the next-to-last 4 values use an asymmetric 4-term moving average, and for the last 4 values available use an one-sided 3 term moving average (Shiskin et al., 1967, Appendix B, Table 1B)

(c) Adjust these seasonal components ($S_t$) to sum to zero (approximately) over any 4 quarter period by subtracting a centered 4-term moving average from them. To obtain the 2 missing values at the end of this average, repeat the last available moving average value 2 times.

(d) Subtract the adjusted seasonal component ($S_t$) from the original series, to give a preliminary seasonally adjusted series ($I_t$+$T_t$). The seasonal component for the last 2 value is missing as a result of step (a): for these last 2 quarters use the estimated seasonal component for the corresponding month of the preceding year.

(e) Apply a 9-, 13- or 23-term Henderson (1916) moving average to the seasonally adjusted series, and subtract the resulting trend-cycle series from original series to give a second estimate of the seasonal and irregular components ($S_t$ and $I_t$).

(f) Apply a weighted 7-term moving average to each quarter separately, to obtain a second estimate of the seasonal component.

(g) Repeat step (c)

(h) Subtract these final estimates of the seasonal component from the original series, giving the seasonally adjusted series ($I_t$+$T_t$).

Unless otherwise stated, our regressions and predictions based on X11-adjusted data use $T_t + I_t$, i.e. they exclude the seasonal component. With quarterly data, the X11 procedure requires a minimum of twelve observations per firm, so our requirement of 56 observations for regression estimates is largely sufficient for the deseasonalization process as well.

To illustrate the effect of X11 on quarterly data, we provide two examples of firms for which we plot the original and deseasonalized time series of quarterly CFO, one apparently subject to seasonality (Figure A), and one without seasonality (Figure B).

We also report in the table below (see variable definitions in Table 1) the correlations between unadjusted and deseasonalized numbers for each of the variables used in the analysis. The results indicate that deseasonalized numbers are highly correlated with the original data, except for depreciation and amortization. “Other” accruals were not deseasonalized, but simply calculated as the difference between deseasonalized aggregate accruals and deseasonalized individual components, i.e. as a residual.

| N=15,694 | Spearman correlation | Pearson correlation |
|---|---|---|
| CFO | 0.861 | 0.966 |
| ACC | 0.745 | 0.907 |
| EARN | 0.939 | 0.990 |
| ΔAR | 0.806 | 0.994 |
| ΔAP | 0.774 | 0.855 |
| ΔINV | 0.833 | 0.946 |
| DEPAMOR | 0.970 | 0.908 |
| OTHER | 0.796 | 0.895 |

**Examples of CFO time-series before and after deseasonalization through the X11-procedure**

Figure A: firm with apparent seasonality in quarterly CFOs (Gvkey: 1239)

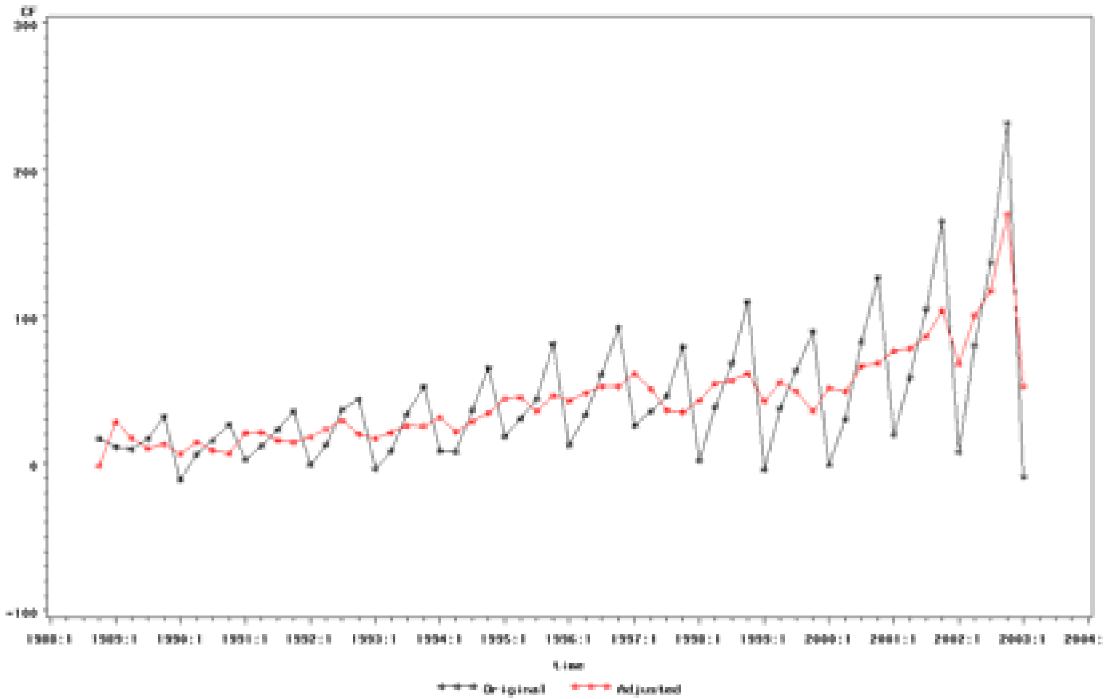
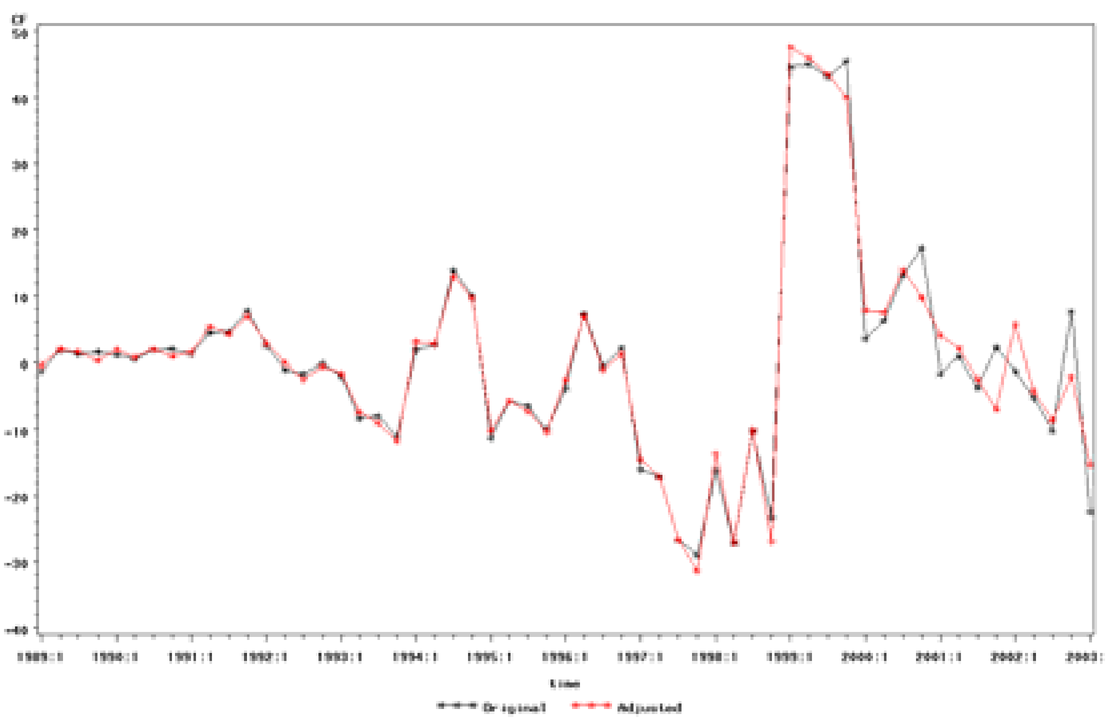



Figure B: firm with no apparent seasonality in quarterly CFOs (Gvkey: 12658)



## Appendix C: The modified Jones (1991) model

We estimate discretionary accruals (DISC_ACC) as the residual from the following firm-specific regression:

$$\frac{\text{ACC}_{\text{t}}}{\text{Total Assets}_{\text{t-1}}} = \alpha \frac{1}{\text{Total Assets}_{\text{t-1}}} + \beta_1 \left( \frac{\Delta\text{REV}_{\text{t}} - \Delta\text{REC}_{\text{t}}}{\text{Total Assets}_{\text{t-1}}} \right) + \beta_2 \frac{PPE_t}{\text{Total Assets}_{\text{t-1}}} + \varepsilon_t$$

ACC is total accruals, defined as income before extraordinary items & discontinued operations (Data8) minus (cash flow from operations (Data108) net of extraordinary items/discontinued operations that affect cash flows (Data78)).
ΔREV is change in Sales (Data2).
ΔREC is Data103 if available. If the data item is not available, we use the change in AR (Data37).
All the variables above are deseasonalized using X11.
PPE is net Property, Plant & Equip, Data42.
DISC_ACC is the residual of the regression, namely,

$$DISC\_ACC_t = \frac{\text{ACC}_{\text{t}}}{\text{Total Assets}_{\text{t-1}}} - \left[ \frac{\hat{\alpha}}{\text{Total Assets}_{\text{t-1}}} + \widehat{\beta_1} \left( \frac{\Delta\ \text{REV}_{\text{t}} - \Delta\text{REC}_{\text{t}}}{\text{Total Assets}_{\text{t-1}}} \right) + \widehat{\beta_2} \frac{PPE_t}{\text{Total Assets}_{\text{t-1}}} \right].$$

## Table 1: descriptive statistics

This table reports summary statistics for variables in the holdout period of the sample, i.e. from the third fiscal quarter in 2002 to the fourth quarter in 2006. The sample includes all firm-quarters preceded by 56 consecutive observations with data available for all variables in the table. Sample size is 16,549 when accruals are aggregated, 12,327 for accrual components, 13,920 for free cash flow and 14,932 for discretionary accruals, non-discretionary accruals, book-to-market, volatility of CFO and seasonality.

| | Mean | Std. Dev. | 25% | Median | 75% |
|---|---|---|---|---|---|
| ASSETS | 5,808 | 28,422 | 156 | 741 | 3,016 |
| MKTCAP | 6,766 | 24,785 | 148 | 744 | 3,344 |
| CFO | 0.0213 | 0.0493 | 0.0074 | 0.0240 | 0.0409 |
| ACC | -0.0129 | 0.0521 | -0.0252 | -0.0115 | 0.0018 |
| EARN | 0.0083 | 0.0467 | 0.0036 | 0.0135 | 0.0243 |
| ΔAR | -0.0076 | 0.0438 | -0.0183 | -0.0041 | 0.0048 |
| ΔAP | 0.0048 | 0.0361 | -0.0085 | 0.0024 | 0.0154 |
| ΔINV | -0.0085 | 0.0307 | -0.0154 | -0.0024 | 0.0014 |
| DEPAMOR | 0.0287 | 0.0178 | 0.0176 | 0.0253 | 0.0362 |
| OTHER | 0.0375 | 0.0948 | 0.0045 | 0.0294 | 0.0662 |
| FCF | 0.0071 | 0.0467 | -0.0009 | 0.0132 | 0.0254 |
| ABS_DISC_ACC | 0.0202 | 0.0321 | 0.0050 | 0.0115 | 0.0237 |
| ABS_NONDISC_ACC | 0.0145 | 0.0147 | 0.0062 | 0.0113 | 0.0183 |
| SEASONALITY | 0.0004 | 0.0269 | -0.0077 | 0.0000 | 0.0091 |
| CFO_VOLATILITY | 0.0232 | 0.0187 | 0.0114 | 0.0180 | 0.0287 |
| BOOK-TO-MARKET | 0.5650 | 0.5175 | 0.2977 | 0.4667 | 0.7104 |

Variable definitions with Compustat Quarterly data item numbers (all variables are scaled by ASSETS, except ASSETS and MKTCAP, which are expressed in million dollars):
ASSETS: total assets (Data44) as of the beginning of the quarter.
MKTCAP: market value of equity as of the end of the fiscal quarter (from CRSP, Price × Shares outstanding at the end of fiscal quarter)
CFO: cash flow from operations (Data108).
EARN: income before extraordinary items & discontinued operations (Data8).
ACC: EARN minus (CFO - extraordinary items/discontinued operations that affect cash flows (Data78)).
ΔAR: change in accounts receivable from previous quarter (Data103 if available, ΔData37 otherwise).
ΔINV: change in inventories from previous quarter (Data104 if available, ΔData38 otherwise).
ΔAP: change in accounts payable from previous quarter (Data105 if available, ΔData46 otherwise).
DEPAMOR: depreciation and amortization (Data77).
OTHER: ACC – (ΔAR + ΔINV – ΔAP – DEPAMOR).
FCF: EARN (Data8) – (1-δ) × (Capital expenditure (Data90) – Depreciation (Data77)) – (1- δ) × Δ Working Capital, where Working capital = (Current Assets (Data40) – Current Liabilities (Data49)) and δ is Debt (Debt in Current liabilities, Data45+ Long term Debt, Data51) to total assets (Data44) ratio.
ABS_DISC_ACC: Absolute value of discretionary accruals, as measured using the modified Jones (1991) model, estimated on a firm-specific basis, see Appendix C.
ABS_NONDISC_ACC: absolute value of non-discretionary accruals. Non-discretionary accruals are the difference between total accruals and discretionary accruals.
SEASONALITY: difference between total cash flow from operations and deseasonalized cash flow from operations.
CFO_VOLATILITY: Standard deviation of quarterly deseasonalized cash flow from operations from t-16 to t-1.
BOOK-TO-MARKET: ratio of book value (Data59) of equity to market value of equity, as of the beginning of the fiscal quarter.

**Table 2: Summary of firm-specific regression results**

This table reports summary statistics for coefficients in firm-specific regressions of one-quarter ahead cash flow from operations and market capitalization. The coefficients are estimated using 56 consecutive quarterly observations over rolling windows, starting from the first fiscal quarter of 1987.

| | Dependent variable: $CFO_{t+1}$ | | | | | Dependent variable: $MKTCAP_{t+1}$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Q1 | Median | Q3 | Mean | Std. Dev. | Q1 | Median | Q3 |
| *Model 1 (N=16,549)* | | | | | | | | | | |
| Intercept | 0.0190 | 0.0189 | 0.0112 | 0.0191 | 0.0282 | 1.3273 | 1.3952 | 0.5846 | 0.9361 | 1.5448 |
| CFO | 0.1842 | 0.2691 | -0.0111 | 0.1664 | 0.3687 | 6.4588 | 14.3054 | 0.1253 | 2.6518 | 9.0134 |
| $R^2$ | 8.09% | 13.54% | -0.95% | 2.38% | 11.73% | 6.89% | 11.61% | -0.99% | 2.08% | 10.06% |
| *Model 2 (N=16,549)* | | | | | | | | | | |
| Intercept | 0.0174 | 0.0166 | 0.0099 | 0.0172 | 0.0260 | 0.9976 | 1.3515 | 0.4204 | 0.6955 | 1.2063 |
| CFO | 0.3644 | 0.4968 | 0.1021 | 0.3895 | 0.6421 | 23.6222 | 32.2929 | 5.7757 | 15.7165 | 31.8475 |
| ACC | 0.2664 | 0.4872 | 0.0263 | 0.2186 | 0.5101 | 20.8262 | 30.9259 | 4.2215 | 12.3207 | 27.7030 |
| $R^2$ | 12.69% | 16.53% | 0.57% | 6.96% | 19.61% | 25.55% | 20.70% | 8.59% | 21.74% | 39.55% |
| *Model 3 (N=16,549)* | | | | | | | | | | |
| Intercept | 0.0190 | 0.0182 | 0.0121 | 0.0199 | 0.0281 | 1.0888 | 1.3758 | 0.4650 | 0.7597 | 1.3276 |
| EARN | 0.3017 | 0.5014 | 0.0470 | 0.2709 | 0.5610 | 21.9380 | 30.9702 | 4.8272 | 13.2813 | 29.4849 |
| $R^2$ | 8.94% | 14.44% | -0.77% | 2.84% | 12.90% | 23.32% | 20.41% | 6.18% | 18.55% | 36.74% |
| *Model 4 (N=12,327)* | | | | | | | | | | |
| Intercept | 0.0094 | 0.0365 | -0.0064 | 0.0094 | 0.0261 | 0.9106 | 1.9176 | 0.1726 | 0.7265 | 1.4453 |
| CFO | 0.3355 | 1.0693 | 0.0209 | 0.3375 | 0.6165 | 21.8475 | 31.5010 | 4.7697 | 13.2081 | 28.5958 |
| $\Delta$AR | 0.1908 | 1.3548 | -0.1882 | 0.1341 | 0.5226 | 16.9327 | 36.6139 | 0.7616 | 8.3110 | 22.8994 |
| $\Delta$INV | 0.4567 | 4.9156 | -0.0632 | 0.2391 | 0.6400 | 13.0609 | 156.3166 | 0.3436 | 8.4391 | 23.8046 |
| $\Delta$AP | -0.4567 | 1.8547 | -0.7136 | -0.3526 | -0.0846 | -17.9243 | 31.7867 | -25.0108 | -9.9917 | -2.7853 |
| DEPAMOR | 0.0264 | 1.7794 | -0.5426 | -0.0094 | 0.5710 | -18.6138 | 73.7745 | -38.0973 | -13.7426 | 2.6167 |
| OTHER | 0.2832 | 1.0822 | -0.0104 | 0.2205 | 0.5270 | 19.0486 | 30.6056 | 3.0924 | 10.2049 | 24.3896 |
| $R^2$ | 19.20% | 17.78% | 5.67% | 15.65% | 29.39% | 37.86% | 20.87% | 21.61% | 37.51% | 53.49% |

See Table 1 for variable definitions.

## Table 3: firm-specific absolute prediction errors

This table reports mean and median absolute prediction errors (ABSE) where cash flow from operations (CFO), free cash flow (FCF) and market capitalization (MKTCAP) as of the beginning and the end of fiscal quarter t+1 are predicted, using firm-specific regressions based on three sets of predictors (deseasonalized using the X11 procedure described in Appendix B): current CFO ($ABSE_1$), current CFO and accruals ($ABSE_2$), current earnings ($ABSE_3$). The columns labeled "Accruals contribution" report the mean and median improvement in prediction from accruals by comparing absolute prediction errors from CFO versus CFO and accruals at the firm-quarter level. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization. Results are expressed as a percentage of total assets.

| | Means | | | | Medians | | | |
|---|---|---|---|---|---|---|---|---|
| | CFO ($ABSE_1$) | CFO & ACC ($ABSE_2$) | EARN ($ABSE_3$) | Accruals contribution | CFO ($ABSE_1$) | CFO & ACC ($ABSE_2$) | EARN ($ABSE_3$) | Accruals contribution |
| $CFO_{t+1}$ | 2.19 | 2.16 | 2.18 | 0.03* | 1.34 | 1.29* | 1.31 | 0.01* |
| $CFO_{t+1,t+2}$ | 1.69 | 1.64† | 1.67 | 0.05* | 1.05 | 1.01* | 1.04 | 0.01* |
| $CFO_{t+1,t+4}$ | 1.36 | 1.30‡ | 1.34 | 0.06* | 0.88 | 0.82* | 0.86 | 0.01* |
| $CFO_{t+1,t+8}$ | 1.13 | 1.08† | 1.10 | 0.05* | 0.74 | 0.69* | 0.71 | 0.01* |
| $FCF_{t+1}$ | 2.07 | 2.00 | 1.99 | 0.06† | 1.14 | 1.08* | 1.08 | 0.01* |
| $FCF_{t+1,t+2}$ | 1.93 | 1.89 | 1.89 | 0.04‡ | 1.09 | 1.04* | 1.04 | 0.01* |
| $FCF_{t+1,t+4}$ | 1.76 | 1.64 | 1.66 | 0.13* | 1.01 | 0.96‡ | 0.99 | 0.01* |
| $FCF_{t+1,t+8}$ | 1.74 | 1.52‡ | 1.52 | 0.22* | 0.91 | 0.89‡ | 0.90 | 0.01* |
| $MKTCAP_t$ | 59.63 | 54.00* | 53.35 | 6.67* | 31.93 | 26.52* | 26.90 | 2.19* |
| $MKTCAP_{t+1}$ | 65.52 | 59.89* | 59.62 | 6.55* | 33.50 | 27.74* | 27.88 | 2.30* |

*,‡,† indicate significance at the 0.01, 0.05, 0.10 two-tailed levels respectively. A significance indicator next to $ABSE_1$ ($ABSE_2$) means that mean or median $ABSE_1$ is significantly lower (greater) than $ABSE_2$. A significance indicator next to a mean or median "accruals' contribution" means that it is significantly different from zero.

$CFO(FCF)_{t+1,t+n}$: average cash flow from operations (free cash flow to equity) from quarter t+1 to t+n, scaled by total assets at t+n-1. Free cash flow to equity is defined as net income – (1- δ) × (Capital expenditure (Data90) – Depreciation (Data77)) – (1- δ) × Δ Working Capital, where Working capital = (Current Assets (Data40) – Current Liabilities (Data49)) and d is Debt (Debt in Current liabilities, Data45+ Long term Debt, Data51) to total assets (Data44) ratio.

$MKTCAP_t(_{t+1})$: market capitalization as of the beginning (end) of fiscal quarter t+1, scaled by total assets.

## Table 4: firm-specific absolute prediction errors with accrual components

This table reports mean and median absolute prediction errors (ABSE) where cash flow from operations (CFO), free cash flow (FCF), and market capitalization (MKTCAP) are predicted, using firm-specific regressions based on four sets of predictors (deseasonalized using the X11 procedure described in Appendix B): current CFO ($ABSE_1$), current CFO and accruals ($ABSE_2$), current earnings ($ABSE_3$), current CFO and individual components of accruals ($ABSE_4$). The columns labeled "Accruals contribution" report the mean and median improvement in prediction from accruals by comparing absolute prediction errors from CFO versus CFO and accruals at the firm-quarter level. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization. Results are expressed as a percentage of total assets.

| | Means | | | | Medians | | | |
|---|---|---|---|---|---|---|---|---|
| | CFO ($ABSE_1$) | CFO & ACC ($ABSE_2$) | EARN ($ABSE_3$) | CFO & ACCS ($ABSE_4$) | CFO ($ABSE_1$) | CFO & ACC ($ABSE_2$) | EARN ($ABSE_3$) | CFO & ACCS ($ABSE_4$) |
| $CFO_{t+1}$ | 2.12 | 2.08 | 2.11 | 2.21 | 1.33 | 1.28* | 1.31 | 1.33 |
| $CFO_{t+1,t+2}$ | 1.64 | 1.59† | 1.62 | 1.65 | 1.04 | 1.00* | 1.02 | 1.02 |
| $CFO_{t+1,t+4}$ | 1.31 | 1.25‡ | 1.28 | 1.26 | 0.86 | 0.80* | 0.84 | 0.79 |
| $CFO_{t+1,t+8}$ | 1.10 | 1.04† | 1.06 | 1.00 | 0.73 | 0.66* | 0.68 | 0.63 |
| $FCF_{t+1}$ | 2.06 | 1.99 | 2.01 | 2.10 | 1.13 | 1.07* | 1.07 | 1.09 |
| $FCF_{t+1,t+2}$ | 1.89 | 1.79† | 1.80 | 1.82 | 1.10 | 1.05* | 1.05 | 1.09 |
| $FCF_{t+1,t+4}$ | 1.73 | 1.62‡ | 1.64 | 1.65 | 1.02 | 0.96* | 0.98 | 0.98 |
| $FCF_{t+1,t+8}$ | 1.71 | 1.49‡ | 1.52 | 1.55 | 0.90 | 0.88* | 0.90 | 0.89 |
| $MKTCAP_t$ | 57.13 | 51.25* | 53.35 | 49.68 | 31.93 | 26.52* | 26.90 | 24.72 |
| $MKTCAP_{t+1}$ | 62.43 | 56.13* | 59.62 | 54.92 | 33.50 | 27.74* | 27.88 | 25.94 |

*,‡,† indicate significance at the 0.01, 0.05, 0.10 two-tailed levels respectively. A significance indicator next to $ABSE_1$ ($ABSE_2$) means that mean or median $ABSE_1$ is significantly lower (greater) than $ABSE_2$.

$CFO(FCF)_{t+1,t+n}$: average cash flow from operations (free cash flow to equity) from quarter t+1 to t+n, scaled by total assets at t+n-1. Free cash flow to equity is defined as net income – (1- δ) × (Capital expenditure (Data90) – Depreciation (Data77)) – (1- δ) × Δ Working Capital, where Working capital = (Current Assets (Data40) – Current Liabilities (Data49)) and δ is Debt (Debt in Current liabilities, Data45+ Long term Debt, Data51) to total assets (Data44) ratio.

$MKTCAP_t(_{t+1})$: market capitalization as of the beginning (end) of fiscal quarter t+1, scaled by total assets.

## Table 5: Multivariate analysis of accruals' contribution to cash flow predictions

This table reports regression results where the dependent variable is the difference between the absolute prediction errors for measures of future cash flows based on (1) CFO and accruals and (2) CFO only; the higher this measure, the more accruals improve upon CFO in predicting future cash flows. Coefficients on industry and time fixed-effects are omitted. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization. All regressions include two-digit SIC and fiscal quarter fixed effects.

| Dependent variable is Accruals' contribution for the prediction of | $CFO_{t+1}$ Coefficients *(t-statistics)* | $CFO_{t+1,t+4}$ Coefficients *(t-statistics)* | $MktCap_t$ Coefficients *(t-statistics)* |
|---|---|---|---|
| INTERCEPT | -0.002 | 0.002 | 0.234* |
| | *(0.83)* | *(1.09)* | *(1.65)* |
| FOURTH_QUARTER | 0.001 | | |
| | *(1.08)* | | |
| ABS_DISC_ACC | -0.065*** | -0.064*** | -3.519*** |
| | *(3.79)* | *(4.06)* | *(4.52)* |
| ABS_NONDISC_ACC | 0.033** | 0.000 | -0.814 |
| | *(2.30)* | *(0.00)* | *(1.38)* |
| SIGN_ACC | 0.001*** | 0.001** | 0.026** |
| | *(3.03)* | *(2.38)* | *(2.44)* |
| SEASONALITY | -0.007 | 0.004 | 0.621** |
| | *(0.96)* | *(0.77)* | *(2.25)* |
| CFO_VOLATILITY | 0.036*** | 0.032*** | 1.816*** |
| | *(3.12)* | *(3.09)* | *(3.80)* |
| FIRM SIZE | 0.000 | 0.000*** | -0.002 |
| | *(1.34)* | *(3.78)* | *(0.59)* |
| BOOK-TO-MARKET | -0.001*** | -0.001** | -0.039*** |
| | *(2.75)* | *(2.08)* | *(2.74)* |
| N | 14,932 | 11,663 | 14,932 |
| Adj. $R^2$ | 2.55% | 3.31% | 3.91% |

*,**,*** indicate significance at the 0.10, 0.05, 0.01 two-tailed levels respectively.

Variable definitions:

FOURTH_QUARTER: Indicator variable equal to one if the dependent variable is measured over the fourth fiscal quarter, zero otherwise.

ABS_DISC_ACC: Absolute value of discretionary accruals, as measured using the modified Jones (1991) model, estimated on a firm-specific basis.

ABS_NONDISC_ACC: absolute value of non-discretionary accruals. Non-discretionary accruals are the difference between total accruals and discretionary accruals.

SIGN_ACC: indicator variable equal to one if total deseasonalized accruals are strictly positive, zero otherwise.

SEASONALITY: difference between total cash flow from operations and deseasonalized cash flow from operations.

CFO_VOLATILITY: Standard deviation of quarterly deseasonalized cash flow from operations from t-16 to t-1.

FIRM SIZE: natural logarithm of market capitalization as of the beginning of the fiscal quarter.

BOOK-TO-MARKET: ratio of book value of equity to market value of equity, as of the beginning of the fiscal quarter.

The independent variables are winsorized at 1% and 99% level.

## Table 6: Returns on hedge portfolios based on future market capitalization predictions

This table reports mean equal-weighted 90-day stock returns for portfolios going long on the highest quintile and short on the lowest quintile of the distribution of future return prediction. Portfolios are rebalanced every fiscal quarter, either as of the first day of the quarter, or on the filing date of the Form 10-K or 10-Q. We compute predicted quarterly stock returns using contemporaneous market capitalization and out-of-sample predictions of one-quarter-ahead market capitalization (plus dividends), both divided by shares outstanding at the end of quarter t, with three sets of predictors: CFO only, CFO and aggregate accruals, aggregate earnings, all deseasonalized using the X11 procedure. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization. In Panel A (B), the results are based on raw (size-adjusted) returns.

Panel A: Raw returns

| | CFO<br>(1) | CFO & accruals<br>(2) | Earnings<br>(3) | (2) – (1) | *p-value for (2) – (1)* |
|---|---|---|---|---|---|
| 90 days from fiscal quarter beginning | 6.34% | 8.58% | 8.19% | 2.24% | *0.01* |
| 90 days from 10-K/Q filing date | 4.56% | 5.72% | 5.25% | 1.16% | *0.06* |
| 180 days from 10-K/Q filing date | 9.18% | 10.83% | 10.06% | 1.66% | *0.09* |
| 270 days from 10-K/Q filing date | 12.70% | 14.31% | 13.37% | 1.61% | *0.07* |
| 365 days from 10-K/Q filing date | 16.63% | 17.33% | 17.24% | 0.70% | *0.29* |

Panel B: Size-adjusted returns

| | CFO<br>(1) | CFO & accruals<br>(2) | Earnings<br>(3) | (2) – (1) | p-value for (2) – (1) |
|---|---|---|---|---|---|
| 90 days from fiscal quarter beginning | 5.89% | 8.83% | 8.07% | 2.94% | *<.01* |
| 90 days from 10-K/Q filing date | 2.94% | 3.75% | 3.14% | 0.82% | *0.04* |
| 180 days from 10-K/Q filing date | 5.05% | 6.34% | 5.09% | 1.29% | *0.02* |
| 270 days from 10-K/Q filing date | 6.92% | 9.11% | 7.27% | 2.19% | *0.03* |
| 365 days from 10-K/Q filing date | 8.25% | 10.87% | 9.47% | 2.62% | *0.32* |

**Figure 1: Mean firm-specific regression coefficients on the cash flow and accrual components of earnings for different levels of aggregation of future cash flows as the dependent variable**

This figure plots mean firm-specific regression coefficients on current cash flow from operations (CFO) and accruals (ACC) where the dependent variable is future CFO. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization. The horizontal axis represents the level of aggregation of the dependent variable, from one to eight quarters.

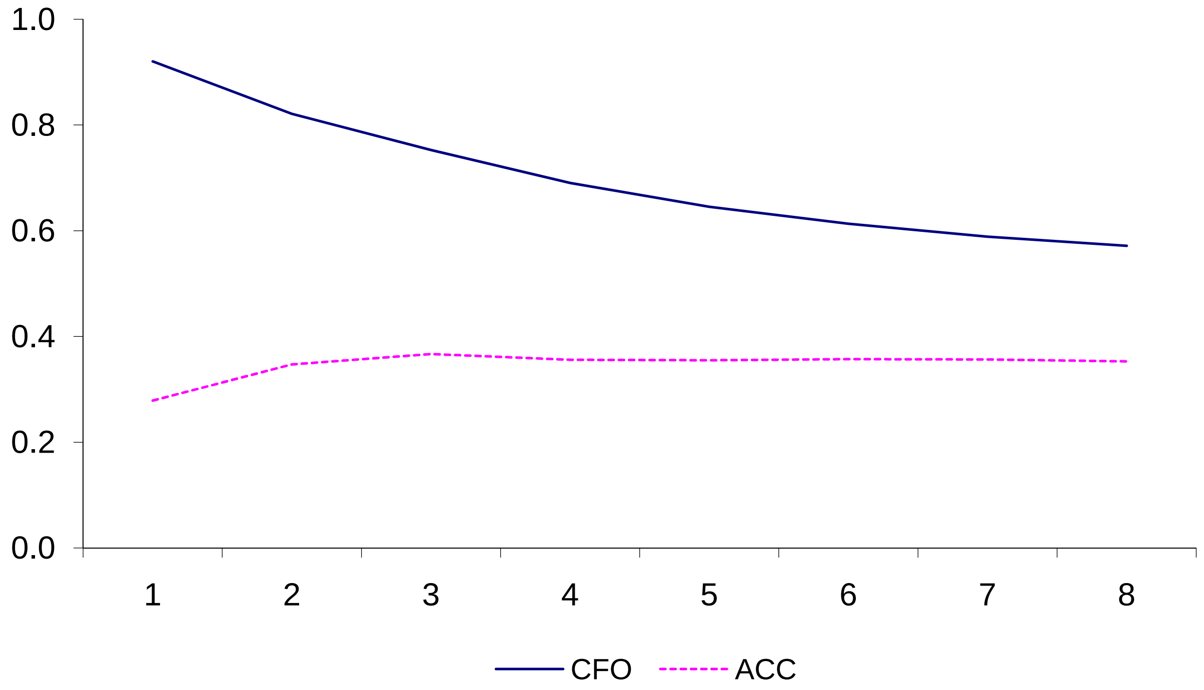


**Figure 2: incremental contribution of accruals beyond current CFO in predicting future CFO as a function of the level of aggregation of future CFO**

This figure plots the incremental contribution of accruals to the prediction of future cash flows from operations (CFO) compared to current CFO alone. It is measured by ($ABSE_1$ – $ABSE_2$) / $ABSE_1$ where $ABSE_1$ ($ABSE_2$) is the mean or median firm-specific absolute prediction error when current CFO (current CFO and accruals) is the predictor. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization. The horizontal axis represents the number of quarters of future CFO aggregated. Contributions at the mean and median level are plotted separately.

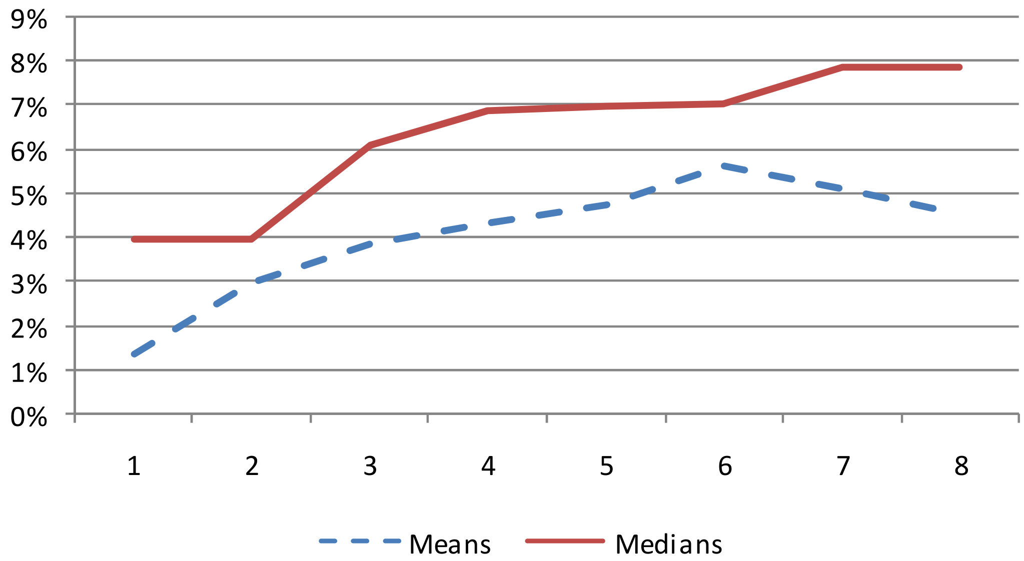


**Figure 3: Returns on hedge portfolios based on future market capitalization predictions**

This figure plots differences in hedge portfolio returns between a portfolio based on returns predicted by (a) cash flow from operations and accruals and (b) cash flow from operations only. We compute predicted quarterly stock returns using contemporaneous market capitalization and out-of-sample predictions of one-quarter-ahead market capitalization (plus dividends), both divided by shares outstanding at the end of quarter t. The hedge returns are mean equal-weighted 90-day stock returns for portfolios going long on the highest quintile and short on the lowest quintile of the distribution of future return prediction. Portfolios are rebalanced every fiscal quarter, as of the filing date of the most recent Form 10-K or 10-Q. The returns are plotted fiscal quarter by fiscal quarter. The sample includes all firm-quarters from the third quarter of 2002 to the fourth quarter of 2006 preceded by 56 consecutive observations available for CFO, accruals, and market capitalization.